KIT
Knowledge, Innovation, Territory

Applied Research 2013/1/13

Final Scientific Report – Volume 1
Version 13/11/2012

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

This report presents the final results of an Applied Research Project conducted within the framework of the ESPON 2013 Programme, partly financed by the European Regional Development Fund.

The partnership behind the ESPON Programme consists of the EU Commission and the Member States of the EU27, plus Iceland, Liechtenstein, Norway and Switzerland. Each partner is represented in the ESPON Monitoring Committee.

Information on the ESPON Programme and projects can be found on www.espon.eu

The web site provides the possibility to download and examine the most recent documents produced by finalised and ongoing ESPON projects.

This basic report exists only in an electronic version.

List of authors

BEST – Politecnico di Milano, LP

Prof. Roberta Capello (Project scientific coordinator)
Prof. Roberto Camagni
Dr. Camilla Lenzi (Project manager)
Dr. Andrea Caragliu

CRENOS – University of Cagliari, P2

Prof. Raffaele Paci
Prof. Emanuela Marrocu
Prof. Stefano Usai
Dr. Alessandra Colombelli
Dr. Marta Foddi

AQR – University of Barcelona, P3

Prof. Rosina Moreno
Prof. Jordi Suriñach
Prof. Raúl Ramos
Dr. Ernest Miguélez

London School of Economics, P4

Dr. Riccardo Crescenzi
Prof. Andrés Rodríguez-Pose
Prof. Michael Storper

University of Economics in Bratislava, P5

Prof. Milan Buček
Dr. Miroslav Šipikal
Dr. Rudolf Pástor

Cardiff University, P6

Prof. Phil Cooke
Dr. Selyf Morgan
Julie Porter

Table of contents

List of figures

List of maps

List of tables

List of annexes

Chapter 1. The Community Innovation Survey (CIS)[1]

1. A methodological note

1.1. The Community Innovation Survey

The Community Innovation Survey (CIS) is a survey designed to obtain information on innovation activities within enterprises, as well as various aspects of the process such as the effects of innovation, sources of information used, costs etc.

Data are collected on a four-yearly basis.

The first CIS (CIS1) was a pilot exercise, held in 1993 while the second survey (CIS2) was carried out in 1997/1998, except Greece and Ireland where it was launched in 1999.

The third survey (CIS3) was implemented in 2000/2001 in most of the participating countries.

The CIS4 was launched in 2005, based on the reference period 2004, with the observation period 2002 to 2004.

The fifth survey CIS 2006 was launched in 2007, based on the reference period 2006, with the observation period 2004 to 2006.

The last survey CIS 2008 was launched in 2009, based on the reference period 2008, with the observation period 2006 to 2008.

CIS covers EU Member States, EU Candidate Countries, Iceland and Norway.

Country coverage however differs in the different waves.

CIS3 was run in the 25 EU Member States, Candidate Countries, Iceland and Norway.

CIS4 was run in the 27 EU Member States, Candidate Countries, Iceland and Norway.

CIS2006 and CIS2008 were run in the 27 EU Member States, Candidate Countries, and Norway.

However, participating countries are free not to release some information which thus might appear as confidential in EUROSTAT database and are not available (e.g. some UK and Iceland data for CIS4).

EUROSTAT in fact reports that confidentiality of CIS data is flagged by Member States.

In order to ensure comparability across countries, EUROSTAT, in close cooperation with the EU Member States, developed a standard core questionnaire starting with CIS3 data collection, with an accompanying set of definitions and methodological recommendations. The responsibility for the survey at a national level is in most cases, with the National Statistical Office or a national Ministry. EUROSTAT collects aggregated data and micro-data from countries.

Still, problems of comparability across waves represent a rather pressing issue. Different waves may in fact have different sectoral coverage. For example, CIS3 has a different sectoral coverage from CIS4 and CIS2006; also, CIS2008 uses NACE Rev.2 classification of economic activities, whereas previous waves were based on NACE Rev.1.1 classification of economic activities. This limits the scope of comparisons across waves to the comparison between CIS4 and CIS2006.

The CIS is designed to obtain information on innovation activities within enterprises with 10 or more employees. Enterprises are classified by type of innovation activity according to the following definitions.

Innovation: an innovation is a new or significantly improved product (good or service) introduced to the market or the introduction within an enterprise of a new or significantly improved process. Innovations are based on the results of new technological developments, new combinations of existing technology or the utilisation of other knowledge acquired by the enterprise. Innovations may be developed by the innovating enterprise or by another enterprise. However, purely selling innovations wholly produced and developed by other enterprises is not included as an innovation activity. Innovations should be new to the enterprise concerned. For product innovations they do not necessarily have to be new to the market and for process innovations the enterprise does not necessarily have to be the first one to have introduced the process.

Product innovators: introduced new and significantly improved goods and/or services with respect to their fundamental characteristics, technical specifications, incorporated software or other immaterial components, intended uses, or user friendliness. Changes of a solely aesthetic nature and the pure sale of product innovations wholly produced and developed by other enterprises are not included.

[1] [1] This chapter has been written by Roberta Capello, Andrea Caragliu and Camilla Lenzi, BEST – Politecnico di Milano.

Process innovators: implemented new and significantly improved production technologies or new and significantly improved methods of supplying services and delivering products. The outcome of such innovations should be significant with respect to the level of output, quality of products (goods or services) or costs of production and distribution. Purely organisational or managerial changes are not included.
More in details, EUROSTAT makes available the data on firms that introduce **only product innovation**, firms that introduce **only process innovation**, firms that introduce **both product & process innovation**. This sharper distinction is in our option better suited to fully acknowledge the different set of capabilities necessary to complete and introduce into the market these different types of innovation. In our estimation strategy, thus, we will make use of this information.
It is important to clarify that only product innovators represent a sub-sample of product innovators, namely those that introduce product innovation without introducing process innovations. On parallel, only process innovators represent a sub-sample of process innovators, namely those that introduce process innovation without introducing product innovations. The following table clarifies this distinction. The third category is composed of innovators that introduce both product and process innovations. The three categories together represent the largest group of innovators, those that introduce product and/or process innovations (indicated in yellow in the table reported below)[2].

Table 1.1. Definition of product innovation and process innovation

		PRODUCT INNOVATORS	
		Yes	**No**
PROCESS INNOVATORS	**Yes**	PRODUCT & PROCESS INNOVATORS	ONLY PROCESS INNOVATORS
	No	ONLY PRODUCT INNOVATORS	----

The last category of innovators is composed of those firms that introduce **marketing and/or organizational** (i.e. non-technological) innovation to one of their markets and aims at better capturing innovation processes in services. Marketing innovation is defined as the introduction of 'Significant changes to the design or packaging of a good or service" or "New or significantly changed sales or distribution methods, such as internet sales, franchising, direct sales or distribution licenses". An organisational innovation is defined as the introduction of either "New or significantly improved knowledge management systems to better use or exchange information, knowledge and skills within your enterprise", "A major change to the organisation of work within your enterprise, such as changes in the management structure or integrating different departments or activities" or "New or significant changes in your relations with other firms or public institutions, such as through alliances, partnerships, outsourcing or sub-contracting.
Unfortunately, EUROSTAT provides data at NUTS0 level only (and only for those participating countries allowing for data release) and there are limited official sources of CIS data at the regional level (NUTS2 or NUTS1).
Some regional data may come from some National Statistical Offices. This is the case of Italy, Romania, Czech Republic, UK.
Unfortunately, however, the information coming from these sources are not consistent and directly comparable. In fact, the types of innovation covered may differ and the weighting procedure are not necessarily harmonized or still awaiting for approval by EUROSTAT.
For instance, UK provides information on Product innovators and Process innovators whereas Italy provides information on Only Product innovators only and Only Process innovation
This seriously hampers the opportunity to use these data in a comparative perspective.

Regional data are also available from the Annex to the Methodology Report of the Regional Innovation Scoreboard (RIS) but only for the largest category of innovators, i.e. product and/or process innovators, and for a selected group of countries, whereas the data for the others are estimated and not released.

[2] This distinction makes further complex the comparability of CIS NUTS2 data coming from National Statistical Offices. In fact, some countries, as it will be discussed more in details below, make CIS NUTS2 data publicly available, but unfortunately, they refer to different categories of innovators, which eventually prevents their use in a comparative perspective.

Table 1.2 lists European countries participating to CIS4 according to the NUTS level of data availability, as reported in RIS Methodology Report (2009).

Table 1.2. European countries participating to CIS4

NUTS0	CY, DE, DK, EE, IE, LT, LU, LV, MT, NL, SE
NUTS1	AT, BE, BG, FR, UK
NUTS2	CZ, ES, FI, HU, GR, IT, NO, PL, PT, RO, SI, SK

1.2. NUTS2 data estimation methodology

We estimate regional data (i.e. NUTS2 level) starting from the national data (i.e. NUTS0 level) available from EUROSTAT in order to ensure comparability across countries. To do so we used weights to redistribute the NUTS0 data at NUTS2 level. At present, we concentrated our efforts on CIS4 wave only.

Firstly, we estimated the regional respondents sample. We redistributed the NUTS0 value according to the regional employment share.

Next, we estimated the regional sample of only product innovators, only process innovators, product and process innovators, and marketing and/or organizational innovators. To this end, we used different weights according to the different types of innovations. All weights are computed as regional share of national values of the selected variables. The weights aim at capturing both a functional as well as a sectoral dimension. The former is captured by looking at the share of professions, the latter by looking at the sectoral specialization. In absence of any a priori assumption on different relevance of the functional vs the sectoral dimension, we attributed equal importance to the selected weights.

Table 1.3 shows the selected weights.

Table 1.3: Selected weights

TYPE of INNOVATION	Weights
Only PRODUCT	% scientists, % employment in high-tech (DL)
Only PROCESS	% employment in manufacturing, % technicians, % managers
PRODUCT & PROCESS	% scientists, % employment in high-tech (DL), % employment in manufacturing, % technicians, % managers
Marketing &/or organisational	% managers, % employment in services

The choice of the weights is based on logical expectations.

Product innovation is expected to take place at a greater extent in regions characterised by a larger endowment of advanced high-tech sectors, such as electrical and electronic equipment manufacturing (share of employment in the sector DL according to Nace Rev.1.1 classification), and advanced functions such as R&D (i.e. share of scientists). The definition used of high-tech sectors is restricted to advanced manufacturing sectors, since these are the sectors that are expected to generate product innovation. Sectors that can deploy product innovation are left aside.

Process innovation is expected to take place at a greater extent in regions characterised by a larger endowment of manufacturing sectors in which new production technologies or methods for producing goods can be introduced (share of employment in manufacturing) and a larger share of functions deeply involved into the production process implementation and monitoring (i.e. share of technicians and managers).

Product and process innovation is expected to take place at a greater extent in regions characterised by both a larger endowment of advanced high-tech sectors, such as electrical and electronic equipment manufacturing (share of employment in the sector DL according to Nace Rev.1.1 classification), and advanced functions such as R&D (i.e. share of scientists) as well as a larger endowment of manufacturing sectors in which new production technologies or methods for producing goods can be introduced (share of employment in manufacturing) and a larger share of functions deeply involved into the production process implementation and monitoring (i.e. share of technicians and managers).

Marketing and/or managerial innovation is expected to take place at a greater extent in regions characterised by a larger endowment of the service sector (share of employment in services), and a larger share of managerial functions (i.e. share of managers).

1.3. Robustness of the estimates

To check the robustness of our estimates we implemented a series of benchmark exercises. In detail, we implemented three types of tests, namely on the equality of means, on the equality of standard deviation, and of Kolmogorof-Smirnoff, to assess whether our estimates diverge from the original sample distribution.

We performed two sets of comparisons.

First, we compared our estimates of the share of only product innovators, the share of only process innovators and the share of product and process innovators with regional data from National Statistical Offices. These latter have been rescaled at the National value available from EUROSTAT, since the National figures available from EUROSTAT and National Statistical Offices may differ according to different strata weighting procedures. The tests could be implemented only on limited set of countries, namely Italy, Romania and Czech Republic that publicly release these data on their websites.

Next, to support further our estimates, we made use of data on product and/or process innovators from RIS. In particular, we compared our estimates of product and/or process innovators, obtained as sum of the first three categories of innovators (i.e. only product innovators, only process innovators, product and process innovators), with RIS data. The tests could be implemented only on those countries whose data are available in the annex to the RIS methodology report.

Still, some problems of comparability remain. For example, the France NUTS0 data available from RIS on the share of product and/or process innovators is different from the France NUTS0 data available from EUROSTAT (in particular, the former is smaller than the latter), which may affect the mean value of our estimates.

Table 1.4 summarizes the results of these tests.

Overall, they indicate that our estimates do not statistically differ in their mean, standard deviation and distribution from the official data released either by National Statistical Offices or by RIS. Although for some countries, the tests indicate that either the mean or the standard deviation can be statistically different, the output of the Kolmogorov-Smirnoff test lends support to our estimates and indicates that the distribution of the original sample does not statistically differ from that of our estimates.

Table 1.4. Consistency tests

Sample	Type of innovation				
	Product only				
	Mean estimates	**Mean benchmark estimates**	**Mean difference**	**Std. Dev. Difference**	**Kolmogorov-Smirnoff test (different distr.)**
IT[*]	4.41	4.53	N.S.	N.S.	Not significant; p-value equals 0.94.
RO[*]	1.95	1.69	N.S.	> ; p<0.05	
	Process only				
	Mean estimates	**Mean benchmark estimates**	**Mean difference**	**Std. Dev. Difference**	**Kolmogorov-Smirnoff test (different distr.)**
IT[*]	14.27	14.00	N.S.	N.S.	Not significant; p-value equals 0.95.
RO[*]	4.72	4.82	N.S.	> ; p<0.01	
	Product and process				
	Mean estimates	**Mean benchmark estimates**	**Mean difference**	**Std. Dev. Difference**	**Kolmogorov-Smirnoff test (different distr.)**
CZ[*]	14.48	14.38	N.S.	< ; p< 0.05	
IT[*]	8.90	9.01	N.S.	N.S.	Not significant; p-value equals 0.98.
RO[*]	13.87	13.15	N.S.	< ; p< 0.01	
	Product and/or process				
	Mean estimates	**Mean benchmark estimates**	**Mean difference**	**Std. Dev. Difference**	**Kolmogorov-Smirnoff test (different distr.)**
AT[§]	49.03	50.03	N.S.	N.S.	
BE[§]	42.37	46.61	N.S.	N.S.	
BG[§]	15.03	15.21	N.S.	N.S.	
CZ[§]	37.03	36.05	N.S.	N.S.	
ES[§]	29.97	29.06	N.S.	> ; p<0.01	
FI[§]	34.45	34.52	N.S.	N.S.	
FR[§]	27.55	24.37	N.S.	> ; p<0.01	
GR[§]	29.72	39.30	< ; p<0.01	N.S.	
HU[§]	18.09	17.37	N.S.	N.S.	Not significant; p-value equals 0.98.
IT[§]	31.77	32.21	N.S.	N.S.	
PL[§]	23.07	38.95	N.S.	N.S.	
PT[§]	39.40	38.95	N.S.	N.S.	
RO[§]	20.18	17.74	N.S.	N.S.	
SI[§]	34.11	23.85	> ; p<0.05	N.S.	
SK[§]	22.43	20.01	N.S.	N.S.	
UK[§]	25.80	42.08	NA	NA	
IT[*]	31.77	27.59	N.S.	N.S.	

RO*	20.18	20.54	N.S.	N.S.	

Marketing and organizational

	Mean estimates	Mean benchmark estimates	Mean difference	Std. Dev. Difference	Kolmogorov-Smirnoff test (different distr.)
AT§	80.52	80.52	N.S.	N.S.	Not significant; p-value equals 0.51.
BE§	80.33	70.36	N.S.	N.S.	
BG§	0.76	0.94	N.S.	N.S.	
CZ§	54.83	54.23	N.S.	N.S.	
ES§	35.72	32.53	> ; p<0.05	N.S.	
FI§	69.13	72.81	N.S.	N.S.	
FR§	55.78	56.04	N.S.	> ; p<0.05	
IT§	49.12	51.39	N.S.	N.S.	
PL§	26.88	27.43	N.S.	N.S.	
PT§	64.49	67.43	N.S.	N.S.	
RO§	33.71	32.10	N.S.	N.S.	
SI§	54.35	54.28	N.S.	N.S.	
SK§	19.65	18.15	N.S.	> ; p<0.05	
UK§	42.14	43.44	N.S.	> ; p<0.05	

* *Source of data used as benchmark: National Statistical Offices.*
§ *Source of data used as benchmark: Regional Innovation Scoreboard 2009.*

1.4. Ad-hoc solutions to specific cases

In some cases, the methodology described above was not applicable either because of the lack of data on EUROSTAT (e.g. UK) or the lack of data on weights (e.g. Norway). We detail below the solutions adopted in such cases. ESPON Contact Point have been contacted to ask for help with some successful results.

The benchmark vector for the marketing and organizational innovation measure is made available in the Regional Innovation Scoreboard 2009. In order to be able to compare our estimates with the RIS data, we applied our methodology to the RIS national data, instead of Eurostat national data. For this purpose, we estimated the marketing and organizational vector as follows. The numerator of our ratio (number of innovative firms in marketing and organization) has been calculated by multiplying the total national sample by the percentage of innovative firms as from the RIS. This national number has been then spit into regional values according to the regional weights mentioned before, while the denominator (the total number of firms) has been calculated following our standard methodology, i.e., by assigning the total national CIS sample according to regional shares of value added. As a result, **the marketing and organizational vector has been structured in order to isolate the possible bias stemming from different samples**.

Results of the comparisons are therefore of particular importance in this specific case, since **the almost perfect adherence of our results to the RIS ones point at a satisfactory estimation procedure**. For those countries for which we are able to calculate basic statistics, mean values cannot be considered statistically different across countries, but for the case of Spain; the standard deviation is instead statistically different only for France, Slovakia, and the UK (and in particular higher for our estimates). More importantly, **the Kolmogorov-Smirnoff test for the equality of distributions cannot be rejected at any conventional significance level**. All these comparisons have been run on standardized data, the only available RIS regional data.

The satisfactory results of our estimates guarantee that our methodology rightly captures the phenomenon, and therefore we applied it to the Eurostat national data.

<u>Norway</u>

Data on weights are not available since Norway does not participate to LFS survey from which data are drawn. However, EUROSTAT provides the NUTS0 data for only product innovation, only process innovation and product and process innovation. Also, RIS provides NUTS2 data on product and/or process innovation. Therefore, in order to estimate the NUTS2 data for only product innovation, only process innovation and product and process innovation, we applied the regional share of product and/or process innovation available from RIS to NUTS0 data from EUROSTAT on only product innovation, only process innovation and product and process innovation.

Analogously, marketing and organizational innovation shares have been calculated by assigning each Norwegian region the share of national marketing and organizational innovation issued in the RIS data set.

<u>UK</u>

EUROSTAT does not provide NUTS0 data on UK for the following variables:
- only product innovation
- only process innovation
- product and process innovation
- product and/or process innovation

However, the Department of Trade and Industry (DTI) provide the following data
- product innovation
- process innovation

which however are limitedly comparable with the data on only product innovation and only process innovation available for the other countries (see section 1.1 and table 1.1 above). To estimate product and process innovation as well as product and/or process innovation we summed up product innovation and process innovation. Unfortunately, this bears the risk of double counting (and overestimation) since both categories include also firms performing both product and process innovation.

As for marketing and organizational innovation, we proceeded along the lines of the other vectors. A national share of firms innovating in marketing and organization has been inferred from DTI documents. This share has been applied to the EUROSTAT national CIS sample, thus obtaining a regional number of innovative firms. Next, the denominator (i.e. the total number of firms in the regional CIS sample) has been obtained by splitting the national CIS sample according to regional value added shares. Finally, the ratio has been calculated between these two values according to our methodology above explained.

Switzerland

Data on weights are not available since Switzerland does not participate to LFS survey from which data are drawn. Also, Switzerland does not participate to CIS so that CIS NUTS0 data neither are available. However, the Swiss ESPON Contact Point enabled us to access data on product innovation and process innovation, but not on only product innovation, only process innovation, product and process innovation, product and/or process innovation.

To estimate product and process innovation as well as product and/or process innovation we summed up product innovation and process innovation. Unfortunately, this bears the risk of double counting (and overestimation) since both categories include also firms performing both product and process innovation.

The data on marketing/organizational innovation is unfortunately not available.

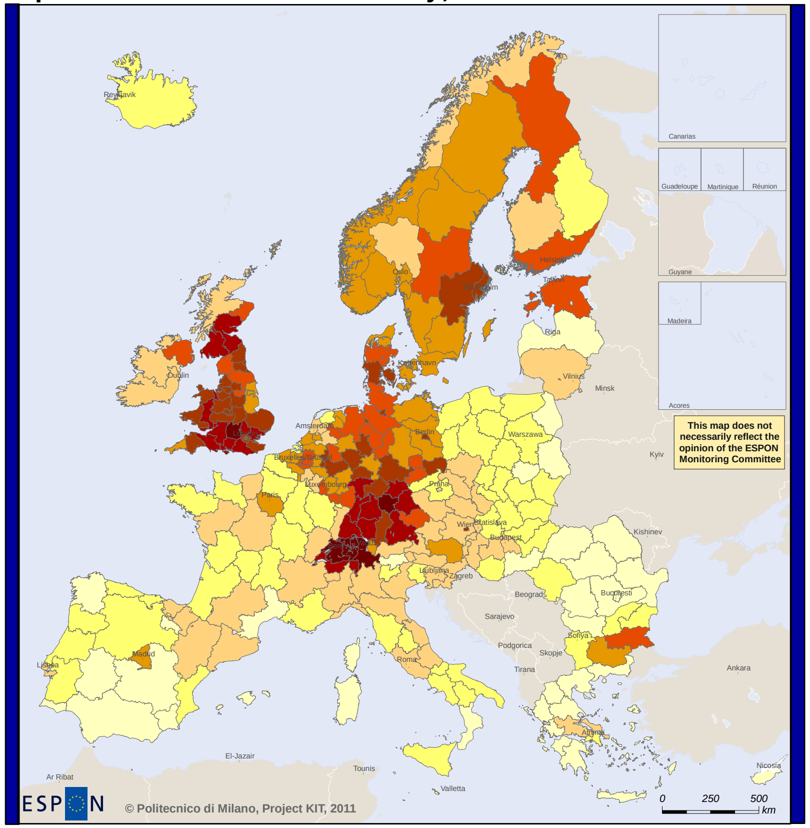
Iceland does not disclose information on only product innovation, only process innovation, product and process innovation, product and/or process innovation for CIS4. The data used thus refer to CIS3. This bears a problem of comparability due to the different sectoral coverage of the two different CIS waves. Also, the data on marketing/organizational innovation is unfortunately not available since questions on this issue were firstly introduced in CIS4.

The former Yugoslav Republic of Macedonia, Croatia, Turkey did not participated to CIS4.

Liechtenstein does not collect innovation statistics.

1.2. Regional innovation statistics

Map 1.1. Product innovation only, CIS 2004



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

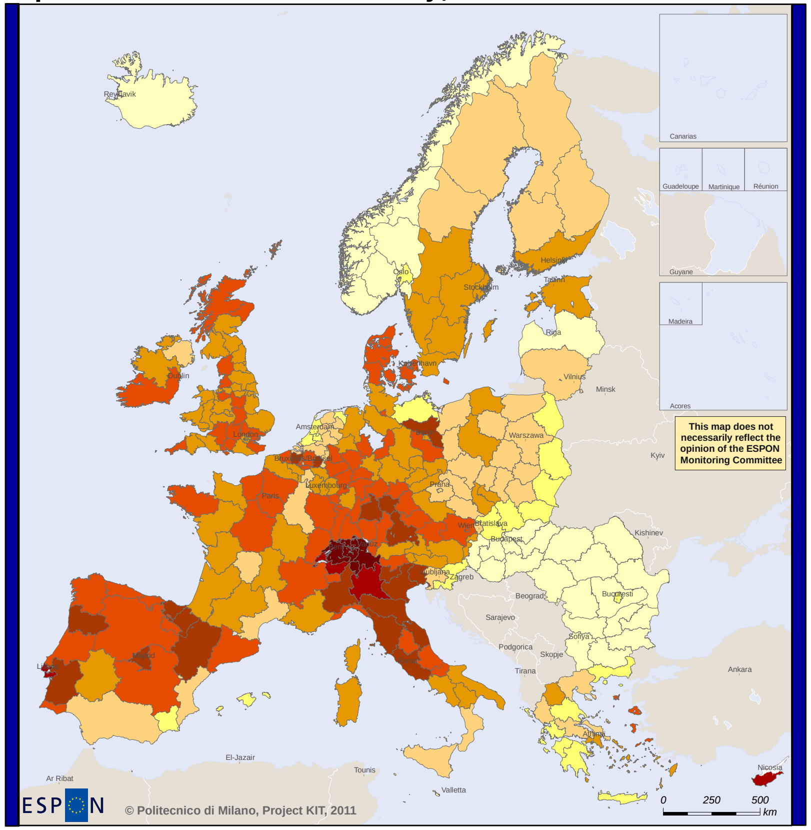
Regional level: NUTS2
Source: Politecnico di Milano, 2011
Origin of data: Community Innovation Survey 2004
© EuroGeographics Association for administrative boundaries

KIT estimates
Share of product innovation only

- NA
- 0 - 3.26
- 3.27 - 5.92
- 5.93 - 9.12
- 9.13 - 12.80
- 12.81 - 17.30
- 17.31 - 23.43
- 23.44 - 33.45
- 33.46 - 44.42

Switzerland: share of product innovation.
Iceland: CIS3 data.
Latvia and Slovenija: CIS 2006 data.

Map 1.2. Process innovation only, CIS 2004



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

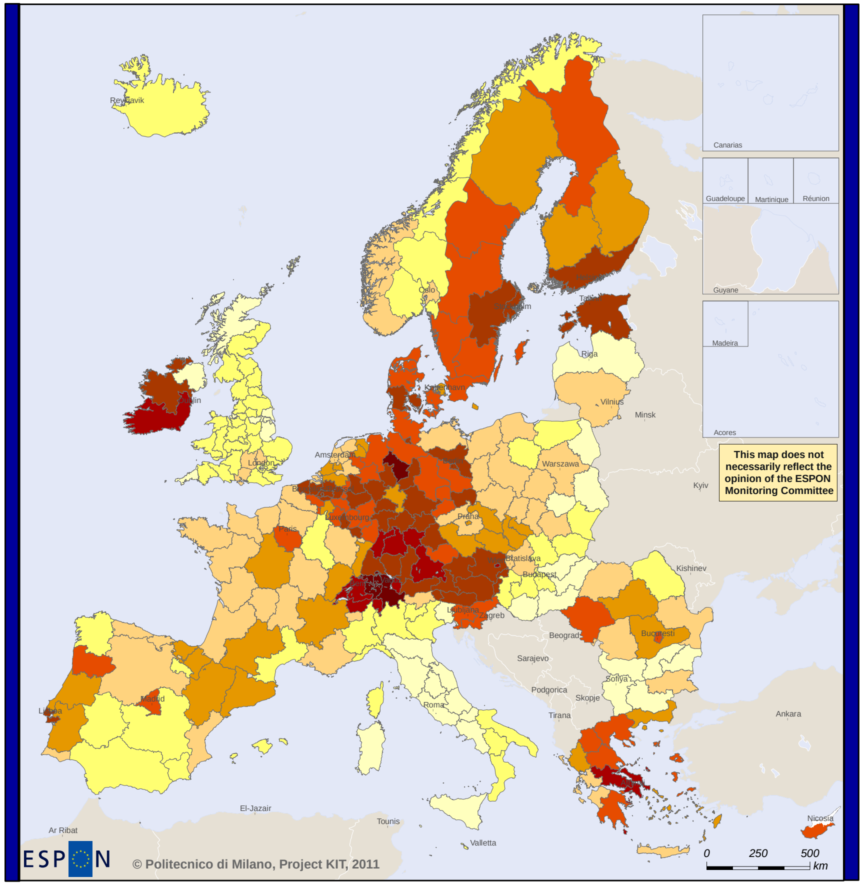
Regional level: NUTS2
Source: Politecnico di Milano, 2011
Origin of data: Community Innovation Survey 2004
© EuroGeographics Association for administrative boundaries

KIT estimates
Share of process innovation only

- NA
- 0 - 5.40
- 5.41 - 8.09
- 8.10 - 10.09
- 10.10 - 12.32
- 12.33 - 14.71
- 14.72 - 18.01
- 18.02 - 25.92
- 25.93 - 55.08

Switzerland: share of process innovation.
Iceland: CIS3 data.
Latvia and Slovenija: CIS 2006 data.

Map 1.3. Product and process innovation, CIS 2004



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

Regional level: NUTS2
Source: Politecnico di Milano, 2011
Origin of data: Community Innovation Survey 2004
© EuroGeographics Association for administrative boundaries

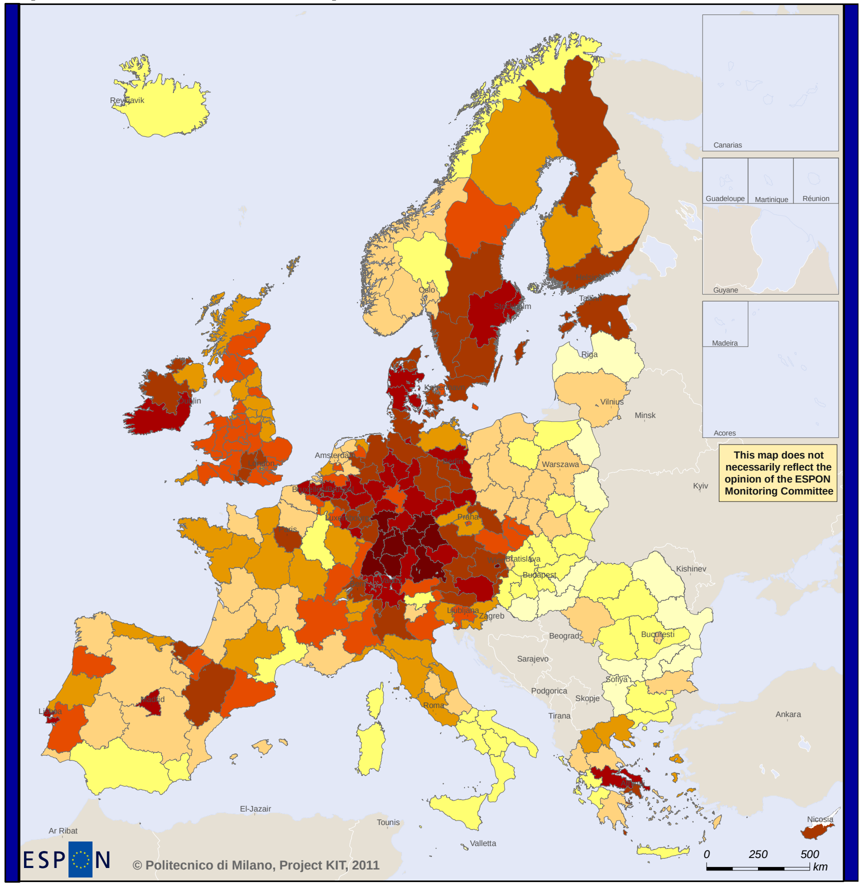
KIT estimates

Share of both product and process innovation

- NA
- 0 - 7.79
- 7.80 - 10.24
- 10.25 - 13.15
- 13.16 - 16.69
- 16.70 - 21.37
- 21.38 - 28.34
- 28.35 - 42.63
- 42.64 - 98.82

Switzerland: share of product and process innovation.
Iceland: CIS3 data.
Latvia and Slovenija: CIS 2006 data.

Map 1.4. Product and / or process innovation, CIS 2004



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

Regional level: NUTS2
Source: Politecnico di Milano, 2011
Origin of data: Community Innovation Survey 2004
© EuroGeographics Association for administrative boundaries

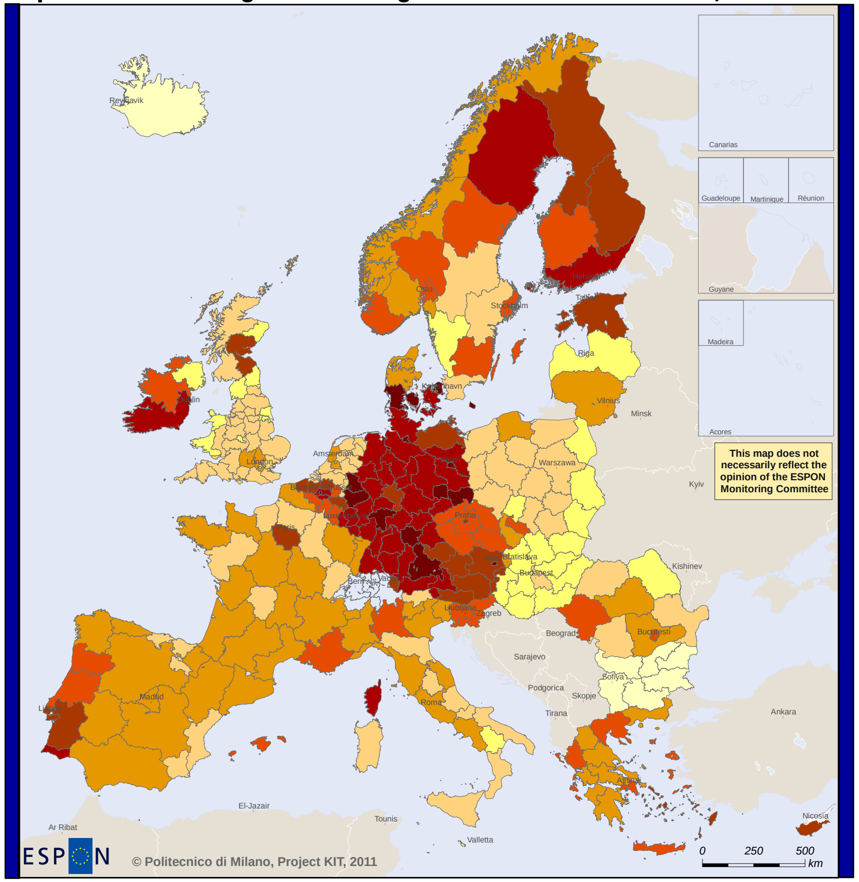
KIT estimates

Share of product and/or process innovation

- NA
- 0 - 16.31
- 16.32 - 23.53
- 23.54 - 28.72
- 28.73 - 33.97
- 33.98 - 40.04
- 40.05 - 47.53
- 47.54 - 59.06
- 59.07 - 87.10

Switzerland: share of product and process innovation.
Iceland: CIS3 data.
Latvia and Slovenija: CIS 2006 data.

Map 1.5. Marketing and / or organizational innovation, CIS 2004



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

Regional level: NUTS2
Source: Politecnico di Milano, 2011
Origin of data: Community Innovation Survey 2004
© EuroGeographics Association for administrative boundaries

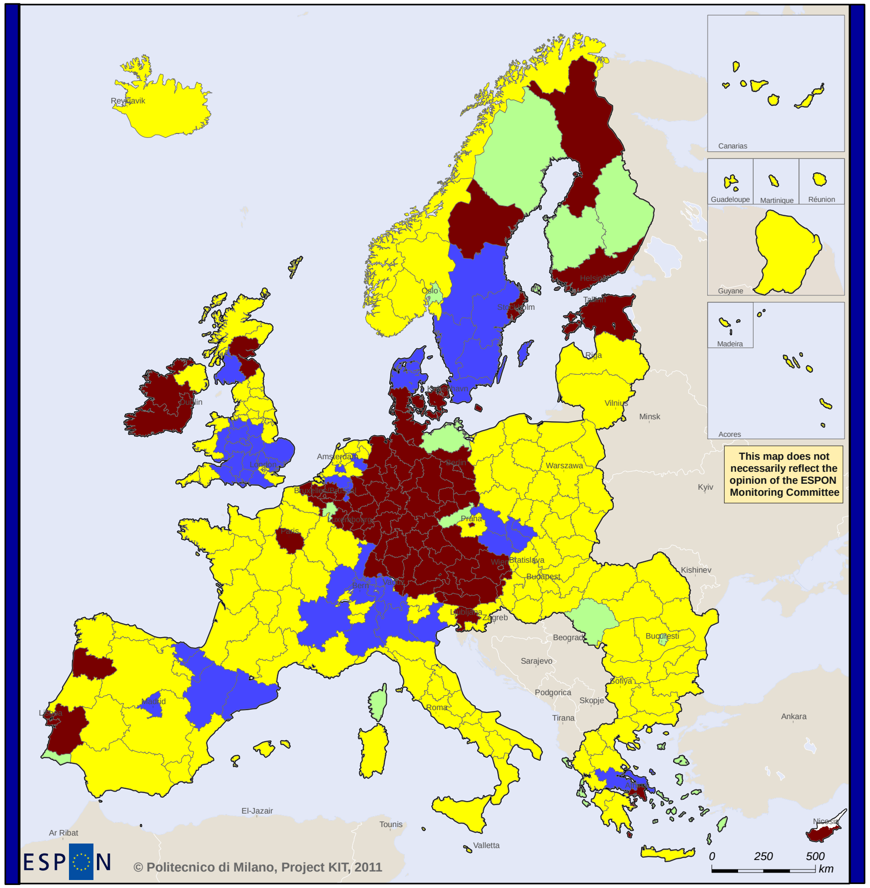
KIT estimates

Share of marketing and organizational innovation

- NA
- 0 - 9.05
- 9.06 - 15.24
- 15.25 - 19.81
- 19.82 - 23.53
- 23.54 - 29.56
- 29.57 - 37.50
- 37.51 - 48.05
- 48.06 - 78.36

Switzerland: share of product and process innovation.
Iceland: CIS3 data.
Latvia and Slovenija: CIS 2006 data.
Sweden: CIS 2008 data.

Map 1.6. Product and / or process and marketing and / or organizational innovation



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

Regional level: NUTS2
Source: Politecnico di Milano, 2011
Origin of data: IGEAT Matrix 2004
© EuroGeographics Association for administrative boundaries

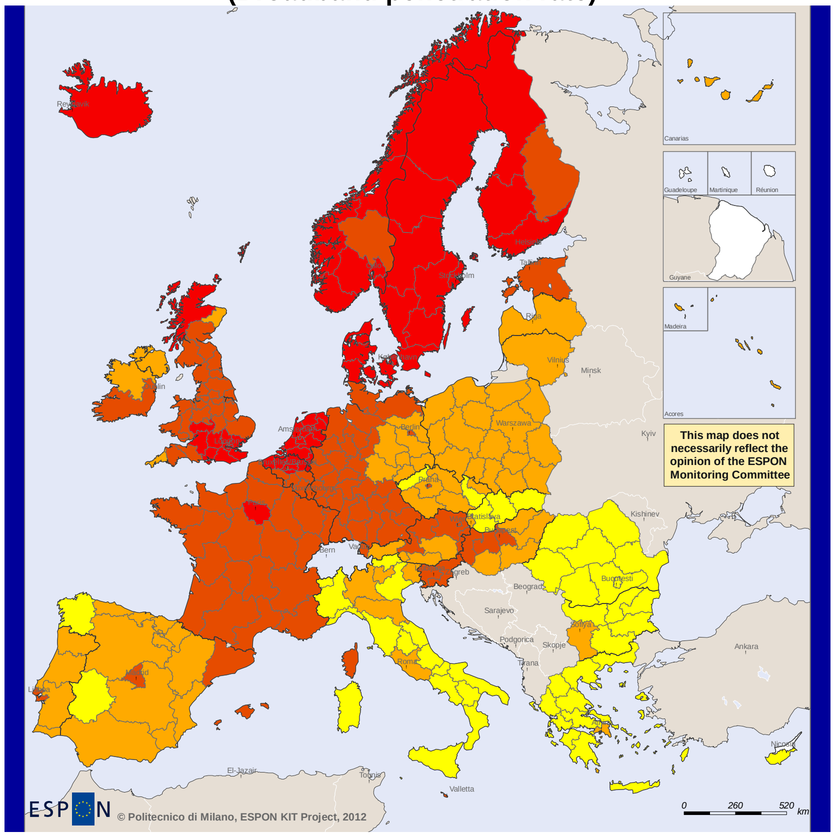
Product and/or process and marketing and organizational innovation

- Hard and soft innovators
- Hard innovators
- Sub performers
- Soft innovators

Number	Typology	Meaning
1	Hard and soft innovators	Performance higher than the European average in both product and/or process and marketing and organizational innovation
2	Hard innovators	Performance higher than the European average in product and/or process innovation; and lower than the European average in marketing and organizational innovation
3	Sub performers	Performance lower than the European average in both product and/or process and marketing and organizational innovation
4	Soft innovators	Performance higher than the European average in marketing and organizational innovation; and lower than the European average in product and/or process innovation

Map 1.7. Social innovation

Households propensity to adopt innovation (Broadband penetration rate)



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

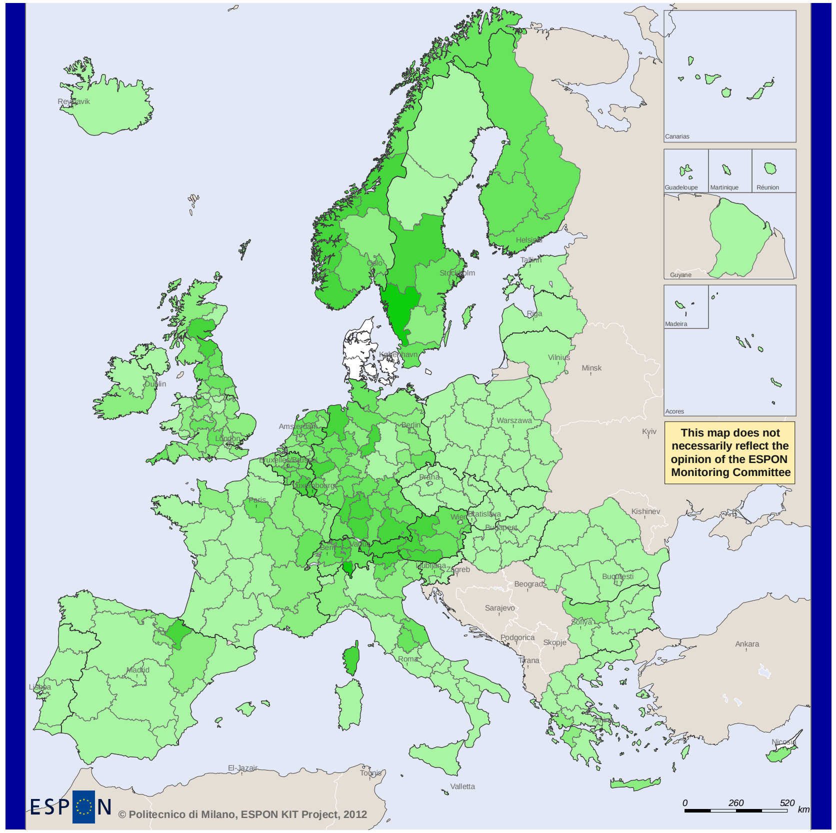
Regional level: NUTS2
Source: Own elaboration, 2011
Origin of data: EUROSTAT ICT Survey, 2006-2009
© EuroGeographics Association for administrative boundaries

Legend

- No data
- < 29,50
- 29,51 - 45,250
- 45,26 - 61
- > 61

Map 1.8. Environmental innovation

Environmental innovation: Green patents per 1,000 pop.



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

Regional level: NUTS2
Source: Own elaboration, 2011
Origin of data: EPO and CRENoS, 2000-2006
© EuroGeographics Association for administrative boundaries

Legend

- No data
- < 0,003
- 0,004 - 0,005
- 0,006 - 0,010
- 0,011 - 0,022
- > 0,022

Chapter 2. Territorial patterns of innovation in Europe[3]

2.1. Territorial patterns of innovation

2.1.1. A proposed definition and a framework

The paradigmatic jump in interpreting regional innovation processes lies nowadays in the capacity to build - on the single approaches developed for the interpretation of knowledge and innovation - a conceptual framework interpreting not a single phase of the innovation process, but the *different modes of performing the different phases of the innovation process*, highlighting the *context conditions* (internal and external to the region) that accompany each innovation pattern. In this way, we are able to take into consideration alternative situations where innovation builds on internal knowledge, or where local creativity allows, even in front of the lack of local knowledge, an innovative application thanks to knowledge developed elsewhere and acquired via scientific linkages, or where innovation is made possible by an imitative process of innovations developed outside the region.

This new interpretative paradigm – the innovation patterns paradigm, stressing complex interplays between phases of the innovation process and spatial context or territorial conditions – adds two new elements with respect to the previous theoretical paradigms (Capello, 2011). First of all, it disentangles knowledge from innovation, addressing the two as different (and subsequent) phases of an innovation process, each phase calling for specific local elements for its development, and having a different natural location depending on the presence of the factors that support their development. This approach departs from the assumption of a invention-innovation short circuit taking place inside individual firms (or their territories) operating on advanced sectors, as well as an immediate interaction between R&D/higher education facilities on the one hand and innovating firms on the other, thanks to spatial proximity.

The temporal sequentiality between knowledge source and innovation, and between innovation and economic performance – the so called "linear model of innovation" – has been heavily criticized since it is rooted in the idea that innovation can be analyzed as a "rational" and "orderly" process (Edgerton, 2004). However, we strongly believe that: i) scientific advance in many cases is a major source of innovation, fully recognizing that they are neither necessary nor sufficient conditions for innovation to take place; ii) an alternative model where "everything depends on everything else", with no specific structure of the innovative system fully and clearly specified, does not help in generating a conceptual analytical model able interpret the systemic, dynamic and interactive nature of innovation; iii) self-reinforcing feedbacks from innovation to knowledge and from economic growth to innovation and knowledge play an important role in innovation processes. The impact of science on innovation does not merely reside in the creation of new opportunities to be exploited by firms, but rather in increasing research productivity and therefore the returns to R&D, through the solution and exploitation of technical problems, elimination of research directions that have proven wrong from a scientific perspective and provision of new research technologies (Nelson, 1959; Mowery and Rosenberg, 1998; Balconi et al., 2010). We therefore strongly support the concept of a "spatially diversified linear model of innovation", in which the patterns of innovation are a linearization, or partial block linearization of an innovation process where feedbacks, interconnections and non-linearities, in the form of increasing returns, find a prominent role.

Secondly, the concept of "patterns of innovation" calls for the identification of the context conditions, both internal and external to the region, that support the different innovation phases; these context conditions become integral part in the definition of a *territorial pattern of innovation*. In this sense, the approach does not look for the territorial capabilities that allow territories (in general) to exploit innovation and knowledge, like the presence of human capital. The conceptual framework looks for the *territorial specificities (context conditions)* that

[3] This chapter has been written by Roberta Capello and Camilla Lenzi, BEST – Politecnico di Milano.

are behind *different modes of performing the different phases of the innovation process* and that become integral parts of a territorial pattern of innovation.

An integrated conceptual framework like this one identifies the local conditions that guarantee: a) the shift from local knowledge to innovation; b) the acquisition of external knowledge to innovate locally; c) the acquisition of external innovation for imitation with different degrees of creativity. In order to identify the context conditions that accompany each phase of the innovation process we can make use of the existing and well established literature; the conceptual effort rests on the identification of the combination of the different context conditions that allow the presence of different phases of the innovation process, and give rise to alternative patterns of innovation.

2.1.2. Differentiated territorial patterns of innovation
A territorial pattern of innovation is made of a combination of *territorial specificities (context conditions)* that are behind *different modes of performing the different phases of the innovation process*. Among all possible combinations, the most interesting ones are the following, reflecting different knowledge and innovation aspects:

a) an endogenous innovation pattern in a scientific network, where the local conditions are all present to support the creation of knowledge, its local diffusion and transformation into innovation and its widespread local adoption so that higher growth rates can be achieved. Given the complex nature of knowledge nowadays, this pattern is expected to show a tight interplay in the creation of knowledge with other regions, and therefore being in an international scientific network. This pattern can be easily built from the conceptual point of view on all the literature dealing with knowledge and innovation creation and knowledge diffusion;
b) a creative application pattern, characterized by the presence of creative actors interested and curious enough to look for knowledge, lacking inside the region, in the external world, and creative enough to apply external knowledge to local innovation needs. This approach is conceptually built on the literature on regional innovation creation;
c) an imitative innovation pattern, where the actors base their innovation capacity on imitative processes, that can take place with different degrees of creativity in the adaptation of an already existing innovation. This pattern is based on the literature dealing with innovation diffusion.

a) An endogenous innovation pattern in a scientific network
A first and straightforward territorial pattern of innovation is an endogenous one referring to a situation in which a region is endowed of local conditions for knowledge creation and for turning knowledge into innovation, so to guarantee a productivity increase and regional growth. This model relies on specific *internal context conditions* that explain knowledge creation and diffusion, as well as innovation by looking at the internal structural conditions of a region, have been widely analyzed by the literature.

Knowledge creation is in general dependent on an urban environment, where material and non-material elements supporting scientific knowledge find a natural location. The main elements that have been underlined as the sources of knowledge creation, being material and non-material, stem from indivisibility and synergies, i.e. from agglomeration and proximity, the two elements characterizing urban environments:

- urban size per se (McCann, 2004), especially concerning the creation of large human capital pools and wide labour markets (Lucas, 1988; Glaeser, 1998);
- diversity, concerning the variety of activities and the possibility for specializations in thin sub-sectors and specific productions, thanks to the size of the overall urban market (Jacobs, 1969 and 1984; Quigley, 1998);
- contacts and interaction, allowing face-to-face encounters reducing transaction costs (Scott and Angel, 1987; Storper and Scott, 1995);

- synergies, thanks to proximity, complementarity and trust (Camagni, 1991 and 1999); in more formalized models, these same effects stem from complexity of the urban system and synergetics (Haken, 1993);
- reduction of risk of unemployment for households, thanks to the thick and diverse urban labour market (Veltz, 1993);
- trans-territorial linkages, emerging from the international gateway role of large cities, particularly crucial in a globalising world (Sassen, 1994).

The literature has not confined itself to the identification of territorial elements of knowledge creation. Reflections on the territorial elements that explain the capacity of a region to use its knowledge for *innovation creation* have been put forward. In particular, creativity and recombination capability to translate scientific, basic or applied knowledge into innovative application, require a relational space, where functional and hierachical, economic and social interactions are embedded into geographical space. Geographical proximity (agglomeration economies, district economies) and cognitive proximity (shared behavioural codes, common culture, mutual trust and sense of belonging) guarantee the *socio-economic and geographical substrate* on which collective learning processes can be incorporated, mainly due to two main processes (Camagni and Capello, 2002):

- the huge mobility of professionals and skilled labour – between firms but internally to the local labour market defined by the district or the city, where this mobility is maximal), and
- the intense co-operative relations among local actors, and in particular customer-supplier relationships in production, design, research, and finally knowledge creation.

The translation of knowledge into innovation is facilitated by interaction and co-operation, by the reduction of uncertainty (especially concerning the behaviour of competitors and partners), of information asymmetries (thus reducing mutual suspicion among partners) and of probability of opportunistic behaviour under the threat of social sanctioning (Camagni, 1991 and 1999), all elements that are confirmed by many regional economics schools (Bellet et al., 1993; Rallet and Torre, 1995; Cappellin, 2003; Camagni and Capello, 2009).

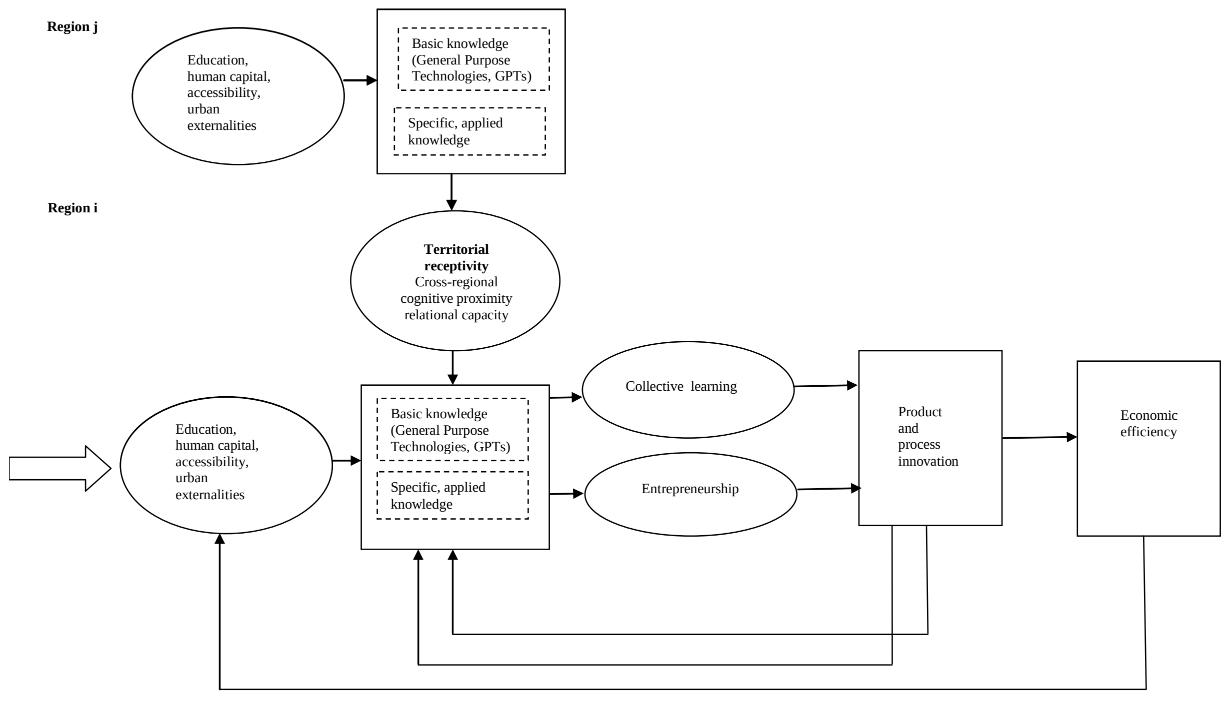
Another group of literature dealing with the capacity of a region to translate knowledge into innovation is the knowledge filter theory of entrepreneurship, put forward by Acs and Audretsch (Acs et al. 2004). It provides an explicit link between knowledge and entrepreneurship within the spatial context, where entrepreneurs are interpreted as the innovative adopters of new knowledge. This theory posits that investments in knowledge by incumbent firms and research organizations such as universities will generate entrepreneurial (innovation) opportunities because not all of the new knowledge will be pursued and commercialized by the incumbent firms. The knowledge filter refers to the extent that new knowledge remains un-commercialized by the organization creating that knowledge. These residual ideas are those that generate the opportunity for entrepreneurship. The interesting aspect of this theory is that the capabilities of economic agents within the region to actually access and absorb the knowledge and ultimately utilize it to generate entrepreneurial activity is no longer assumed to be invariant with respect to geographic space, as has been always thought. In particular, diversified areas, in which differences among people that foster looking at and appraising a given information set differently, thereby resulting in different appraisal of any new idea, are expected to gain more from new knowledge.

Notwithstanding the internal capacities to generate knowledge, given the complex and systemic nature of knowledge and innovation, in most cases regions reinforce and complement their internal knowledge with external one, through diffusive, mostly un-intentional, knowledge patterns based on spatial proximity ("spatial linkages"), subject to strong distance decay effects, and/or through intentional relations based on a-spatial networks or non-spatially mediated channels ("a-spatial linkages") that may take place both at short and long distances based on the organization of different forms of transfer and exchange of information and knowledge than the pure spatial proximity.

An innovation pattern of this kind can be labeled "*endogenous innovation pattern in a scientific network*" (Figure 2.1). In front of a territorial pattern of innovation of this kind, the natural innovation policy aim is the achievement of the maximum return to R&D investments. An aim like this calls for the importance of a specialization in R&D at European level, that guarantees the achievement of a critical mass of researchers, equipments and R&D resources; this critical mass is interpreted as fundamental in order to achieve the desired goal, for the research work to become effective and to achieve an acceptable research performance.

Based on the indivisibility rule associated to research activities in general, and to general purpose technologies in particular, the idea of a smart specialization in R&D activity has pervaded the innovation economic debate, calling for an European Research Area allowing agglomeration processes to occur, giving rise to centres of excellence. This can only be done within an integrated research space in which knowledge is exchanged within a solid and efficient network among centres of excellence, that become regions specialized in the basic inventions. Regions showing "an endogenous innovation pattern in a scientific network" can become one of these centres; the specialization of each centre in general purpose technology research activities can become a policy mission.

Figure 2.1. Endogenous innovative pattern in a scientific network



The innovative model in this territorial innovation pattern is a typical supply-driven model; from scientific activities, from an invention, a subsequent co-invention of applications leads to a number of innovations mainly brought about by inventors and co-inventors of applications.

The conditions for a region to acquire knowledge from outside its boundaries can be regarded as *territorial receptivity* (Table 2.1), broadly defined as the capability of the region to interpret and use external knowledge for complementary research and science advances, or more generally absorptive capacity of a region à la Cohen and Levinthal (1990). More specifically, receptivity is made of different aspects, according to the nature of knowledge, and its diffusion. If a modern view of knowledge is adopted, learning and interaction processes are put at the forefront, and knowledge is considered as complex semi-public or co-operative. Its diffusion is subject to strong spatial barriers and follows widely unpredictable creative processes. Knowledge creation and learning often depend on combining diverse, complementary capabilities of heterogeneous agents.

Given these characteristics, receptivity is first of all dependent on a *relational capability* required to guarantee that a region is in general made of individuals, firms and institutions oriented towards a cooperative and synergic attitude, nourished by trust and sense of belonging, in order to guarantee collective and interactive learning processes. In this sense, our conceptual work takes advantage of the reflections developed in the French school of proximity (Rallet, 1993; Rallet and Torre, 1995; Torre and Rallet, 2005), and in the evolutionary geography school (Boschma and Lambooy, 1999; Boschma, 2005); complexity of science and knowledge evolution, together with bounded rationality which generates cognitive constraints of actors, leads economic agents to search in close proximity to their existing knowledge base, which provides opportunities and sets constraints for further improvement (Boschma, 2005). Knowledge evolution therefore takes place in a cumulative way, localized around a technological paradigm, in cooperation among actors with a strong complementarity within a set of shared competences. For this reason, a third component of territorial receptivity is *cognitive proximity* among regions, necessary for a region to acquire knowledge from another one, to understand and use it in a creative way (Table 2.1).

Table 2.1. Preconditions for interregional exchange of knowledge and innovation

	Territorial Receptivity	*Territorial Creativity*	*Territorial Attractiveness*
Preconditions to receive	Relational capacity	Openness to innovation	Limited labour costs
Preconditions to exchange	Cognitive proximity	Sectoral proximity	Income differentials
Channels for exchange	Scientific networks Co-patenting Migration of inventors	Participation in industrial associations	Foreign direct investments

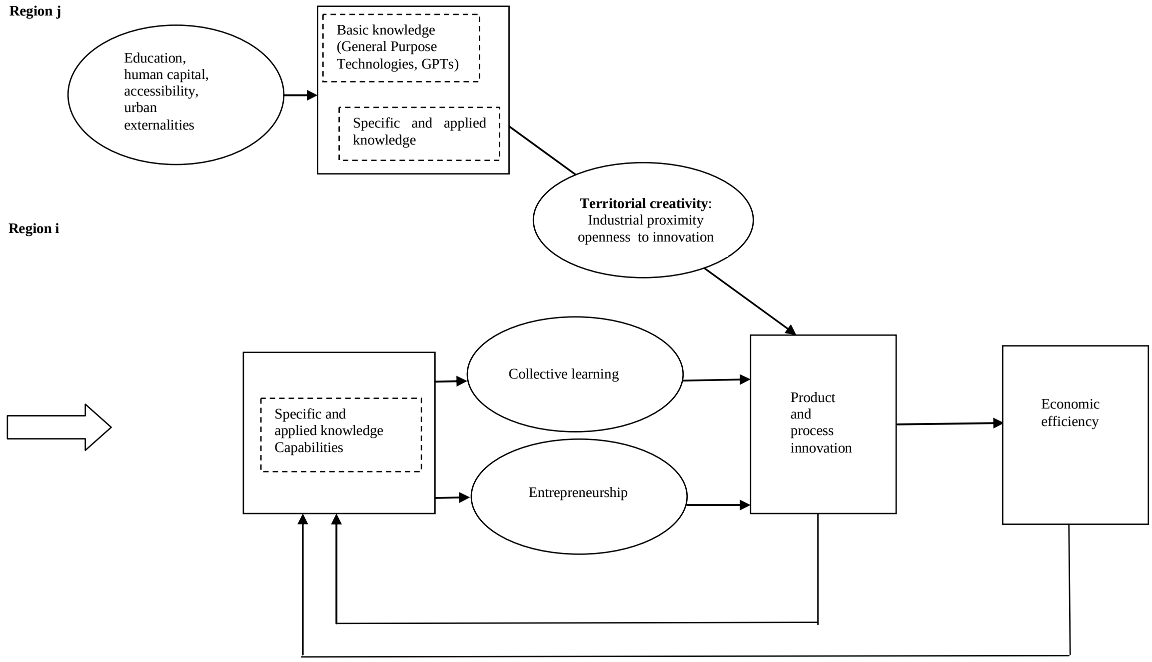
All these features are more easily to be found in metropolitan areas. They are the main sites of innovative activity, the 'incubators' of new knowledge: cities are the principal centres of research, given their large pools of expertise, and the availability of advanced services (finance and insurance) ready to carry the risk of any innovative activity. The fuel for a continuing knowledge and innovation process in cities lies in the density of external, particularly international linkages maintained and developed by individuals, groups, associations, firms and institutions, what is increasingly called relational capital (Camagni, 1999) coupled with a large diversity of competences on which complementary knowledge can find a common cognitive sphere.

b) Creative application pattern

The reality shows also that some regions are late comers and mainly users of general purpose, basic technologies; experience shows that being a latecomer in core technologies has serious implications, that last for long, and are difficult to reverse. Foremost, technological leaders are facilitated to expand into new science and technology fields and create conditions for reiterating such processes in further emerging science and technology area.

Reality is full of examples in which invention and innovation are not intertwined. Factors that enhance the implementation of new knowledge can be quite different from the factors which stimulate invention and innovation. Invention, innovation and diffusion are not necessarily intertwined, even at the local level. The linkage between basic knowledge and innovation is therefore in many cases not so evident, and many regions exist in which innovation takes place on the basis of basic knowledge acquired from outside and of specific know-how in local application sectors. In this case, innovation activity finds its roots in a merging of general purpose technology knowledge, coming from networking with leading regions, with local specialized knowledge in the region (Figure 2.2). In this pattern, a particular case is the investments in the "co-invention of applications" that is development of the applications in one or several important domains of the regional economy, without embarking in expensive basic R&D activities with insufficient critical mass of human and financial resources (Foray, 2009; Foray et al., 2009).

Figure 2.2. Creative application pattern



In this innovation pattern, regions have to succeed in developing an original and unique knowledge domain, based on its productive vocations; therefore regions have to discover the research and innovation areas in which they can hope to excel. This discovery comes from firms, that have to achieve combinations between technologies and various elements of the value chain, and construct very different and unpredicted specific niche competitive advantage. In this sense, this innovation pattern is supply driven, in that it depends on the creativity and recombination capability of potential innovating firms, that - thanks to their internal specific knowledge - identify a gap in a possible application of general purpose technologies, and put their creative effort in order to overcome such a gap.

This does not necessary mean that regions have to specialize in one or a few knowledge domains. In an innovation pattern like this the evolutionary trajectories of innovation can either be specialized, can progress by means of the evolution of "platforms" that combine many technologies, but can also be the result of differentiated technological fields in which local firms operate. The common features of all these possible forms in which this innovation pattern can take place is that the move from invention to innovation resides in creativity, recombination capability, ability to identify at the same time new needs and the right basic technology of local actors, ability to recombine local knowledge and external knowledge anew. In this sense, the innovation process is the result of an active role of collective actors of a region, especially potential innovators/adopters, which leads to innovation creation, despite the lack of ability in knowledge creation.

The territorial conditions for this innovation pattern to occur are linked to the concept of *territorial creativity*. This is made of entrepreneurs able to actually access and absorb the knowledge produced in the world and ultimately utilize it to invent co-applications; this can more easily happen in a context open to innovation, which nourishes itself of external knowledge useful for its local purposes and needs. The probability to interact in this kind of innovative pattern is between regions with a similar technological vocation. Participation to industrial associations and / or the exploitation of external experts represent the channel through which the flow of knowledge comes into the region (Table 2.1).

Regions in which this innovation pattern finds a natural location are the second ranked urban regions, characterized by high accessibility to metropolitan leading regions, with a local labour market fed by human capital in general formed in first ranking urban areas. But it is also the case of highly specialized areas, like local districts, where specialized knowledge cumulates over time and where the needs of technological jumps are often solved by merging specific local competences with new basic knowledge from outside through what has been labeled trans-territorial networking (Camagni, 1991). In the milieu innovation theory, these networking capabilities have always been thought of as a way to feed local specialized knowledge with technological novelties at the frontier, to jump on a new technological paradigm, something impossible to achieve only by cumulating specialized technological knowledge inside the area. This latter bears the inevitable risk to lock the area into a technological pattern, with no possible way out.

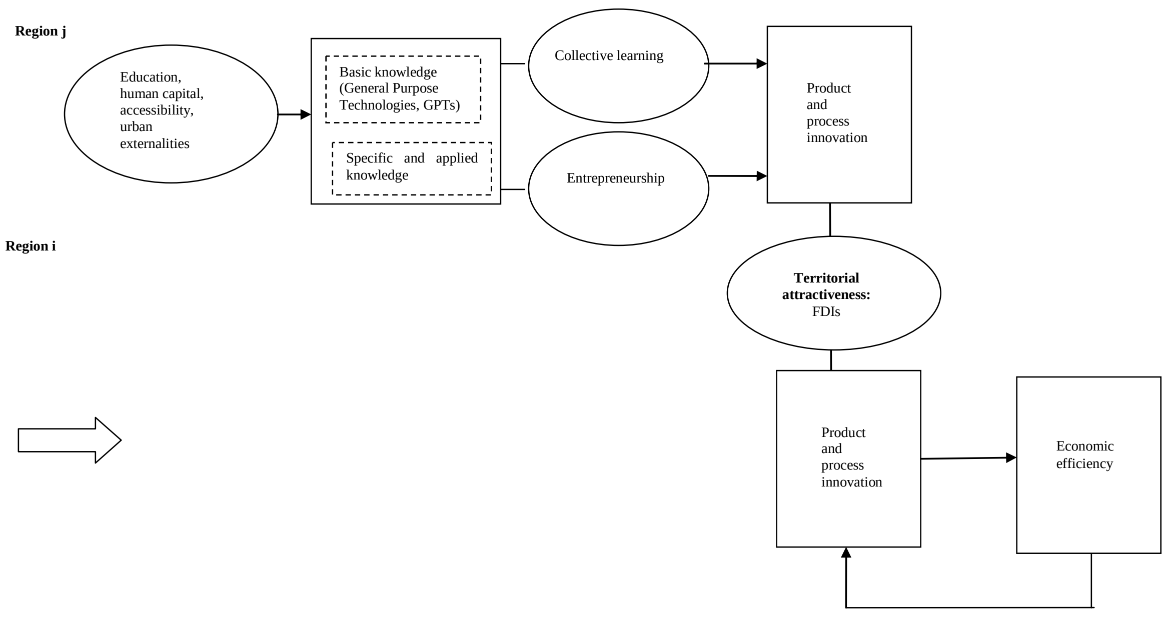
c) Imitative innovation pattern

Another innovation pattern which can be envisaged is an imitative innovation pattern, a situation in which a region innovates since it receives innovation from outside. The pattern presented in Figure 2.3 is an adoption innovation pattern, where the technological developments at the local level are the result of a passive attitude - in terms of invention, knowledge creation and innovation generation – of a region, which is fed by external actors of innovation already developed elsewhere (Figure 2.3). This innovation pattern calls back to the large existing literature on "innovation adoption", which from the work of the geographer Hägerstrand (1952) onward tries to interpret the spatial channels and mechanisms of innovation adoption.

This imitative pattern is not necessarily the less productive and efficient innovation pattern; regions can be creative and fast in the imitation phase, by deepening and improving productivity in existing uses, by adapting existing uses to the specific local needs, by adjusting products to local market interests, by forging innovation processes on local productive needs. Regions can also be more passive and imitate innovation from outside as conceived elsewhere.

Especially in the latter case, the right innovation policy for this pattern has nothing to do with the efficiency in R&D activities, or in supporting co-inventing applications. In this case policy actions have to be devoted to achieve the maximum return to imitation, and this aim is achieved through a creative adaptation of already existing innovation, i.e. through adoption processes driven by creative ideas on the way already existing innovation can be adopted to reply to local needs.

Figure 2.3. Imitative innovation pattern



Channels through which innovation is acquired from outside the areas are in fact foreign direct investments (Table 2.1); product, process, managerial, organizational innovation embedded in large multinationals can be the channel through which innovation is brought into catching-up regions. One of the traditional channels through which external innovation penetrates an area is through foreign direct investments. *Territorial attractiveness* is the precondition for regions to acquire external innovation; a large final market (market seeking) and/or labour cost competitiveness (efficiency seeking) are the preconditions to become attractive areas for FDI (Dunning, 2001 and 2009; Cantwell, 2009). Regions exchanging innovation through FDI are regions with strong income differentials.

Imitative innovation patters are typical of Eastern countries that have, over the last two decades, shown a decisive economic performance, mainly based on foreign direct investments, and all the innovative capacity brought about by multinationals. The efficiency of this innovation pattern can be high, giving rise to strong positive feed-back loops from growth to innovation through higher financial resources to invest in the innovation process. The high rate of growth can produce higher living standards and higher quality of life in these countries. The ways through which innovation is attracted from outside the region may evolve in a second stage towards other channels like mobility of inventors, that find their determinants in economic growth potentials, in expected high wages and in high quality of life potential.

Conceptually speaking, these three patterns represent the different ways in which knowledge and innovation can take place in a regional economy. Each of them represents a different way of innovating, and calls for different policy styles to support innovation. An R&D incentive policy can be extremely useful for the first kind of innovation pattern; incentives to co-inventing application (the typical Schumpeterian profits), enhancing the ability of regions to change rapidly in response to external stimuli (such as the emergence of a new technology) and to promote "shifting" from old to new uses, is a good policy aim for the second pattern. The maximum return to imitation is the right policy aim of the third innovation pattern, and this aim is achieved through a creative adaptation of already existing innovation, i.e. through adoption processes driven by creative ideas on the way already existing innovation can be adopted to reply to local needs.

In the rest of the chapter the aim is to identify whether the innovation patterns exist in the real world. To accomplish such a task, a rich dataset with different indicators, measuring both the knowledge and innovation sphere, as well as the internal and external context conditions to generate and acquire knowledge and innovation, is built for all NUTS 2 of all 27 EU Member countries (sec. 3).

The methodology used to identify the territorial patterns of innovation is a cluster analysis, a statistical methodology able to cluster into groups the observations according to their proximity among variables on which the clusters are identified. In our case, the variables on which we identified the clusters are the degree of knowledge and innovation produced in a region; the variables identifying the context conditions help in identifying the clusters (sec. 4 and 5).

2.2. Data description and methodological notes

2.2.1. The dataset

To identify innovation patterns across European regions, we rely upon an original data set being collected and developed in the frame of an ongoing ESPON (European Spatial Observation Network) project, the KIT (Knowledge, Innovation and Territory) project, which encompasses several dimensions of knowledge and innovation creation and diffusion processes.

Data collection is based on EUROSTAT NUTS2 classification. The choice of using the administrative areas in empirical analyses is a long disputed debate. In particular, we chose

NUTS2 regions for two different reasons. The first reason is a conceptual one; NUTS3 regions are oftentimes too small to encompass functional urban areas, while NUTS1 regions tend to be too large to be able to highlight local effects within their boundaries. The second reason is a practical one, related to the scarcity of data, especially innovation data, at NUTS3.
The richness of our dataset lies on the fact that it all elements that characterize the territorial patterns of innovation, namely:

I. Knowledge and innovation creation;
II. Regional preconditions for knowledge and innovation creation;
III. Inter-regional knowledge and innovation flows;
IV. Regional preconditions to acquire external knowledge and innovation.

Grouped in this way, indicators are fully mentioned and described in Table 2.2. Most of them are traditional indicators, others are more innovative, and require an explanation on the way they are built.

I. Knowledge and innovation creation

Knowledge data mostly rely upon patent data available from the OECD REG-PAT database[4] from which we make use of selected information. Firstly, a region's knowledge base size is measured through a traditional indicator of the share of a region's patents in Europe in the period 1998-2001 as well as by the level of R&D expenditures on GDP in the period 2000-2002.

Moreover, a list of indicators capturing the type of knowledge - in terms of its basic nature, generality, originality - present in the region has been built. The degree of basic knowledge in the region has been measured through the presence of General Purpose Technologies (GPTs) in a region, we computed for each region *i* a technological specialization index on the basis of the number of patents applied for by in GPTs[5]. The focus on these technologies is motivated by the fact that they are considered to have wider applications, large adoption and diffusion potential and, ultimately, greater economic impact (Foray et all., 2009). The specialization index is computed as the share of GPTs at regional level for the period 1998-2001 with respect to the European share of patents in GPTs.

Pervasiveness is captured through a *generality* index (Hall et al., 2001), that is an adapted Herfindal index on the technological classes[6] of the citations received (i.e. *forward citations*) by the patents applied for by in the period 1998-2001. More general and pervasive knowledge is used in a wider spectrum of diverse technological applications and it is thus of greater technological value than more specific and targeted knowledge.

Originality of the knowledge produced, i.e. the extent to which the knowledge being developed in each region is original as compared to the state of the art and recombines pieces of knowledge distributed across different technical fields, is measured through an *originality* index (Hall et al., 2001). This is also an adapted Herfindal index on the technological classes of the citations made (i.e. *backward citations*) by the patents applied for by in the period 1998-2001. More original knowledge is likely to be associated to previously unexplored technological applications and to more radical inventions.

[4] Patents are assigned to regions according to the respective inventors residence address as available in patent documents. Fractional count is applied. The authors gratefully acknowledge Crenos - University of Cagliari (Italy) for access and use of their patent database.
[5] GPTs includes nanotechnology, biotechnology and ICTs, as also claimed by some literature (Foray et all., 2009). We assigned patents to these technologies on the basis of their IPC code (see also footnote 3) following the OECD classification.
[6] Every patent is attributed to one or more technological classes according to the International Patent Classification (IPC). We reclassified patents according to a 30 technological field classification that aggregates all IPC codes into 30 technological fields, and next into 7 main technological fields. This is a technology-oriented classification, jointly elaborated by Fraunhofer Gesellschaft-ISI (Karlsruhe), Institut National de la Propriété Industrielle (INPI, Paris) and Observatoire des Sciences and des Techniques (OST, Paris). For the computation of the generality and the originality indexes, we used the 7-class classification.

Lastly, to capture the knowledge that is not directly expressed in patent activities, and is instead embedded in human capital available in a region in the form of *technical and managerial capabilities*, an indicator was derived from a factor analysis synthesizing the share of small and medium size enterprises (SMEs) managers and physical and engineering science associate technicians on total employment. In fact, skilled and specialized human capital has to be considered as an important repository of embedded and tacit knowledge and can identify the pool of capabilities locally available.

Innovation data have been built by the authors on the basis of data from the Community Innovation Survey (CIS) EUROSTAT database. In particular, innovation indicators are based on national CIS4 wave figures (covering the 2002-2004 period), next developed at the NUTS2 level. As in the case of knowledge, a general indicator of the degree of innovation is the degree of product and or process innovation developed in the region. Moreover, to capture the type of different innovation, we made use of different questions of CIS: only product innovations, only process innovations, product and process innovations (both types of innovation simultaneously as well as all the first three main typologies altogether), and marketing and/or organizational innovations.[7]

II. Regional preconditions for knowledge and innovation creation

Indicators on the regional preconditions for knowledge creation are traditional indicators highlighted by the literature. From all indicators, two kinds were available, i.e. the degree of scientific human capital present in the region, measured by the share of inventors and by the share of highly educated people, and the degree of accessibility (transport infrastructure) that exists in the region. What lacks is the presence of high-level functions, like universities and research centres, for those no reliable data exist. The availability of a dummy capturing the size of cities in a region (the so called agglomerated regions) is of help to fill out the lack of these data.

For what concerns the capacity of a region to translate knowledge into innovation, the local preconditions derive from the milieux innovateurs theory and from the knowledge filter theory that stress the presence collective learning and entrepreneurship as elements that allow knowledge to be turned into useful innovative applications. Entrepreneurship is measured as the share of local units, with the exclusion of wholesale and retail sectors that create distortion in the proxy. Collective learning is indirectly measured through the degree of concentration in manufacturing sectors, with the idea that the higher the concentration in particular sectors, the higher the (unintended) exchange of knowledge among local firms, as claimed by the theory of the milieux innovateurs (Camagni, 1999) and innovative clusters (Cooke, 2001, Asheim and Coenen, 2005).

[7] For an in-depth explanation of the estimation methodology of NUTS2 CIS data, see Chapter 1 of this report.

Table 2.2. Indicators and measures

Indicators	Measures	Computation	Year	Source
Knowledge				
R&D	R&D expenditures	Share of R&D expenditures on GDP	Average value 2000-2000	CRENoS database
Knowledge	Share of patents	Regional share of EU total patents	Total patents in the period 1998-2001	Authors' elaboration on CRENoS database
Specialization in GPTs	Index of specialization on patents in GPTs (i.e. nanotech, ICT, biotechnology)	Location quotient of regional GPT patents	Total patents in the period 1998-2001	Authors' elaboration on CRENoS database
Generality	Opposite of the Herfindal index on the technological classes of forward citations*	Generality = 1 $-H_{forward}$ $H_{forward} = \sum_{j=1}^{30}\left(\frac{cit\_forward_{ij}}{cit\_forward_i}\right)^2$	Total patents in the period 1998-2001	Authors' elaboration on CRENoS database
Originality	Opposite of the Herfindal index on the technological classes of backward citations*	Originality = 1 $-H_{backward}$ $H_{backward} = \sum_{j=1}^{30}\left(\frac{cit\_backward_{ij}}{cit\_backward_i}\right)^2$	Total patents in the period 1998-2001	Authors' elaboration on CRENoS database
Capabilities (knowledge embedded in human capital)	Share of SMEs managers and technicians	Factor analysis on the share of managers of SMEs and technicians	Average value 1997-2001	European Labour Force Survey
Innovation**				
Product and/or process innovation	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
Marketing and/or organizational innovation	Firms introducing a marketing and/or an organisational innovation	Share of firms introducing marketing and/or organizational innovations	One value for the period 2002-2004	Authors' estimation on CIS (Eurostat) data
Product innovation	Firms introducing a new product in the market	Share of firms introducing a product innovation	One value for the period 2002-2004	Authors' estimation on CIS (Eurostat) data
Process innovation	Firms introducing a new process in the market	Share of firms introducing a process innovation	One value for the period 2002-2004	Authors' estimation on CIS (Eurostat) data
Product and process innovation	Firms introducing both a new product and a new process in the market	Share of firms introducing both product and process innovations	One value for the period 2002-2004	Authors' estimation on CIS (Eurostat) data
Regional preconditions for knowledge creation				
Scientific human capital	Share of inventors	Share of inventors on population	Average value 1999-2001	AQR elaborations on CRENoS database
Highly educated human capital	Share of highly educated people	Share of people aged 15 and over with tertiary education on total population	Average value 1999-2001	Eurostat
Accessibility	Rail and road network length by usable land	Km of rail and road network on usable land	2000	ESPON
Regional preconditions for innovation creation				
Entrepreneurship	Share of self-employment (local units in wholesale and retail excluded)	Number of local units (wholesale and retail sectors excluded) on total EU local units	Average value 1999-2004	Eurostat
Collective learning	Concentration in manufacturing sectors	Herfindal index on the share of employment in manufacturing sub-sectors***	Average value 1999-2001	Eurostat
Strategic vision on innovation	Perception of innovation as relevant for growth	Factor analysis on Eurobarometer questions on innovation importance to economic performance**** and broadband penetration rate	2005	Eurobarometer 63.4 and Eurostat
Regional preconditions for external knowledge and innovation acquisition				
Receptivity	Capacity of the region to interpret and use external knowledge (proxied by the degree of networking)	5^{th} Framework Program funding per capita	Average value 1998-2002	Authors' elaboration on CRENoS database
Creativity	Sensibility, interest and openness to innovation	Factor analysis on Eurobarometer questions on sensibility, interest and openness to innovation****	2005	Eurobarometer 63.4
Attractiveness	Regional wage differential with respect to the EU average	$W_{Reg\_i} - W_{EU\ average}$	Average value 1999-2001	Eurostat

Inter-regional knowledge and innovation flows				
Knowledge potential	Share of patents in GPT of all other regions weighted by cognitive proximity	Sum of the share of patents of all regions, but the focal one, weighted by the cognitive proximity to the focal region	Total patents in the period 1998-2001	Authors' elaboration on CRENoS database
Capability potential	Capabilities of all the other regions weighted by technological proximity	Sum of the capabilities of all regions, but the focal one, weighted by technological proximity to the focal region	Average value 1997-2001	European Labour Force Survey and Eurostat
Innovation potential	FDI penetration rate	Number of FDI in manufacturing on total population	Average values 2005-2007	FDI-Regio, Bocconi-ISLA
Proximity matrices				
Cross- regional cognitive proximity	Inter-regional knowledge similarity in a digit-1 technological class multiplied by interregional knowledge variety in digit-2 technological classes belonging the digit-1, summed over classes	$\sqrt{\sum_{d1=1}^{7}\left[\frac{(p_{id1} * p_{jd1})}{(\lvert p_{id1} - p_{jd1}\rvert)} * (\sum_{d2=1}^{m}(\lvert p_{id2} - p_{jd2}\rvert))\right]}$	Total patents in the period 1998-2001	Authors' elaboration on CRENoS database
Sectoral proximity	Inter-regional similarity in production specialization	Euclidean proximity between regional location quotients in 6 different manufacturing sectors***	Average values 1998-2001	Eurostat
Regional settlement structure and stage of development				
Agglomerated regions	NUTS2 with more than 300,000 inhabitants and a population density of more than 300 inhabitants per km sq., or a population density between 150 and 300 inhabitants per km sq.	Dummy variable equal to 1 if the region is classified as agglomerated	2000	ESPON
New member states (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

* Patent citations are here classified according to the 7 technology fields classification developed by OST (see also footnote 3 for further details).
** See the website http://www.espon.eu/main/Menu_Projects/Menu_AppliedResearch/kit.html for the estimation methodology.
*** Six manufacturing sub-sectors are considered, namely: Food, beverages and tobacco; Textiles and leather; Coke, refined petroleum, nuclear fuel and chemicals; Electrical and optical equipment; Transport equipment; Other manufacturing.
**** See Annex A.2.1 for the list of variables used in the factor analysis.
***** Similarity is captured as the degree to which the distribution of patents across technological macro-fields in two regions overlaps. It is the product of the share of region's *i* patents in class d_1, i.e. p_{id1}, times the share of region's *j* patents in class d_1, i.e. p_{jd1}, summed over classes. This is discounted by the difference between the share of patents in class d_1 between the two regions to account for the fact that similarity is likely to be higher the more similar the importance of the sector in the two regions is. Similarity equals 1 for regions with exactly the same distribution of patents across classes, and 0 for regions with no patents in the same classes. Inter-regional related variety between regions is measured by the difference between the share of patents in a 2-digit technological classes belonging to a 2-digit class in two regions. The higher the difference between the two regional shares of patents in 2-digit technological classes, the higher the complementarity between regions. Two-digit are represented by the 30 technology fields of the OST classification, and 1-digit by the 7 OST main technological fields (see footnote X for further details on the OST classification). Because of the high skewness of the distribution of this variable, data are transformed using a square root transformation, a methodology largely applied in the literature (Hollanders et al., 2009). Two-digit are represented by the 30 technology fields of the OST classification, and 1-digit by the 7 OST main technological fields (see footnote 3 for further details on the OST classification).

III. Inter-regional knowledge and innovation flows

Knowledge and innovation potential of a region also heavily depend on the capacity of regions to attract, absorb, originally recombine and adopt knowledge and innovations sourced from other regions. To measure the flows of inter-regional knowledge and innovation, i.e. the external knowledge and innovation potential of a region, specific indicators were built.

In particular, to capture the potential benefits that may accrue to each region *i* from the pool of basic (GPTs) knowledge developed by other regions (i.e. *knowledge potential*), we computed the sum of the share of all GPTs patents developed by all the N-*i* regions weighted by a measure of cognitive proximity between each pair of regions. In fact, the flows of basic knowledge are to a limited extent influenced by gravity type behaviours, proxied by physical proximity, and much more by similar background, cognitive map and common basic knowledge that two regions have. For this reason, the potential acquisition of basic knowledge of other regions is weighted by the degree of cognitive proximity that pairs of region have.

Cognitive proximity within actors of a region has been defined in terms of related variety, i.e. the presence of complementary knowledge within a set of shared and common knowledge (Boschma, 2005). This idea is here transferred at the inter-regional level, and it is measured as the inter-regional knowledge similarity in a specific technological field *i* multiplied by the interregional knowledge variety in the technological sub-fields of field *i* among each pair of regions. We in fact assume that the capacity to absorb and to use GPT knowledge sourced from other regions depends on two main elements. First, it positively depends on two regions sharing a common knowledge basis and cognitive frame in macro technological fields (i.e. two regions are similar in their cognitive (i.e. patent) profile). Second, it is more likely when two regions are specialized in different albeit related and complementary technological sub-fields within the same macro field (i.e. provided a common knowledge base, two regions are more likely to exchange complementary rather than the same type of knowledge). Table 2.2 further illustrates the construction of this indicator.

Next, to capture the potential benefits that may accrue to each region *i* from the pool of embedded knowledge available in other regions (i.e. *capabilities potential*), we computed the sum of the capabilities in all the N-*i* regions weighted by a measure of technological proximity between each pair of regions. The exchange of capabilities is in fact higher, the higher the similarities in terms of sectoral specificities is. In particular, sectoral proximity is measured as the distance between pairs of regions in their location quotient on the basis of employment data in six manufacturing sectors. The greater this similarity, the greater the opportunity to benefit from embedded knowledge in human capital sourced from other regions, i.e. capabilities external to the region.

Finally, to take into account the potential benefits that may accrue to each region *i* from the pool of innovations developed in other regions (*innovation potential*), we draw on the evidence that multinational corporations and foreign direct investments (FDIs) can be considered as learning mechanism and innovation diffusion channel (Cantwell and Iammarino, 2003; (Castellani and Zanfei, 2004). We thus computed the number of FDIs in each region in the manufacturing sector and discounted it by the regional population size.

IV. Regional preconditions to acquire external knowledge and innovation

The knowledge and innovation potentials are likely to be enhanced by specific regional preconditions for external knowledge and innovation acquisition.

Receptivity is defined as the capability of the region to get in contact with, interpret and use external knowledge for complementary research and science advances. It therefore represents the precondition of a region to acquire knowledge from outside and make efficient use of it. The degree of relational capital is a good proxy of such a capacity. For this reason, an indicator of the 5th framework funding per capita is built.

Creativity is instead necessary for a region to achieve knowledge and turn it into local innovation, adding to internal specific capabilities, not necessary embedded in formal knowledge. This variable is measured through a factor analysis on the Eurobarometer questions on sensibility, interest and openness to innovation of local population.

Attractiveness is meant to be the capacity of a region to receive innovation developed outside the region and apply it to the local needs. If innovation mainly comes through advanced multinational firms, from which the tissue of local firms can imitate managerial, organizational, product and process innovation, a good proxy of attractiveness is the low labour cost, measured through the regional wage differentials from the European average.

2.2.2. Methodological specificities

To combine regions into groups and to identify different patterns of knowledge and innovation across regions, a cluster analysis was performed, with the aim of describing the variety of attitudes and knowledge and innovation behaviors across European regions. The purpose of the clustering exercise is that of enlightening commonalities and differences across regions. This exercise is next integrated with a multinomial logistic regression, which aims at exploring the relevance of region specific variables in the different knowledge and innovation modes.

In particular, we performed a k-means cluster analysis[8] based on the degree of knowledge and innovation that is in general produced by a region. In our conceptual approach in fact knowledge and innovation take place in different stages of the production process and can mix in a variety of ways. In particular, the cluster analysis was run with two innovation variables and one knowledge intensity variable; for the innovation variables, the share of firms introducing product and/or process innovation and the share of firms introducing marketing and/or organizational innovations were chosen, since they encompass the largest category of innovators and can thus take into account different innovation typologies. For the intensity of knowledge production, the indicator of the region's knowledge base size (i.e. the share of EU total patents) was inserted.

We considered different statistical criteria to identify the appropriate number of clusters to be retained, such as the relationship between within-cluster and between-cluster variance, but also the number of firms per cluster and, more importantly, the interpretability of the results in terms of innovation patterns. We finally extracted five clusters; each cluster includes a reasonable portion of observations, so that they can be plausibly interpreted as patterns of innovation.

Intriguingly, performing an ANOVA exercise on the variables presented in Table 2.2 provides interesting additional information that allows emphasizing the differences among clusters in terms of key distinctive territorial characteristics. Table 2.3 synthesizes the results of the ANOVA exercise and presents the mean value of the variables across the five clusters, in EU27 and (in the last column) the significance level of the ANOVA test.

[8] We opted for the k-means approach since, in the literature, it is preferred to hierarchical approaches (Afifi et al., 2004).

Table 2.3. Mean values by cluster and in EU and ANOVA test statistical significance (p-value)

Variables	Imitative innovation area (1)	Smart and creative diversification area (2)	Smart technological application area (3)	Applied science area (4)	European science-based area (5)	EU average	ANOVA P-value
Number of observation	37	86	67	52	20	262	
Variables used in the cluster exercise							
Knowledge (%)	0,01	0,13	0,40	0,48	1,53	0,35	p<0.01
Product and/or process innovation (%)	18,14	27,58	38,43	46,36	63,16	35,54	p<0.01
Marketing and/or organisational innovation (%)	13,94	22,05	19,61	39,33	51,07	25,99	p<0.01
Knowledge							
R&D (%)	0,4	1	1,71	1,81	2,56	1,37	p<0.01
Specialisation in GPT	0,68	0,65	0,84	0,86	0,92	0,76	p<0.05
Share of patents in GPT (%)	18,66	17,95	22,91	23,58	25,24	20,85	p<0.05
Generality	0,242	0,531	0,730	0,724	0,801	0,592	p<0.01
Originality	0,384	0,636	0,759	0,749	0,804	0,661	p<0.01
Capabilities	-0,30	0,36	-0,04	-0,29	-0,81	-0,01	p<0.01
Innovation							
Product innovation (%)	4,13	5,01	15,38	12,20	23,46	10,40	p<0.01
Process innovation (%)	5,88	10,65	12,23	12,97	13,41	11,05	p<0.01
Product and process innovation (%)	8,13	11,91	13,97	21,66	26,29	14,97	p<0.01
Regional preconditions for knowledge creation							
Scientific human capital (%)	0,001	0,005	0,013	0,018	0,034	0,01	p<0.01
Highly educated human capital (%)	5,38	7,97	10,77	10,91	11,24	9,12	p<0.01
Accessibility (%)	12,42	17,46	31,47	34,70	59,52	26,62	p<0.01
Regional preconditions for innovation creation							
Entrepreneurship (%)	14,39	14,83	10,73	9,24	8,61	12,04	p<0.01
Collective learning	26,10	29,07	29,13	29,50	28,86	28,75	p<0.05
Strategic thinking on innovation	-0,87	-0,36	-0,07	0,22	0,48	-0,14	p<0.01
Regional preconditions for external knowledge and innovation acquisition							
Receptivity (thousands euro per capita)	3799,39	16016,29	25015,88	30147,05	41220,50	21068	p<0.01
Creativity	0,39	-0,05	-0,03	-0,59	-0,96	-0,13	p<0.01
Attractiveness	9,45	1,54	-1,98	-2,66	-8,23	0,25	p<0.01
Inter-regional knowledge and innovation flows							
Knowledge potential[9]	99,07	92,04	102,44	102,31	106,33	99,07	not significant
Capabilities potential	-0,91	0,07	-5,13	-49,50	-92,33	-18,60	p<0.01
Innovation potential	51,57	55,22	55,48	30,73	20,60	47,16	not significant
Regional settlement structure and stage of development							
EU12	30	17	6	3	0	56	not applicable
Agglomerated	4	15	30	15	13	79	not applicable

[9] Because of the high skewness of the distribution of this variable, data are transformed using a square root transformation, a methodology largely applied in the literature (see for example the Regional Innovation Scoreboard 2009 report by Hollanders, Tarantola and Loschky available at http://www.proinno-europe.eu/page/regional-innovation-scoreboard).

2.3. Territorial innovation patterns across European regions

The variables used for the clustering exercise in Table 2.3 at a first sight simply provide a ranking of EU27 regions in terms of their endogenous knowledge and innovation performance, from cluster 1 (the least knowledge and innovation intensive) to cluster 5 (the most knowledge and innovation intensive). However, this description risks to be somehow too straightforward and to hide a greater variety of knowledge and innovation potentials and behaviors. The ANOVA exercise is very helpful in this regard and helps to better qualify the cluster description and identification.

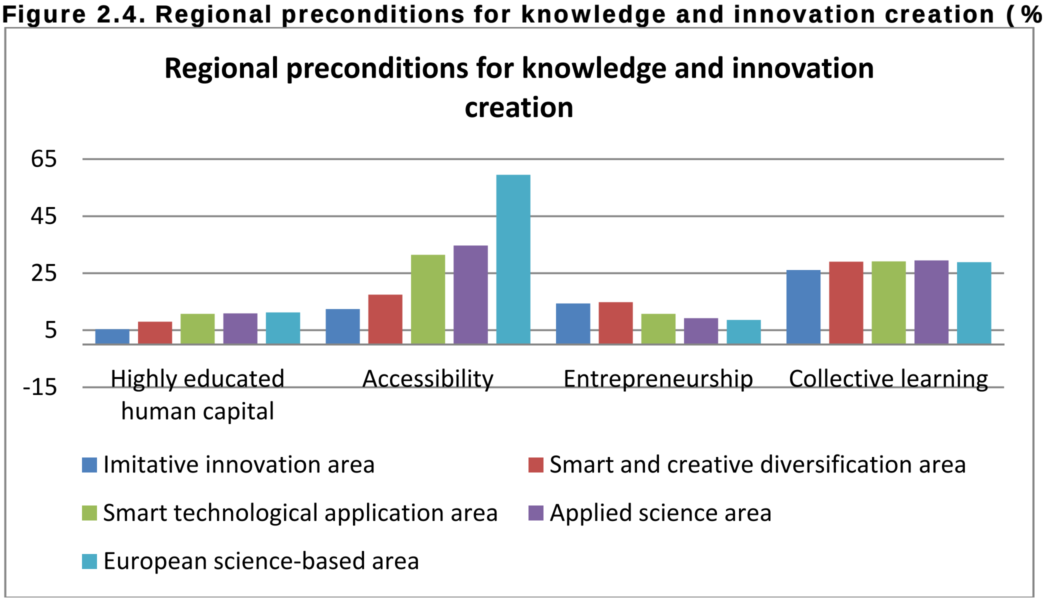
In fact, by carefully looking into the descriptive variables of each cluster, the picture obtained is extremely rich in terms of cases of innovation and knowledge production associated to external and internal preconditions.

The first interesting result is that, differently from the conceptual approach proposed in Section 2.1, we empirically detect a larger variety of possible innovation patterns; we identify two clusters that can be associated to our conceptual Pattern 1, albeit with some relevant distinctions between the two, two clusters that can be associated to Pattern 2, again with some differences between them, and one cluster that can be associated to Pattern 3. Interestingly, the five groups show sizeable differences in the variables considered in the clustering exercise.

Cluster 5: a European science-based area

Cluster 5 is composed of regions that are the most knowledge and innovation intensive. Their innovative attitude is well above the EU average across all dimensions (i.e. product, process, marketing and/or organizational innovation). This couples with a very strong knowledge orientation which is more directed to GPTs than in the other cases (and above the EU average) both in terms of amount of knowledge developed as well as in terms of specialization profile. Interestingly, this knowledge tends to be of greater generality and originality, that is of greater technological value and more radical than the EU average. The regions in this cluster are also well endowed with those pre-conditions frequently associated to greater endogenous capacity of knowledge creation, namely the presence of highly educated population and, more importantly, the presence of scientific human capital, here measured by the share of inventors on total population. Their accessibility is also the highest (Figure 2.4), indicating that, probably, these regions cover to a large extent more urban and metropolitan settings (as confirmed by the variable accounting for the number of agglomerated regions), which are traditionally more open and fertile environments for new ideas generation (Carlino et al., 2007).

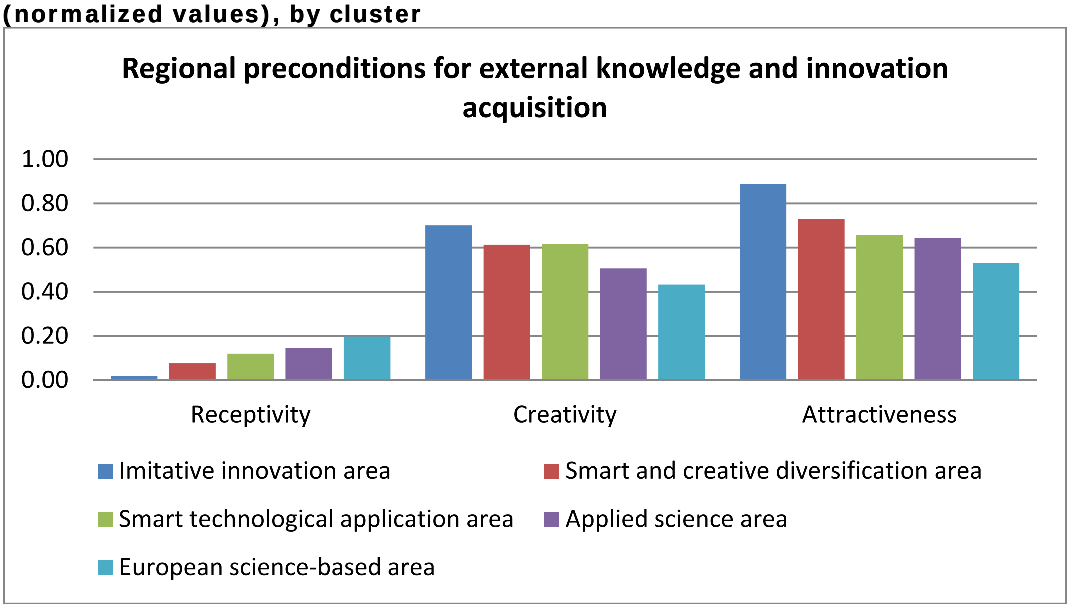
Figure 2.4. Regional preconditions for knowledge and innovation creation (%), by cluster



The indicators of regional preconditions for innovation creation, on the other hand, do not show the highest values across EU27. In particular, these regions are less entrepreneurial than the EU average. However, the variable accounting for collective learning shows a comparable value to the EU average and, interestingly, the regions in this cluster seem to have a more strategic vision and thinking on the role of innovation for performance, competitiveness and economic growth. As to the variables related to the preconditions for knowledge and innovation acquisition, these regions outperform the others in terms of their propensity to networking (i.e. *receptivity*) whereas they look less creative and attractive than the EU average (Figure 2.5). Lastly, their capabilities and innovation potentials are lower than the EU average whereas their knowledge potential is greater than the EU average.

All in all, these observations suggest that these regions show a strong knowledge and innovation orientation which is primarily linked to their endogenous capacity to create new knowledge and to efficiently translate it into new products and processes as well as into managerial and/or organizational changes. This marked orientation suggests that these regions can potentially host the *European Science Based Area* and be part of what has been defined the European Research Area (Foray et al., 2009; Pontikakis et al., 2009). These regions are mostly located in Germany, with the addition of Wien, Bruxelles, and Syddanmark in Denmark.

Figure 2.5. Regional preconditions for external knowledge and innovation acquisition (normalized values), by cluster



Cluster 4: an applied science area

Cluster 4 includes a wider group of regions which share similar characteristics with regions in cluster 5, although most of the variables show lower mean values. In particular, this is the case of the share of EU total patents, which is almost halved, as well as the share of scientific human capital and R&D expenditures. Interestingly, the relevance of GPTs is lower both in terms of share of GPTs patents developed as well as in terms of specialization profile. Importantly, these regions look more entrepreneurial, creative, attractive and with a larger capabilities potential than regions in cluster 5, albeit less than the EU average. These regions thus maintain a rather strong knowledge and innovation intensity, i.e. form a knowledge area, but, differently from the ones in cluster 5, they are less focused on GPTs, and, accordingly, more technologically diversified.

Map 2.1 shows that these regions are mostly agglomerated and located in central and northern Europe, namely in Austria, Belgium, Luxembourg, France (i.e. Paris), Germany, Ireland (i.e. Dublin) Denmark, Finland and Sweden with some notable exceptions at East such as Praha, Cyprus and Estonia and at South such as Lisboa and Attiki.

We are in front of strong knowledge producing regions, that distinguish themselves from the European science-based area for their diversified knowledge production profile. From the normative point of view, these regions have the chance to strengthen their position by specializing themselves in the production of applied knowledge, making use of the basic knowledge produced from the science based area. If this is the case, this group can become the '*an applied science area*' of Europe.

Cluster 3: a smart technological application area

Regions in cluster 3 look quite different from regions in cluster 5. They are comparable to regions in cluster 4 in terms of size of the knowledge base and its characteristics (i.e. relevance of GPTs, generality and originality), show greater endowment of embedded knowledge in human capital (i.e. capabilities) but they are different in terms of innovation profile. In particular, they have a stronger orientation towards product innovation, are somehow weaker in terms of process in innovation (albeit being more innovative than the EU average also according to this dimension) and are among the weakest performers in terms of marketing and/or organizational innovation.

Regional preconditions for knowledge and innovation creation, but entrepreneurship, are similar to those of regions in cluster 4, albeit more limited (Figure 2.4 above). Differently, regional preconditions for knowledge and innovation acquisition, namely creativity and attractiveness, are more favorable to regions in cluster 3 than to regions in clusters 4 and 5, whereas receptivity is comparable to cluster 4. Also, the capabilities and innovation potentials are larger than in cluster 4 and the knowledge potential is comparable to clusters 4 and 5.

All in all, these regions experience the greatest advantage in terms of product innovation, accompanied by a high degree of knowledge potential flows and internal preconditions to translate external knowledge into innovation, thanks to high creativity. These results suggest that these regions are able to efficiently translate internal and external knowledge into new specific commercial applications. Cluster 3 can easily represent our conceptual Pattern 2, the creative application pattern, where co-invention of application is the result of internal creativity and external basic knowledge. It includes mostly agglomerated regions in EU15, such as the northern part of Spain and Madrid, Northern Italy, the French Alpine regions, the Netherlands, Sweden and the UK (Map 2.1). Normative interventions should strengthen these peculiarities and push this group of area to become the '*smart technological application area*' of Europe.

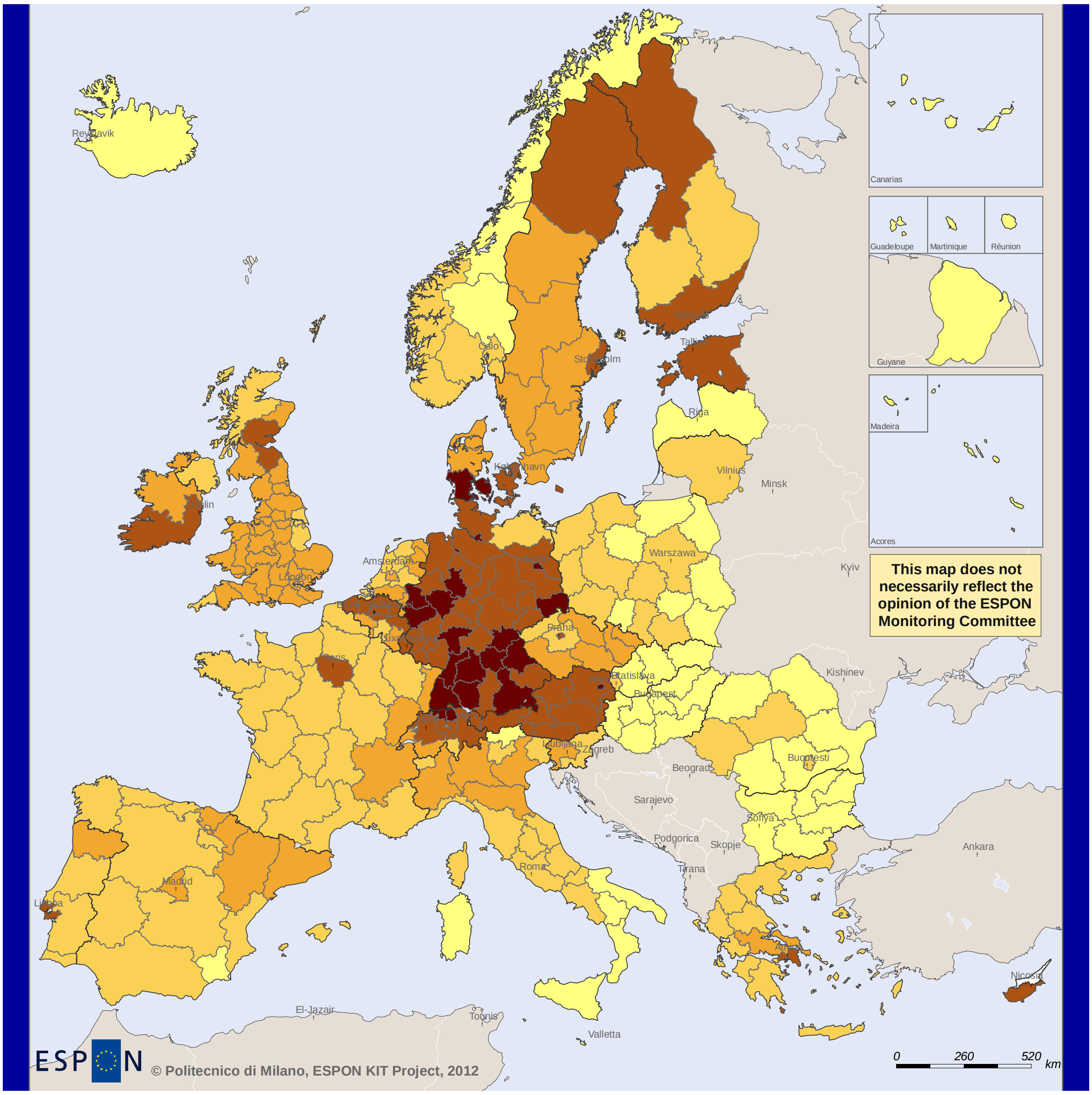
Cluster 2: a smart and creative diversification area

Cluster 2 shows some distinctive traits that clearly discriminate regions in this group from the others. In particular, the knowledge and innovation variables show smaller values than the EU average but the capabilities indicator, which takes the highest mean value in this cluster. This suggests that the not negligible innovation activities carried out in regions belonging to this cluster mainly rely upon tacit knowledge embedded into human capital. Also, regions in this cluster look highly entrepreneurial (this variable takes the highest mean value in this cluster) and, importantly, are strongly endowed with those characteristics such as creativity and attractiveness that help to absorb and to adopt innovations developed elsewhere. Additionally, whereas the knowledge potential does not look prominent, the capabilities and innovation potentials are well above the EU average. Thus, the key advantages of these regions reside in their embedded human capital and the entrepreneurial and creative attitudes that can be wisely exploited in the pursue of upgrading innovative strategies. These regions are mainly located in Mediterranean countries (i.e. most of Spanish regions, Central Italy, Greece, Portugal), in EU12 agglomerated regions in Slovakia and Slovenia, Poland and Czech Republic, few regions in northern Europe, namely in Finland and the UK (Map 2.1).

In these regions, a different type of Pattern 2 emerges with respect to cluster 3. In these regions, internal innovation capacity is highly fed by external knowledge, as it is the case for cluster 3, but the type of knowledge that is acquired from outside is neither basic nor applied formal knowledge; these regions highly take advantages from external knowledge which is embedded in technical and organizational capabilities, in technicians and SMEs managers (Cooke, 2005); thanks to the high degree of creativity present in the area, these regions are able to take advantage from specific capabilities present in regions with similar sectoral profiles, and innovate in different products in different industries (Figure 2.6).

Normative interventions should strengthen this innovative attitude and push these regions to become the ‘smart and creative diversification area’ in Europe.

Map 2.1. Territorial patterns of innovation in Europe



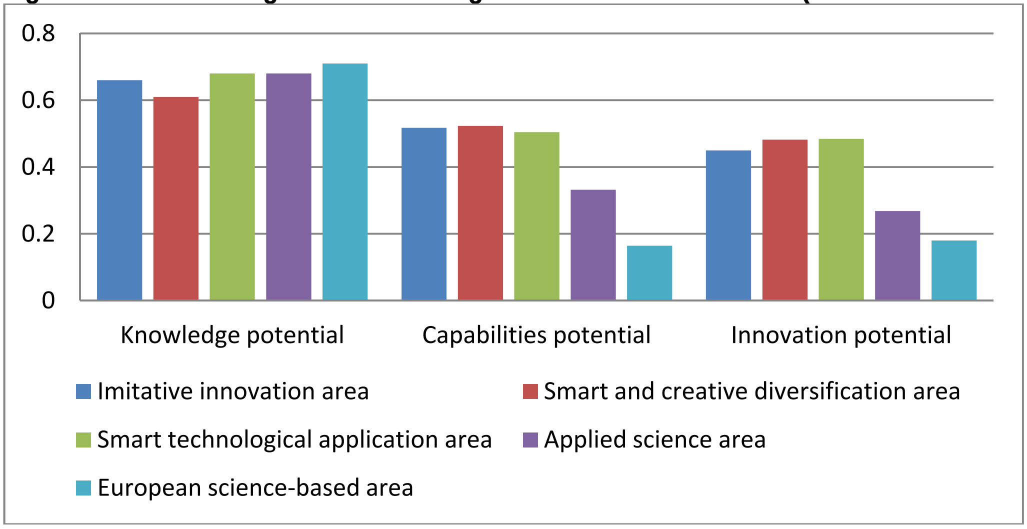
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

Regional level: NUTS2
Source: Own elaboration, 2012
Origin of data: EUROSTAT, 2012
© EuroGeographics Association for administrative boundaries

Legend

- No data
- Imitative innovation area
- Smart and creative diversification area
- Smart technological application area
- Applied science area
- European science-based area

Figure 2.6. Inter-regional knowledge and innovation flows (normalized values), by cluster



Cluster 1: an imitative innovation area

Finally, the last group (i.e. cluster 1) could be associated to Pattern 3. In fact, it is composed of regions that have a rather narrow knowledge and innovation profile and are the least performers in both respect. However, some key distinctive traits characterize this cluster. In particular, entrepreneurship, creativity, attractiveness, capabilities and innovation potentials show greater than the EU average values. Especially attractiveness is stronger than in the other clusters (Figure 2.6). These dimensions can be enhanced and supported to creatively embrace new adoption, imitation and innovation strategies. For this reason, these group of regions can form an "*imitative innovation area*" in Europe. Most of these regions are in EU12 such as all regions in Bulgaria and Hungary, Latvia, Malta, several regions in Poland, Romania, and Slovakia, but also in Southern Italy (Map 2.1).

The high level of creativity, entrepreneurship and collective learning present in thus cluster provide potential assets to turn, in an evolutionary perspective, this area into a smart and creative diversification area, through normative intervention that help exploiting creativity and entrepreneurship for increasing endogenous innovation activities, and not only for imitative innovation.

2.4. The link between territorial elements and innovation patterns

To further support the descriptive evidence presented in Section 4 and to better understand the most relevant territorial elements associated to each knowledge and innovation pattern and their interplay, we compared the five clusters across some key territorial characteristics. This exercise has two additional advantages. First, the identification of the key traits discriminating between clusters associated to the same conceptual pattern, namely, between clusters 2 and 3, and between clusters 4 and 5; second, from a normative point of view, by emphasizing the crucial distinctive characteristics associated to each group of regions, it provides some indications on the most likely directions to which policy intervention could be targeted.

To this aim, we estimated the following multinomial logistic model, where the dependent variable is the probability of region i to belong to cluster j (Pr):

$$\Pr(Y_i = j) = \frac{\exp(x_i'\beta_j)}{\sum_{m=1}^{5}\exp(x_i'\beta_m)} \qquad \textit{for } j = 1, \dots, 5$$

where Y_i is the dependent variable (i.e. cluster membership), x_i are case-specific regressors (including the intercept) and β_j is a vector of coefficients, which is set at zero for cluster 1, which is the base category[10]. Therefore, it is worth emphasizing that the coefficients have to be interpreted in relative terms, i.e. in comparison with the reference category that in Table 2.4 is cluster 1, the imitative innovation area.

On the ground of our conceptual approach (Section 2) and the result of the cluster and ANOVA analyses (Section 4), we selected a set of independent variables that could capture some distinctive regional traits that can be associated to different knowledge and innovation attitudes and patterns. In particular, we mainly focus on regional preconditions to knowledge and innovation creation and acquisition. This choice is functional in our conceptual and empirical strategy as these can more easily become policy targets.

Before discussing the results, it is important to stress that the econometric model is here used for descriptive purposes to compare groups of regions across some key territorial elements. The set of regressions proposed and commented in the following are to be interpreted as descriptive ones, and no causation link is assumed to run from the independent variables to the dependent ones, since they are likely to be affected by endogeneity issues. Therefore, the following regression coefficients are to be interpreted as a set of partial correlation indices, which help to provide a description of the elements that are associated to different knowledge and innovation patterns.

Table 2.4. Territorial characteristics relevance across clusters

	Smart and creative diversification area – Cluster 2		Smart technological application area – Cluster 3		Applied science area – Cluster 4		European science-based area – Cluster 5	
	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
Specialization in GPT	-0,761	0,851	-0,967	1,025	-0,836	1,100	0,419	1,900
Generality	0,788	1,271	3,189**	1,684	1,405	1,864	24,156***	8,944
Capabilities	1,371***	0,427	1,591***	0,442	1,589***	0,479	0,522	0,930
Scientific human capital	6,067	4,385	10,723**	4,549	11,134***	4,575	13,224***	4,617
Highly educated human capital	24,737	17,313	33,667*	18,145	18,729	19,403	3,910	29,132
Accessibility	0,113	4,428	1,720	4,385	2,736	4,425	2,957	4,441
Entrepreneurship	-1,936	5,666	-5,254	6,981	-20,27***	8,056	-21,042	13,368
Collective learning	15,368*	8,072	22,073***	8,569	24,893***	9,083	26,971***	11,109
Strategic thinking on innovation	0,089	0,593	0,180	0,625	0,005	0,636	-0,497	0,770
Receptivity	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Creativity	0,593	0,375	0,898**	0,465	-0,429	0,477	-1,608**	0,711
Attractiveness	-0,078	0,137	-0,032	0,148	-0,063	0,150	-0,259	0,168
Constant	-5,379*	2,927	-11,008***	3,392	-8,851**	3,796	-30,422***	8,960

Robust standard errors. Wald chi2(48) = 207,47; Prob > chi2 = 0.0000; Log likelihood = −231.356; Pseudo $R2$ = 0.3966. ***p < 0.01, **p < 0.05, *p < 0.1. Base case: Cluster 1 (Imitative innovation area).

The comparison between the imitative innovation area (cluster 1) and the smart and creative diversification area (cluster 2) suggests that the key distinctive traits of the latter reside in a larger pool of locally available capabilities (i.e. tacit knowledge embedded into human capital) and, moderately, in a greater level of collective learning that facilitates the circulation, socialization and ri-elaboration of local knowledge. The comparison between the imitative innovation area and the smart technological application area (cluster 3) indicates that the latter has a significantly stronger knowledge orientation in terms of the generality of the knowledge produced as well as the capabilities and the human resources available (both scientific and highly educated human capital). Additionally, the level of collective learning and creativity are higher, supporting the idea of a faster and more efficient recombination of

[10] The ordinal attribute of the dependent variable would make the estimation of an ordinal logit a more appropriate methodological choice. However, this failed to meet the parallel regression assumption and several covariates failed to pass the Brant test assessing the parallel regression assumption at the single variable level. Thus, we resorted to estimate the multinomial logit model described in the text. The multinomial logit model is also preferred because it allows emphasising the differences across groups of regions in the territorial elements most likely associated to each pattern of innovation.

knowledge into new products development. The applied science area is better endowed with capabilities, scientific human capital and collective learning but are far less entrepreneurial than cluster 1 regions. Lastly, the European science-based area (cluster 5) confirms its strong knowledge intensive profile and show greater knowledge generality, a larger scientific human capital base, greater level of collective learning but a lower entrepreneurial attitude. Importantly, no difference emerges among regions in the importance attached to receptivity suggesting that all types of regions can take advantage from the learning, knowledge and innovation opportunities deriving from knowledge networks.

By changing the reference case, some additional insights can be shown on the most relevant distinctions among these groups of regions. In particular, by setting the smart and creative diversification area as reference,[11] its comparison with the smart technological application area, also associated to the conceptual pattern 2, specifies that the two clusters clear differ in the capacity to generate internal knowledge, much more associated to the smart technological application area, which, moreover, shows a stronger capacity to recombine internal and external knowledge via collective learning into superior innovative performance.

Lastly, by setting the applied science area (cluster 4) as reference (estimates not reported but available upon request), its comparison with the European science-based area, also associated to the conceptual pattern 1, specifies that the two clusters clearly differ in their knowledge intensity and generality that guarantees a superior endogenous innovative performance in the European science-based area despite the latter is characterized by a less visible creative attitude and a lower level of attractiveness. Interestingly, the smart technological application area (cluster 3) shows a comparable level of knowledge intensity to the applied science area but differs in terms of its greater entrepreneurial and creative attitude that sustains a superior capacity of screening, selecting and absorbing the most appropriate knowledge and turning it into new products.

All in all, this suggests that the imitative innovation regions exhibit some advantages in terms of entrepreneurship and creativity that could be strategically exploited as key assets in launching innovation upgrading policies. However, the benefits of these policies to fully unfold require also a strong engagement in catching up the other groups of regions especially in terms of human capital and capabilities endowment. The smart and creative diversification regions can rely upon a stronger local knowledge base in terms of capabilities and a high level of entrepreneurship and creativity that guarantee not negligible level of innovation in all dimensions (albeit below the EU average). These elements represent their competitive advantage and have to be supported in innovation policies which, nevertheless, can also be oriented toward promoting a process of greater technological specialization and enhancing the local knowledge base and intensity so to approach the smart technological application regions. These latter have their greatest advantage in the combination of a rather marked technological specialization mixed to a strong knowledge intensity, based both on endogenous knowledge capacity but also on the ability to screen, to select and to absorb external knowledge, and to locally recombine and adapt it via collective learning. This enables a substantial innovation performance (especially in terms of product innovation) not much far from the applied science regions. These share a very similar profile with the European science-based area albeit with a more limited knowledge and innovation intensity, and experience thus the opportunity either to catch up the European science-based area regions by hugely investing in the upgrading of their knowledge basis or to join the smart technological application regions by initiating a process of increasing technological specialization on the one hand, and by promoting an entrepreneurial and creative attitude, on the other. Lastly, European science-based area regions can be considered the most advanced in terms of knowledge and innovation performance and rely this advantage upon their superior knowledge basis. Keeping this status thus requires a mix of policy initiatives oriented to the promotion and support of research activities and the diffusion of scientific and technical competencies.

[11] Estimates not reported but available upon request.

2.5. Conclusions

The main idea put forward in this work is that the pathways towards innovation and modernization are differentiated among regions according to local specificities, and these differentiation explains why a single overall strategy is likely to be unfit to provide the right stimuli and incentives in the different contexts.

The chapter departs from the idea that R&D equals knowledge and that knowledge equals innovation. The distinction between the process of invention in general purpose, basic technology, pervading horizontally different sectors once invention is turned into an innovation, and the process of inventing an application of a basic knowledge in a specific sector, innovating in new products and new market niches is vital to understand the present patterns of innovation. This becomes even more important if we think that the factors that stimulate new knowledge, invention, innovation and innovation diffusion differ; invention and innovation are not necessarily intertwined and this gives rise even at the local level to very different and multi-faced situations; some regions have the capacity to go through all phases of the "linear model", from knowledge creation to innovation and growth, with all feed-backs that can be foreseen from growth to knowledge and innovation. Other regions reinforce this "linear model", exchanging knowledge with other regions gaining complementary assets through a scientific network. There is however a completely different situation in which regions innovate by combining their creative thinking with basic knowledge cumulated in other regions, developing co-inventing applications. Finally, another territorial innovation pattern can be identified by a situation in which regions innovate by creatively imitating innovations developed elsewhere.

This chapter shows that the territorial patterns of innovation conceptually depicted exist in reality. The data show that the real world is even more fragmented than what expected, and that within the same pattern different behaviours exist. Among the knowledge creation patterns, the real data distinguish within the basic knowledge specialized regions, what is called the "European science-based area", where the general purpose technology research activities can be concentrated and economies of scale in research activities exploited. But data tell us also that another group of regions exists where less general and more applied research is produced; these regions should be pushed towards the production of applied diversified knowledge, and leave the basic knowledge been produced by the European science-based area.

Within the creative application pattern, the reality shows two distinct behaviours. From one side, regions emerge that take advantage from specialized formal knowledge and innovate on the basis of this knowledge. These are probably what the literature refers to as the smart technological application areas, where the co-invention of application emerges of basic knowledge produced outside. On the other side, regions exist that exploit knowledge embedded in human capital, in experience, in learning by doing, represented by capabilities built on specific productive vocations of some areas. In this sense, these regions innovate on the basis of external capabilities that, once acquired, merge with local creativity and give rise to a high product innovation performance.

These results strongly suggest that each territorial innovation pattern calls for specific ad-hoc innovation policy goals: the maximum return to R&D investment can be the right goal for a region specialized in knowledge creation, but cannot be at the same time the right policy goal for regions that innovate by exploiting external knowledge, or for regions that imitate innovation processes. For the former, the ad-hoc policy goal is the maximum return to co-inventing applications, which happens when the region promotes changes in response to external stimuli (such as the emergence of a new technology). A maximum return to imitation, pushing towards a creative imitation, is instead the right policy aim for regions that rely on external innovation processes. Each region has to succeed in discovering its territorial innovation pattern, and only through the awareness of the original and unique territorial innovation pattern a region can hope to excel in exploiting innovation efficiency.

A next step for future research is the measurement of efficiency and effectiveness of each pattern of innovation on growth; our impression is that none of these patterns is by definition superior to another and, on the contrary, each territorial pattern may provide an efficient use of research and innovation activities generating growth. But this statement calls for empirical analysis and represents our future research question.

2.6. References

Acs Z. J., Audretsch D. B., Braunerhjelm P. and Carlsson B. (2004) "The Missing Link: the Knowledge Filter and Entrepreneurship in Endogenous Growth", *Centre for Economic Policy Research (CEPR)*, Discussion Paper

Afifi A., Clarck V., May S. (204), *Computer-aided multivariate analysis*, Chapman and Hall, Boca Raton, FL

Asheim B. and Coenen L. (2005) "Knowledge bases and regional innovation systems: Comparing Nordic clusters", *Research Policy*, vol. 34, pp. 11731190

Balconi M., Brusoni S. and Orsenigo L. (2010), "In Defense of a Linear Model", *Research Policy*, vol. 39, pp. 1-13

Bellet M., Colletis G. and Lung Y. (1993), Introduction au Numéro Spécial sur Economie et Proximité, *Revue d'Economie Régionale et Urbaine*, n. 3, pp. 357-361

Boschma R. (2005), "Proximity and Innovation. A Critical Survey", *Regional Studies*, vol. 39, n. 1, pp. 61-74

Boschma R. and Lambooy J. (1999), "Evolutionary Economics and Economic Geography", *Journal of Evolutionary Economics*, vol. 9, pp. 411-429

Camagni R. and Capello R. (2002), "Milieux Innovateurs and Collective Learning: From Concepts to Measurement", in Acs Z.J., de Groot H.L.F., Nijkamp P. (eds.), *The Emergence of the Knowledge Economy*, Springer, Berlin, pp. 15-46

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. (1999),"The City as a Milieu: Applying the Gremi Approach to Urban Development", *Revue d'Economie Régionale et Urbaine,* n. 3, pp. 591-606

Camagni, R. and Capello, R. (2009), "Knowledge-based Economy and Knowledge Creation: The Role of Space", in Fratesi U. and Senn L. (eds), *Growth and Competitiveness in Innovative Regions: Balancing Internal and External Connections*, Springer Verlag, Berlin, pp. 145–166

Cantwell J. (2009), "Location and Multinational Enterprise*", Journal of International Business Studies*, vol. 40, n. 1, pp. 35-41

Cantwell J. and Iammarino S. (2003), *Multinational corporations and European regional systems of innovation*, Routledge, London, UK

Capello R. (2011), "Towards a new Conceptualization of Innovation in Space: Territorial Patterns of Innovation", paper rpesented at the Tinbergen Institute, held in Amsterdam, 18-19 may

Cappellin R. (2003), "Networks and Technological Change in Regional Clusters", in Bröcker J., Dohse D. and Soltwedel R. (eds.), *Innovation Clusters in Interregional Competition*, Springer, Berlin, pp. 53-78

Castellani D. and Zanfei A. (2006), *Multinational firms, innovation and productivity*, Edward Elgar, Cheltenham, UK

Carlino G., Chatterjee, S., Hunt R,M. (2007), "Urban density and the rate of invention", *Journal of Urban Economics*, 61(3): 389-419

Cohen W., and D. Levinthal. 1990. "Absorptive Capacity: a New Perspective on Learning and Innovation", *Administrative Science Quarterly*, vol. 35, n. 1, pp 128-152

Cooke Ph. (2001), "Regional Innovation Systems, Clusters and the Knowledge Economy", *Industrial and Corporate Change*, vol. 10, n. 4, pp. 945-974

Cooke Ph. (2005), "Regionally Asymmetric Knowledge Capabilities and Open Innovation. Exploring 'Globalization 2' – A New Model for Industry Organization", *Research Policy*, 34, 1128-1149

Dunning J. (2001), "The Eclectic (OLI) Paradigm of International Production: Past, Present and Future", *International Journal of the Economics of Business*, vol. 8, n. 2, pp. 173-190
Dunning J. (2009), "Location and the Multinational Enterprise: John Dunning's Thoughts on Receiving the Journal of International Business Studies 2008 Decade Award", *Journal of International Business Studies*, vol. 40, n. 1, pp. 20-34
Edgerton D. (2004), "The Linear Model did not Exist. Reflections on the History and Historiography of Science and Research in Industry in the Twentieth Century", in Grandin K., Worms N. and Widmalm S. (eds). *The Science Industry Nexus*, Science History Publications, Sagamore Beach, pp. 31-57
Foray D. (2009), "Understanding Smart Specialisation", in Pontikakis D., Kyriakou D. and van Bavel R. (ed), *The Question of R&D Specialisation*, JRC, European Commission, Directoral General for Research, Brussels, pp. 19-28
Foray D., David P. and Hall B. (2009), "Smart Specialisation - the Concept", *Knowledge Economists Policy Brief* , n. 9
Glaeser E. (1998), "Are Cities Dying?", *Journal of Economic Perspectives*, vol. 12, pp. 139-160
Hägerstrand T. (1952), "The Propagation of Innovation Waves", *Lund Studies in Geography, Human Geography*, n. 4, pp. 3-19
Hall BH, Jaffe A, Trajtenberg M. 2001. The NBER patent citations data file: lessons, insights and methodological tools. NBER Working Paper 8498.
Jacobs J. (1969), *The Economy of Cities*, New York, Random House
Jacobs J. (1984), *Cities and the wealth of nations*, New York, Random House
Licht G. (2009), "How to Better Diffuse Technologies in Europe", in Research Commissioner Janez Potočnich's Extert Group (ed.), Knowledge for Growth,
Lucas R. (1988), "On the Mechanics of Economic Development", *Journal of Monetary Economics*, vol. 22, 38-39
McCann Ph. (2004), "Urban Scale Economies: Statics and Dynamics", in Capello R., Nijkamp P. (2004), 31-56
Mowery C. D. and Rosenberg N. (1998), *Path of Innovation: Technological Change in 20th Century America*, Cambridge University Press, Cambridge, Mass.
Nelson R. (1959), "The Simple Economics of Basic Scientific Research", *Journal of Political Economy*, vol. 67, n. 3, pp. 297-306
Pontikakis D., Chorafakis G. and Kyriakou D. (2009), "R&D Specialization in Europe: From Stylized Observations to Evidence-Based Policy", in Pontikakis D., Kyriakou D. and van Bavel R. (eds.), *The Question of R&D Specialisation*, JRC, European Commission, Directoral General for Research, Brussels, pp. 71-84
Quigley J. M. (1998), "Urban Diversity and Economic Growth", *Journal of economic perspectives*, vol. 12, n. 2, pp. 127-138
Rallet A. and Torre A. (eds.) (1995), *Économie Industrielle et Économie Spatiale*, Economica, Paris, pp. 273-293
Sassen S. (1994), *Cities in a World Economy*, Thousands Oaks, Pine Forge Press
Scott A.J. and Angel D.P. (1987), 'The US Semiconductor Industry: a Locational Analysis', *Environment and Planning A,* vol. 19*, pp.* 875-912
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
Torre A. and Rallet A. (2005), "Proximity and Localization", *Regional Studies*, vol. 39, n. 1, pp. 47-59
Veltz P. (1993) "D'une Géographie des Coûts à une Géographie de L'organisation: Quelques Thèses sur L'évolution des Rapports Entreprises/Territoires", *Révue Economique,* n. 4

Annex A.2.1. Eurobarometer Survey

To extract the factor 'Strategic vision on innovation', we used the following questions from the Eurobarometer Survey 63.4:

- Innovation simplifies everyday life (% of people mentioning this statement)
- A company that sells an innovative product or service improves the image of all its products or services (% of people mentioning this statement)
- A company which does not innovate is a company that will not survive (% of people mentioning this statement)
- Innovation is essential for improving economic growth (% of people mentioning this statement)
- Broadband penetration rate (%of households with broadband access) from Eurostat.

To extract the factor 'Creativity', we used the following questions from the Eurobarometer Survey 63.4:

- In general, to what extent are you attracted towards innovative products or services, in other words new or improved products or services? (% of people that are very or fairly attracted to new products)
- Compared to your friends and family, would you say that you tend to be more inclined to purchase innovative products or services? (% of people that are more inclined than the average to buy innovative products)
- - In general, when an innovative product or service is put on the market and can replace a product or service that you already trust and regularly buy, do you quickly try the innovative product or service at least once? (% of people that shift easily consumption patterns towards innovative products)
- Innovative products or services are most of the time gadgets (% of people not mentioning this statement)
- - Innovative products or services are a matter of fashion (% of people not mentioning this statement)
- The advantages of innovative products or services are often exaggerated (% of people not mentioning this statement)

We extracted the two factors by means of principal component analysis and applied a varimax with Kaiser normalization rotation method. The percentage of variance explained is 62,54. In this analysis, within each component, we considered the variables with a factor loading greater than 0.55.

Chapter 3. Knowledge and regional performance[12]

3.1 Introduction

The scientific literature has achieved a large consensus on the fact that regional competitiveness – and consequently regional growth – is not entirely dependent on traditional production factors endowment, such as physical capital and labour, but is strongly related to the presence of local intangible resources such as culture, competence, innovative capacity, knowledge. In this spirit, in the Green Paper of the Territorial Cohesion and on the European Research Area, the European Commission has called for a particular attention at the territorial dimension of innovation and knowledge creation. The heterogeneity across regions in their capacity to create knowledge and innovation, but also in their abilities to exploit the spatial diffusion of knowledge across the European territory, motivates an in-depth analysis of the territorial dimension of the knowledge economy. The knowledge system should be enhanced thanks to the third generation of innovation policy within the Europe 2020 strategy which is going to implement the initiative "Innovation Union" (see European Commission, 2011).
In an attempt to provide mainly quantitative answers to these calls, we assess the influence that the creation of new knowledge has on the economic performance of European regions. We firstly analyze what are the main factors of the innovation process and, in a second step, how the innovation process affects economic growth. We pursue this aim by adopting parametric and non-parametric methods to investigate both production and knowledge creation processes at regional level. More specifically, the analysis is based on regression models, in particular spatial econometric ones, and on Data Envelopment Analysis (DEA). While regression models are particularly suitable to measure central tendencies of a given phenomenon, DEA is more adequate for benchmarking analysis, as it permits to identify the best performing units within a given set of entities. Since, in general, the two methods provide different indications on the same object of analysis, we employ both of them in a complementary guise in order to gain wider and different insights on the European regional economic performance.
The first part of the analysis, is devoted to the investigation of the impact of intangible assets on the innovative capacity of a region. We present results for a knowledge production function (Griliches, 1979) where, in addition to the traditional R&D input, we also include the human capital endowment (Usai, 2011) and other economic and institutional variables which characterize the regional environment (Crescenzi et al., 2007). Moreover, the model is specifically parameterized to allow for spatial technological spillovers (Greunz, 2003, Moreno et al. 2005; Autant-Bernard and LeSage 2010).
In the second part of this document, the analysis focuses on the measurement of the effects of innovation and knowledge (that is, technological and human capital) on regional output by estimating a spatial Cobb-Douglas production function. The spatial econometric setting is adopted in order to assess at the same time the contribution of each region's internal capability, represented by intangible as well as traditional tangible inputs, and the role of potential spillovers coming from neighboring territories.
An important objective of both the econometric and the data envelopment analysis is the in-depth investigation of individual characteristics of regions, in order to assess their specific reactivity to changes in innovation and human capital together with their relative efficiency.
The remainder of the chapter is organized as follows. Section 3.2 starts with the discussion of data, indicators and the territorial disaggregation used in the descriptive and the analytical parts. Section 3.3 reports a brief description of the methodological tools adopted to study the economic performance of European regions in terms of both new knowledge creation and productivity. Section 3.4 presents and discusses the results related to the spatial knowledge production function, while section 3.5 reports the production function estimation findings. Section 6 concludes offering some general remarks

[12] This chapter has been written by Marta Foddi, Emanuela Marrocu, Raffaele Paci, Stefano Usai, University of Cagliari, CRENoS

3.2. Dataset description

The aim of this section is to provide a brief description of all the variables included in the empirical analysis. The list of the indicators and the sources of data are reported in Table 3.1. A list of the 31 ESPON countries together with the number of NUTS2 regions in each country (for a total of 287 region for the whole of Europe) is reported in Table 3.2.

We collect data for the period 2000-2007 for all the 287 regions and for all variables. For some variables we estimate missing data by using information at a higher territorial disaggregation level (i.e. NUTS1) and in contiguous years.[13]

The performance of the regional economy is measured by Gross Domestic Product (GDP) in millions of Euro. Population – measured by the number of residents at the 1st of January – is included to account for the relative size of each region.

The labour factor is represented by the number of employees with 15 years and over. The physical capital endowment is calculated with the perpetual inventory method starting from investments data over the period 1980-2000. The research and development (R&D) effort is measured by the total intramural R&D expenditure in millions of euro. The human capital endowment is represented by the number of economically active individuals with at least a tertiary education degree (ISCED 5-6).[14] Finally, due to the fact that the innovation activity represented by patents' applications is not smooth and continuous over time for all the regions included in our sample, our proxy is constructed by computing moving average values for four three-year periods, 2002-04, 2003-05, 2004-06 and 2005-07. Patenting activity is measured by EPO applications, which are associated to regions on the basis of the inventors' addresses[15]. This strategy ensures that we have to deal with a low number of zero values and at same time it returns a more reasonable and reliable picture of innovation activities of European regions.

In the regression analysis we assess the impact of the intangible assets by distinguishing regions on the basis of their knowledge endowment and innovation activity. At this end we adopt the *Territorial Pattern of Innovation* typology, recently proposed by Capello and Lenzi (2011), which permits to identify the following five groups of regions.

European science-based group is composed of regions that are the most knowledge and innovation intensive and are also well endowed with highly educated population and scientific human capital measured by the share of inventors on total population.

Applied science group includes a wider group of regions, which share similar characteristics with regions in the previous cluster but they look more technologically diversified, entrepreneurial, creative, attractive and with a larger capabilities potential, albeit less than the EU average.

Smart technological application regions have a strong orientation towards product innovation, are somehow weaker in terms of process innovation (albeit being more innovative than the EU average) and are among the weakest performers in terms of marketing and organizational innovation. In terms of size of the knowledge base and its characteristics, they are comparable to *Applied science* regions although they show a greater endowment of embedded knowledge in human capital.

Smart and creative diversification regions show an endowment of knowledge and innovation variables lower than the EU average. This suggests that the not negligible innovation activities carried out in these regions mainly rely upon tacit knowledge embedded into human capital and entrepreneurial and creative attributes. These elements represent their key advantages that can be wisely exploited in the pursue of upgrading innovative strategies.

Imitative innovation group consists of regions that have a rather narrow knowledge and innovation profile and are the least performers in both areas of analysis. However, this cluster is characterized by entrepreneurship, creativity, attractiveness, capabilities and innovation potentials greater than the EU average. These features indicates some potential assets which may turn, in an evolutionary perspective, this cluster into a smart and creative diversification area. This change may be induced through normative interventions aimed at helping economic

---

[13] For a detailed description of the procedures used to deal with missing data see Annex A.3.1.

[14] For a general overview of the territorial pattern of human capital and R&D in the enlarged Europe see Colombelli et al. (2011).

[15] If there are multiple inventors, the application is divided equally among all their respective regions (fractional counting), avoiding thus double counting. Data comes from REGPAT, a database made available by OECD.

agents to exploit creativity and entrepreneurship for increasing indigenous innovation activities, other than for imitative innovation.

Table 3.1. Variables description and sources

Variables	Description	Measurement unit	Source	Years
Patents	EPO patent applications per priority year & residence region of inventors	Number	CRENoS elaboration on OECD REGPAT database	2000-2007
R&D expenditure	Total intramural R&D expenditure	Millions of euro	Eurostat	2000-2007
Human capital	Economically active population with Tertiary education attainment - 15 years and over	Thousands	Eurostat	2000-2007
Population	Number of resident people at 1st January	Thousands	Eurostat	2000-2007
GDP	Gross Domestic Product	Millions of euro	Eurostat	2000-2007
Capital	Fixed stock of capital	Millions of euro	CRENoS elaborations on Cambridge Econometrics data	2000-2007
Employment	Number of employees - 15 years and over	Thousands	Eurostat	2000-2007
Investments	Gross fixed capital formation	Millions of euro	Eurostat	2000-2007

Table 3.2. Regions and NUTS level

Code	Country	Nuts	Number of regions
AT	Austria	2	9
BE	Belgium	2	11
BG	Bulgaria	2	6
CH	Switzerland	2	7
CY	Cyprus	0	1
CZ	Czech Republic	2	8
DE	Germany	2	39
DK	Denmark	2	5
EE	Estonia	0	1
ES	Spain	2	19
FI	Finland	2	5
FR	France	2	26
GR	Greece	2	13
HU	Hungary	2	7
IE	Ireland	2	2
IS	Iceland	0	1
IT	Italy	2	21
LI	Liechtenstein	0	1
LT	Lithuania	0	1
LU	Luxembourg	0	1
LV	Latvia	0	1
MT	Malta	0	1
NL	Netherlands	2	12
NO	Norway	2	7
PL	Poland	2	16
PT	Portugal	2	7
RO	Romania	2	8
SE	Sweden	2	8
SI	Slovenia	2	2
SK	Slovakia	2	4
UK	United Kingdom	2	37
TOTAL			287

3.3. Methodological issues

In this section we present a brief description of the methodological tools adopted to analyze the economic performance of the European regions in terms of productivity and of new knowledge creation. For both productivity and knowledge the study is based on regression models, in particular spatial econometric ones, and on Data Envelopment Analysis (DEA).
The regression parametric method is well-known and in what follows we only discuss in some detail the distinctive features of the spatial specifications. The DEA approach, firstly developed by Farrell (1957), is a non-parametric method, based on mathematical programming techniques. While with a regression model, one estimates the average behavior of the phenomenon at hand, the DEA method aims at identifying the best performing units (regions in our case) among a set of entities whose objective is to convert multiple inputs into multiple outputs. In recent years DEA has been applied to analyze the behavior of entities involved in a wide range of activities and contexts, such as firms, hospitals, universities, cities, regions and countries. Thanks to its high flexibility it has been proved successful in identifying various sources of inefficiency, in particular in studying benchmarking practices. As a matter of fact, DEA does not require to choose a specific functional form for the relation linking inputs to outputs and it is capable of handling multiple inputs and outputs, expressed in different units of measurement, as long as they are the same for all the decision making units (DMUs). The best performance is characterized in terms of efficiency, so that the most performing units define the efficient frontier, which "envelope" all the other units. These are then evaluated by calculating their deviations from the frontier. In the analysis presented in the subsequent sections we focus on "technical" efficiency.
The main difference between the regression method and the DEA can be easily appreciated by considering Figure 3.1: the frontier is defined by only one unit (B), the best one, which represent a benchmark for all the other less efficient units, while the regression line in the attempt to capture the central tendency passes through all the data points, regardless of their level of efficiency.
In general, the two methods provide quite different indications for the same phenomenon, so in this study we employ both of them in a complementary – rather than alternative – way in order to gain more and different insights on the European regional economic performance.

3.3.1. Spatial econometric models
In order to take into account spatial dependence across the 287 regions included in our sample we estimate panel versions of the Spatial Error Model (SEM) and of the Spatial Autoregressive Model (SAR). The results are contrasted with a simple pooled model and a fixed effects one. In all models, thanks to the inclusion of interactive dummy variables, we allow the parameters of interest to change according to the individual characteristics of each region and also with respect to the territorial classification of innovative regions into the five groups previously presented. The two spatial specifications are reported below:

Spatial error model: $y_{it} = \beta X_{it} + \varepsilon_{it}$ with $\varepsilon_{it} = \lambda W \varepsilon_{it} + u_{it}$

Spatial autoregressive model: $y_{it} = \beta X_{it} + \rho W y_{it} + u_{it}$

where *y* is the dependent variable, *X* is a set of explanatory variables (including interactive dummies), *u* is a i.i.d error process and *W* is the matrix of spatial weights used to describe the geographic interconnectivity among the regions. In our case each entry of *W* is the inverse of the distance between a given pair of regions; note that in all the estimation and testing procedures the *W* matrix is max-eigenvalue normalized.
The spatial error model is a liner model with a spatially autocorrelated error, which only requires to tackle such a correlation in order to ensure efficiency of the estimators.
The autoregressive model, on the other hand, comprises an additional term (the spatially averaged value of all-other regions dependent variable values), which explicitly capture possible cross-border externalities in the form of production or knowledge spillovers. Given the presence of the spatially lagged term the usual interpretation of the coefficients as partial derivatives does not hold and the effect on *y* of a unit change in the *x* regressor is given by the sum of a direct effect (change in a given region's regressor plus feedbacks effects) and an

indirect or spillover one (change in other regions' regressor). Both specifications are estimated by applying the Maximum Likelihood method.

3.3.2. Data Envelopment Analysis

To illustrate how the DEA approach[16] operates we consider Figure 3.2 where we report the same units of Figure 3.1, which are labeled from A to H. In this case we are assuming constant return to scale (CRS) and, as said before, the frontier is identified, on the basis of the available empirical information, by DMU B, which is fully efficient. According to Cooper et al. (2007) a DMU is said to be fully (100%) efficient if the performance of other DMUs does not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs. Note that this notion refers to "technical" efficiency and it does not require a priori information on prices or weights accounting for the relative importance of inputs or outputs.
Focusing on DMU D, its efficiency is given by the ratio *p/q*, assuming this is equal to 0.75 it means that if it proportionally reduces all the inputs to the 75% of the their actual amounts, it could still produce the same level of output. In this way DMU D would be projected horizontally towards the efficient frontier. Under the assumption of constant returns to scale (CRS), the same efficiency gain would be obtained by a vertical projection, in this case with the same input amount DMU D could produce a level of output 33% (1/0.75=1.33) greater with respect to the previously produced one. DMU B is called the benchmark or reference unit for DMU D.
In the first case we have an *input*-oriented measure of efficiency, while in the second case the measure is an *output*-oriented one. Note that under the assumption of CRS the two orientation identify the same frontier and the same set of efficient DMUs, only the measures associated with the inefficient DMU can be different. Note also that in the case of DMU D efficiency can be achieved by each movement in the area k-D-l (Figure 3.2).
More formally, to get an efficiency measure for all the units included in the sample it is necessary to solve a nonlinear programming model. Consider a set of *n* DMUs, with each DMU *i* (*i*=1, …. *n*) using *m* inputs, x_{ij} (*j*=1,…*m*) to get *r* (*r*=1, …*s*) outputs y_{ir}, following Charnes et al. (1978) this amount to solve the following maximization problem for each DMU; considering DMU_0:

$$\max h_0(\mathrm{u},\mathrm{v}) = \sum_{\mathrm{r}=1}^{\mathrm{s}} \mathrm{u_r\, y_{0r}} \bigg/ \sum_{\mathrm{j}=1}^{\mathrm{m}} \mathrm{v_j\, x_{0j}}$$

s.t. $\sum_{\mathrm{r}=1}^{\mathrm{s}} \mathrm{u_r\, y_{0r}} - \sum_{\mathrm{j}=1}^{\mathrm{m}} \mathrm{v_j\, x_{0j}} \leq 0$ for all *i*

with $\mathrm{u_r}, \mathrm{v_j} \geq 0$ for all *r, j*

the additional constraint $\sum_{\mathrm{j}=1}^{\mathrm{m}} \mathrm{v_j\, x_{0j}} = 1$ ensures that an infinite number of solutions is ruled out.

This is known as the *multiplier* ratio-form of DEA as the ratio of outputs to inputs is used to measure the efficiency of a DMU with respect to all other DMUs (when multiple inputs and/or multiple outputs are present this formulation simplify the case as it is reduced to the ratio between a "virtual" output and a "virtual" input).
When the output to inputs ratio is maximized the model is referred to as input-oriented model; conversely, we have an output-oriented model when the ratio is inverted and a minimization problem is solved.

[16] This description is mainly based on Coelli (1996) and Cooper et al. (2007).

By recourse to duality in linear programming it is possible to reformulate the problem above in its *evelopment* ratio-form:

$\theta^* = \min \theta$
s.t.:

$\sum_{i=1}^{n} x_{ij}\,\lambda_i \le \theta x_{0j}$ for all *j*

$\sum_{i=1}^{n} y_{ir}\,\lambda_i \ge y_{0r}$ for all *r*

□$_i$ ≥ 0 for all *i*

The envelopment formulation is in general preferred as it entails a lower number of constraints (M+S<N+1).

The solution of the problem requires finding optimal values for the weights *u* and *v* (or λ) such that the technical efficiency of DMU_0 is maximized, subject to the constraints that the efficiency measures of all the other DMUs are less or equal to 1, $\theta_i \le 1$. Note that the weights may change from one DMU to the other as their magnitude has to reflect how highly an item (input or output) is evaluated with respect to the others.
The last model is also known as "Farrell model" and it can only provide measure of "weak" efficiency as it does not account for the presence of possible non-zero input or output slacks.
The case of *weak* efficiency (or mix inefficiency) is more easily described by referring to Figure 3.3, where the situation with two inputs (X_1, X_2) and one output (Y) is depicted.
The efficient frontier is defined by DMU E, D and C. All others DMUs are inefficient. As explained above the efficiency measure for DMU A, for instance, is given by the ratio 0P/0A, and its benchmarks are DMU E and DMU D. The case of DMU B is different, its efficiency is calculated by 0B'/0B, but note that further gains could be obtained by moving leftwards along the efficient frontier from the weak efficient point B' to point C. Differently from parametric methods which return smooth frontiers, this may happen because the dotted line crosses the piece-wise frontier in a straight trait, so that the same level of output can be obtained by using a smaller amount of input X_1. The distance CB' is known as input slack, in this case for the X_1 input. In the DEA literature it is recommended to provide an accurate indication of technical efficiency by reporting both the Farrell measure of efficiency (such as B0/B'0 for DMU B) and any non-zero input and output slack. When there are more inputs and outputs it is not a simple task to identify the nearest efficient point (such as C in figure 3.3). As a solution, some authors propose to solve a second-stage LP problem for each DMU by maximizing the sum of the slacks while keeping fixed the efficiency measure θ, obtained from the first stage. This approach presents a number of drawbacks, it is not anymore invariant to different units of measurement of inputs and outputs and, most importantly, as the sum of slacks is *max*imized and not *min*imized it identifies the furthest, rather than the nearest, efficient point. For these reasons, in the analysis presented in sections 4 and 5, following Coelli (1996), we carry out the more computationally demanding multi-stage DEA problem, which overcomes the limitations of the two-stage approach as it allows to identifies efficient points whose inputs and output combinations are as much as possible similar to the ones of the inefficient DMU. Note also that Coelli (1996) emphasizes that the importance of the slacks has been somehow overstated; in certain cases their presence ("an artifact of the frontier construction") is mainly due to a very reduced dimension of the sample data, with a large number of DMUs the frontier line becomes smoother so that straight traits become less likely to appear. In the analysis presented in the next sections we devote limited attention to slack measures as the size of our sample – 287 regions – is reasonably large.

Since the assumption of constant returns to scale is rarely attainable in real-world situations as it requires that each DMU is operating at an optimal scale, in what follows we brief describe the Varying Return to Scale (VRS) model, suggested by Banker et al. (1984). With respect to the CRS model the linear programming problem is augmented with an additional convexity constraint ($\sum_{i=1}^{n} \lambda_i = 1$ in the envelopment problem formulation above). The VRS approach allows to envelop the data more tightly so that technical efficiency measures are always

greater or equal to the ones obtained under the assumption of CRS. The aim is to isolate "pure" technical inefficiency from "scale" inefficiency. Operationally this is done by carrying out both a CRS and VRS DEA, if for a given DMU there is a difference in the technical scores this is interpreted as evidence of scale inefficiency.
This is illustrated by referring to Figure 3.4, in which for simplicity there is only one input and one output, and where we report both the CRS and the VRS frontiers. For DMU F, under CRS and adopting an input orientation, the technical inefficiency is measured by the segment FFc, while assuming VRS the technical inefficiency would be just FFv so that the difference, FcFv is entirely due to scale inefficiency. Also in this case the efficiency of DMU F can be expressed by the ratio measures: θ_{crs}=AFc/AF, θ_{vrs}=AFv/AF, scale inefficiency=AFc/AFv. In order to have information on whether a DMU is scale inefficient because it operates along the increasing or the decreasing trait of the VRS frontier it is required to solve an additional DEA problem (which entails a change in the convexity constraint, $\sum_{i=1}^{n} \lambda_i \leq 1$), whose solution returns a Non-Increasing Return to Scale (NIRS) frontier (the narrow continuous line in Figure 3.4). For a given DMU, if the NIRS technical score is different from the VRS one than that DMU is facing increasing returns to scale (as it is the case for DMU F); on the other hand if the technical score is the same along the NIRS and the VRS frontier than decreasing returns are occurring.
In the analysis presented in sections 3.4 and 3.5 we will present and discuss the European regions technical efficiency scores devoid of the scale effects under the assumption of varying returns to scale.

Figure 3.1. Regression model vs DEA

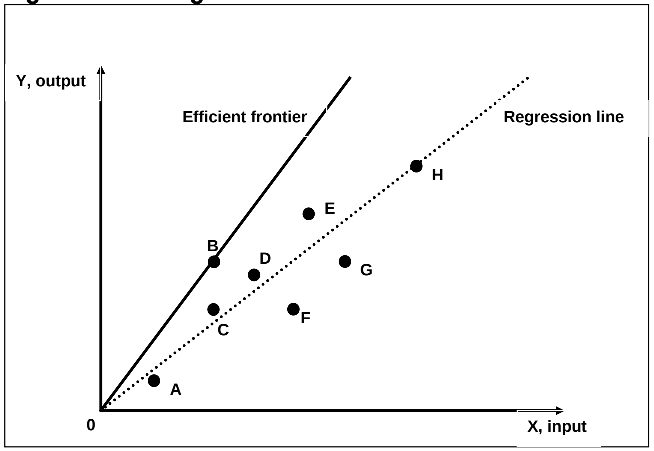


Figure 3.2 DEA-CCR model, one input-one output

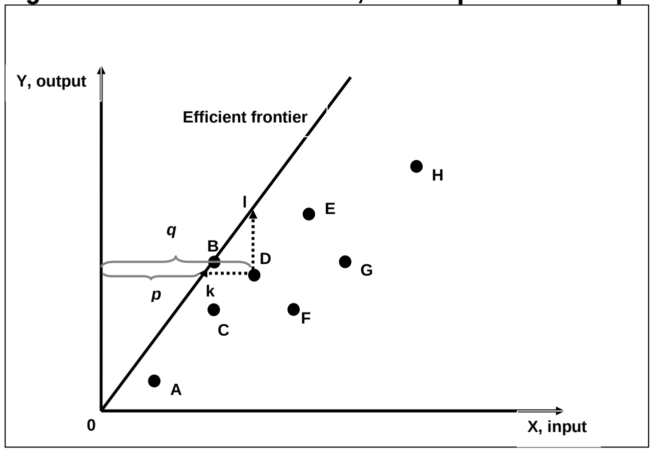


Figure 3.3 DEA-CCR model, two inputs-one output

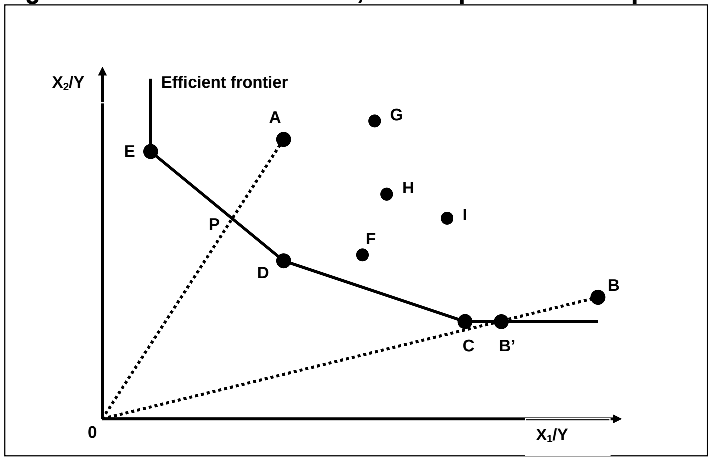
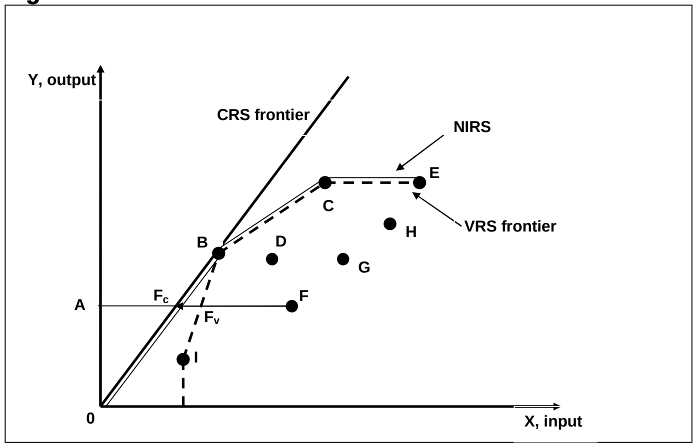


Figure 3.4 DEA-BCC model



3.4. Knowledge production function

In this section we present the analysis aimed at investigating the returns of R&D expenditures and human capital on the regional innovative capacity. The analysis is carried out by employing both parametric and non parametric methods. The former is based on the theoretical framework of the knowledge production function (KPF, Griliches, 1979) for which we adopt an empirical spatial specification (as in Moreno et al. 2005 and Marrocu et al. 2011a), which allows us to assess the characteristics of the geographical technological spillovers (effective spatial distance, role of national borders, contiguity, cluster of technological similar regions). The non parametric Data Envelopment Analysis, on the other hand, permits to single out the best practices among the European regions (or typologies of territories) in performing innovation activities and to identify the less efficient ones in converting R&D investments and human capital into the creation of new knowledge.

3.4.1. Econometric analysis

The econometric analysis is based on the estimation of Knowledge Production Function models. As described in section 3.2, due to the intrinsic features of the patenting activity we consider a four-period panel, each period comprises three years according to a moving average kind of structure: 2002-04, 2003-05, 2004-06, 2006-07. The values of the dependent variable are computed for each region as three-years average of the number of patent applications to EPO. This allows to deal with a small number of zero-value observations and, at the same time, to get a less volatile, more reliable, picture of the innovation dynamics in Europe. As it is well known, the production of knowledge is characterized by a delay between the expenditure in R&D and the production of a new innovation formalized through the application for a patent (Jaffe, 1986 and 1989). Therefore, the explanatory variables are included with a lag of two years with respect to the initial year of the four periods considered (i.e 2000 for t=1, 2002 for t=2 and so on).

Following the well-established literature on the estimation of knowledge production functions, as a determinant of the innovation activity we include the expenditure in R&D. However, some authors (Cohen and Levinthal, 1990) have emphasized that the effectiveness of this investment depends crucially on the absorptive capacity of a territory, which, in turn is linked to the availability of highly skilled human capital. For this reason, we augment the traditional KPF model by including also the human capital endowment, measured by the number of people with at least a university degree; we also include the resident population as a control variable to account for the relative dimension of the regions. The log-linearized version of the basic model is formalized as follows:

$$patents_{it} = \alpha + \beta_1 r\&d_{it} + \beta_2 hk_{it} + \beta_3 pop_{it} + \varepsilon_{it} \qquad (1)$$

where *i*=1,…287 and *t* as explained above; lower letters indicate log-transformed variables.

In Table 3.3 we first present three non-spatial specifications, which allow us to test for the presence of spatial dependence. The first model is the simplest version of the basic model, which includes a common constant, in the second one we include country dummies in order to account for institutional factors, which, when overlooked, may induce spatial dependence; the third specification, with Fixed Effects (FE), is the most general one, as we allow for individual regional intercepts. Note, however, that when we estimate the FE model the R&D input turns out to be not significant. Since this is quite a puzzling result, which may be due to the small number of time periods considered, in what follows we devote limited attention to such a specification. According to the robust LM tests (bottom panel of Table 3.3), as a matter of fact, we find evidence of spatial dependence in all the three different specifications. For this reason, in the subsequent (4)-(8) models we propose the estimation of spatial specifications starting from the basic model augmented with the inclusion of country dummies. The SEM model (4) exhibits significant coefficients for all the variables included; human capital, with an estimated coefficient of 0.65, outperforms R&D, which has a coefficient equal to 0.42, in enhancing the innovation activity at the regional level in Europe. It is also worth noting that the spatial autoregressive coefficient of the error term turns out to be highly significant and sizeable, signaling the importance of spatial correlation among regions. In the case of the knowledge creation process, it is therefore, reasonable to argue that such a dependence may be

attributable to the presence of spillovers, which cross the borders according to various degrees of proximity among regions. Although we are aware that the notion of proximity cannot be limited to the simple spatial one, as it includes also technological and organizational dimensions (Boschma 2005, Marrocu et al. 2011b), in this study we assume that geographical vicinity is an adequate proxy to capture the interconnectivity among the regions which makes possible the existence of knowledge spillovers. Since the SEM specification eliminates spatial spillovers by construction, we test their relevance within SAR specifications.
The first one is reported in column (5), whose results confirm the higher effectiveness of human capital with respect to R&D expenditure[17]: an increase of 1% in the human capital endowment induces an increase of 0.63% in patent activity while the same increase in R&D expenditure induces a variation in patents equal to only 0.43%.
The coefficient associated with the spatially lagged dependent variable is significant and its magnitude highlights the economic relevance of knowledge spillovers: for the same endowments of R&D and human capital, the closer is a region to the most innovative areas, the higher the benefit in terms of new knowledge creation. Note also that model (5) returns a higher value for the squared correlation (0.85) between actual and fitted values, the SAR model thus provides a better goodness-of-fit with respect to the SEM one. The estimated coefficients for both the main determinants of innovative capacity, R&D and human capital, can be considered as average estimates for the whole of Europe since in regression (5) we constraint the estimate to be the same across all regions.
Given the well-known heterogeneity across European regions and territories, we try to assess its relevance by relaxing the assumption that the estimated coefficients are the same across all the 287 regions.
We first choose to allow for the highest level of diversification by considering heterogeneous parameters for each of the main inputs in turn. We thus estimate a SAR model with individual R&D coefficients while keeping the human capital parameter common for all regions, and then another SAR model in which we allow for the opposite. Due to a likely problem of limited number of degrees of freedom, reasonable results are found only for the second model, which is reported in column (6) of Table 3.3; although the model exhibits the highest value for the goodness-of-fit measure, note that the R&D coefficient is no longer significant.
The evidence found for the human capital regional effects is summarized by depicting in Map 3.1 their spatial distribution: the highest values are concentrated in the centre of Europe and in the Scandinavian peninsula. More specifically, the presence of a large endowment of graduate population produces its largest impact in regions belonging to Finland and Sweden but also to France, North of Italy, Germany, Spain, Denmark, Austria and Netherlands. We can observe that among these regions there are territories strongly specialized in the manufacturing sector such as Emilia-Romagna, Lombardia, Veneto, Piemonte for Italy, Rhône-Alpes for France and Stuttgart for Germany. Moreover, in the highest elasticity group there are regions where very important cities are located such as Stockholm, Île-de-France, Cataluña, Düsseldorf, Wien, Berlin, Lazio, Köln, Comunidad de Madrid, Hannover. We can also notice that in these same towns very important universities can be found. Lowest values are, on the contrary, strongly spatially concentrated in regions belonging to New Accession countries, mainly in the Eastern part of Europe. Within this group there are also territories with other specialization than the manufacturing sector like overseas territories, Região Autónoma da Madeira and Região Autónoma dos Açores for Portugal, Valle d'Aosta for Italy, Guyane, Martinique, Guadeloupe for France, Ciudad Autónoma de Melilla and Ciudad Autónoma de Ceuta for Spain. Therefore, we can conclude that returns to human capital, in terms of knowledge production, are likely to accrue in those regions where a critical endowment of human capital is already concentrated.
In order to analyze whether the effects of R&D change also across territories, i.e. groups of regions, we choose to permit a lower degree of regional heterogeneity by making use of the regional taxonomy developed by Capello and Lenzi (2011), described in section 3.2. They identifies five mutually exclusive groups of regions according to their propensity to innovate: the most innovative regions are those in the "European research-based area", followed by regions in "Applied science", "Smart technological application", "Smart and creative

[17] Due to the very large number of interactive terms included in our models, in discussing the econometric results we mainly focus on point estimates, rather than on direct/indirect effects. Note, however, that the relative relevance of the explanatory variables is maintained.

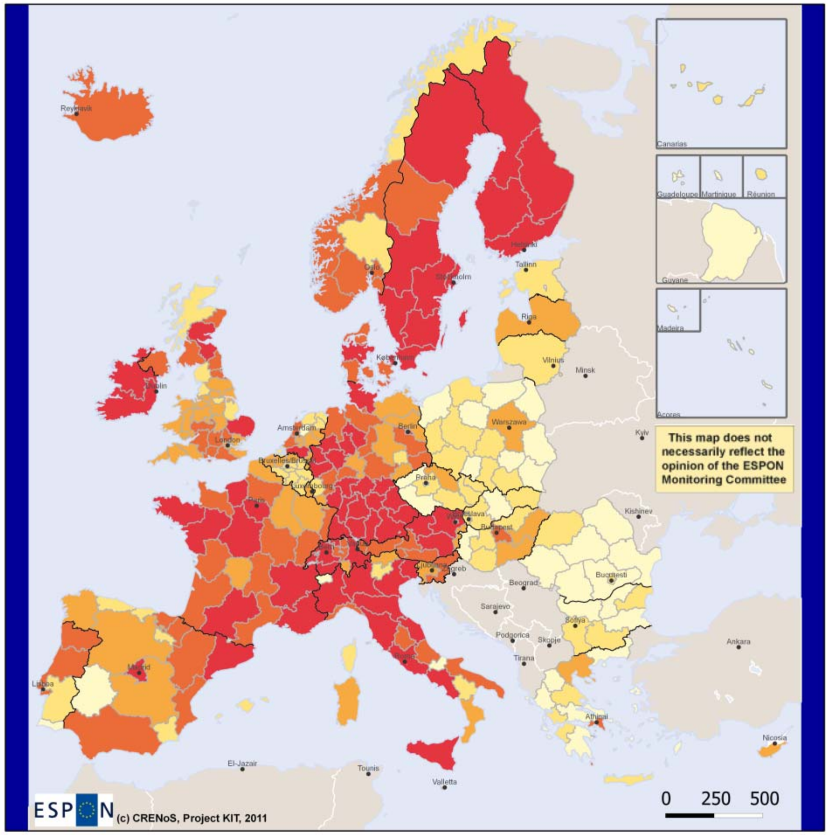
diversification” and “Imitative innovation” groups. This estimation strategy is expected to overcome the degrees of freedom problem. The model for R&D varying coefficients is reported in column (7) and the corresponding model for human capital in the last column (8). It is worth remarking that the coefficient of human capital in (7), and conversely the one for R&D in (8), is pretty robust with respect to the inclusion of the five interactive terms for the other intangible input; the estimates are, as a matter of fact, quite similar to those obtained in specification (5).

Focusing on model (7), the areas of “Smart technological application” and of “Smart and creative diversification” present the highest R&D coefficients (0.48 and 0.47, respectively), while the lowest value is shown by the “Imitative innovation” group (0.36). These results suggest that the R&D expenditure effort has his largest impact on knowledge production for those regions with strong orientation towards product innovation but for which the endowment of knowledge and innovation variables is smaller than the EU average. This result confirm that the knowledge endowment rely upon tacit knowledge and that it is embedded into human capital, entrepreneurial and creative attitudes. Moreover, if we look at Map 3.2, where we observe the spatial distribution of these values, we see that the lowest R&D coefficients, that is those for the Imitative innovation group, are concentrated on the Eastern part of Europe where most New Entrants countries are located.

The same kind of results are found for model (8) with respect to the varying coefficient of human capital. We observe the highest human capital elasticity values for the most knowledge and innovation intensive groups of regions: Smart Technological Application Area (0.46), Applied Science Area (0.44) and European science-based area (0.44).

Then, both R&D and human capital are less effective in the regions with the lowest propensity to innovate, while for the other four groups the models provide evidence of a clear patterns of diminishing returns to scale in knowledge production, regions with the highest endowments of both R&D and human capital show a lower return for the marginal unit of each input employed, while regions in the two “smart” groups seem enjoying higher returns. The spatial distribution of the estimated coefficients is shown in Map 3.3 and it is very similar to the map reporting the spatial pattern for the R&D coefficient.

Map 3.1 Elasticity of knowledge production to human capital by region (average 2000-2007)



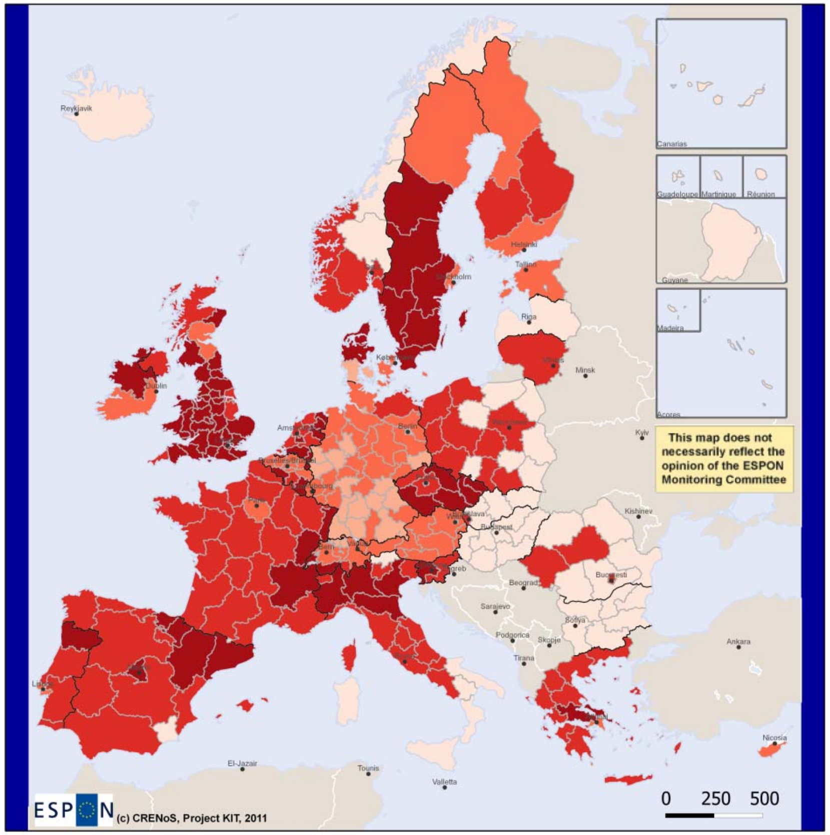
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

(c) EuroGeographics Association for administrative boundaries
Source: CRENoS elaboration, 2011
Origin of data: Eurostat
Regional level: NUTS 2

Legend

- no data
- <0.70: Low elasticity
- 0.71 - 0.89: Medium - low elasticity
- 0.9 - 0.99: Medium elasticity
- 1.0 - 1.10: High elasticity
- >1.10: Very high elasticity

Map 3.2 Elasticity of knowledge production to R&D by territorial patterns of innovation (average 2000-2007)



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

(c) EuroGeographics Association for administrative boundaries
Source: EUROSTAT
Origin of data: Author's elaboration
Regional level: NUTS 2

Legend

- no data
- Imitative innovation area = 0.360
- European science-based area = 0.414
- Applied science area = 0.423
- Smart and creative diversification area = 0.469
- Smart technological application area = 0.476

Map 3.3 Elasticity of knowledge production to human capital for by territorial patterns of innovation (average 2000-2007)

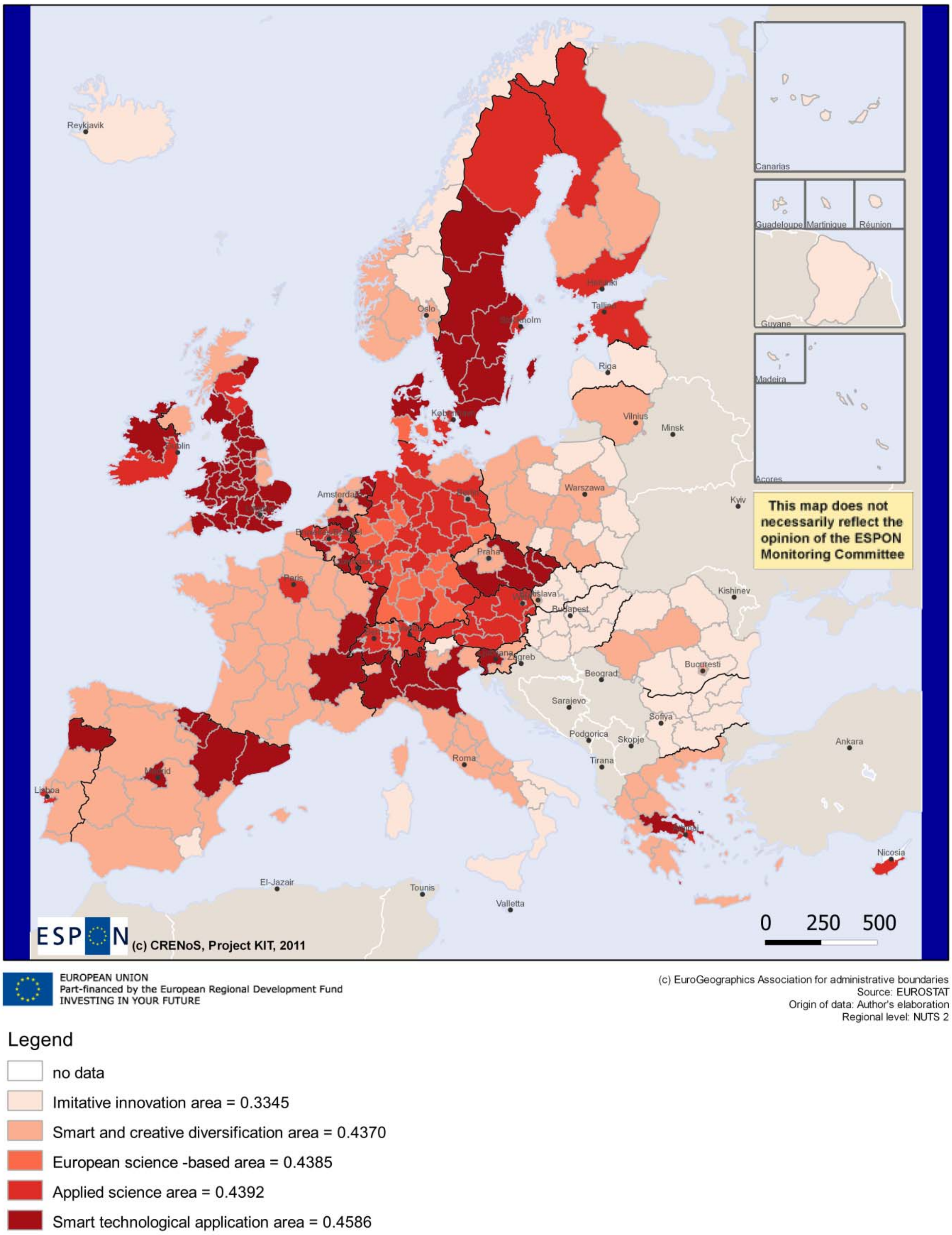


Table 3.3 - Spatial Knowledge Production Function

Dependent Variable: Patents

	1	2	3	4	5	6	7	8
Model	**Pooled**	**Pooled**	**FE**	**SEM**	**SAR**	**SAR**	**SAR**	**SAR**
Estimation method	OLS	OLS	OLS	ML	ML	ML	ML	ML
R&D	1.102 ***	0.495 ***	0.130	0.418 ***	0.430 ***	0.123		0.403 ***
	(34.155)	(8.624)	(1.418)	(7.828)	(8.011)	(1.341)		(7.518)
Human Capital	0.300 ***	0.699 ***	0.577 ***	0.648 ***	0.629 ***		0.582 ***	
	(2.776)	(4.115)	(3.471)	(3.999)	(3.985)		(3.593)	
R&D*Imitative Innovation							0.360 ***	
							(5.725)	
R&D*Smart & Creative divers.							0.469 ***	
							(8.252)	
R&D*Smart Techn. Applic.							0.476 ***	
							(8.600)	
R&D*Applied science							0.423 ***	
							(7.440)	
R&D*European science-based							0.414 ***	
							(7.544)	
HK*Imitative Innovation								0.335 **
								(2.080)
HK*Smart & Creative divers.								0.437 ***
								(2.756)
HK*Smart Techn. Applic.								0.459 ***
								(2.894)
HK*Applied science								0.439 ***
								(2.811)
HK*European science-based								0.439 ***
								(2.784)
HK regional individual terms						Yes		
Population	0.023	0.367 *	1.420	0.442 ***	0.447 ***	-0.322 **	0.463 ***	0.613 ***
	(0.224)	(2.237)	(0.918)	(2.825)	(2.926)	(-2.479)	(2.974)	(4.033)
Spatial autoregressive coefficient - λ				0.968 ***				
				(85.423)				
Spatial autoregressive coefficient - ρ					0.500 ***	0.433 ***	0.422 ***	0.326 ***
					(12.177)	(2.840)	(9.139)	(7.287)
Constant	Yes	Yes	No	No	No	No	No	No
Fixed effects	No	No	Yes	No	No	No	No	No
Country dummies	No	Yes	No	Yes	Yes	No	Yes	Yes
Rbar-squared	0.739	0.825	0.017					
Corr-squared				0.455	0.847	0.969	0.850	0.858
Diagnostics								
Robust LM test - No spatial lag	17.1		0.005					
p-value	0.000		0.946					
Robust LM test - No Spatial error	1187		14.02					
p-value	0.000		0.000					
LM test - No Spatial error		56.043						
P-value		0.000						

Panel estimation for three-years periods: 2002-04, 2003-05, 2004-06, 2005-07 and 287 regions; total number of observations 1148
The dependent variable is computed for each period as a three-year average of the number of patent applications at EPO
The explanatory variables are considered with a lag of two years with respect to the initial year of each period
All variables are log-transformed. R&D is total expenditure, Human Capital (HK) are thousands people with tertiary education
For the definition of groups of regions see text page 3
For spatial models and tests the weight matrix is the max-eigenvalue normalized matrix of inverse distance in kilometers
Asymptotic t-statistics in parenthesis; significance: ***1%; **5%; *10%

It is worth comparing the results of the knowledge production function we have estimated for the European case with those obtained by Crescenzi et al. (2012) for the case of USA, China and India.[18] More specifically, their results suggest that the three countries possess distinct regional innovation dynamics. In China, patenting activity is concentrated in denser, richer regions. The innovation system appears to be driven by the density-R&D nexus, and more broadly by traditional agglomeration factors – partly reflecting a state-driven economy. India presents a more straightforward 'R&D plus spillovers' story, in a large number of urban cores. Unlike China, spillover variables, migration and wider social and institutional conditions are important for patenting. In the US, innovation occurs largely in self-contained zones relying on their own R&D inputs, favorable local socio-economic environments and on large pools of skilled individuals. The common ground of the modeling framework for the different countries is that it draws on elements of endogenous growth theory, new economic geography and innovation systems literatures, which contextualizes the descriptive findings and forms the basis of the regression analysis.

To facilitate the comparisons the estimation results for the four areas are reported in Table 3.4. The regional knowledge production function links patenting activity to R&D expenditures, human capital and, to control for each region's size, resident population.

The most striking result is that R&D expenditure turns out to be positive and significant in all macro areas considered, although it displays huge differences in the elasticity levels which follow a clear decreasing returns pattern. Indeed, the lowest elasticity of knowledge production to R&D expenditure is shown by USA, which is the area where the R&D investment is at the highest level. The European average elasticity is equal to 0.43, while a much higher return is found for China (1.3) and India (0.99), which are two large economies in an initial stage of investing specific resources in formal innovation activities.

The second important result is that human capital exerts a relevant role on knowledge production only in Europe, whereas it appears not significant in the other three countries. However, it has to be considered that when human capital is not included alone in the regression but is incorporated as one of the components of the "social filter" (Crescenzi and Rodriguez-Pose 2009), then it plays a relevant role for the case of USA, China and India (Crescenzi et al, 2012), too. This means that in the European regional innovation model the availability at the local level of an adequate endowment of highly educated labour forces plays a key role *per se* in influencing the process of knowledge creation. On the other hand, in other territorial contexts it is the combination of elements that compose the social filter which positively enhances the creation of knowledge.

Table 3.4. Knowledge production function, indicative comparison across continents

Dependent Variable: Patents

	Europe	USA	China	India
Model	SAR	FE	FE	FE
Estimation method	ML	OLS	OLS	OLS
R&D [1]	0.430 ***	0.041 **	1.303 ***	0.995 ***
	(8.011)	(2.050)	(4.059)	(3.713)
Human Capital	0.629 ***	0.627	0.022	0.631
	(3.985)	(0.739)	(0.135)	(0.798)
Included control variables				
Population	Yes	Yes	Yes	Yes
Country dummies	Yes			
Year dummies		Yes	Yes	Yes
DelhiTrend				Yes
R-squared	0.847	0.365	0.731	0.776
Number of territorial units	287	179	30	19

***Source*: Europe, CRENoS Unit (table 3 regr 5); other countries, LSE Unit. ESPON/KIT Project**

[1] Total R&D for Europe and India, S&T Expenditure for China, Private R&D for the USA

Panel estimation period: 2000-2007 for Europe; 1995-2007 for the other countries

All variables are log-transformed and include a constant

Robust t-statistics in parenthesis; significance: ***1%; **5%

[18] See Crescenzi et al. (2012) for a detailed explanation of the variables and methodologies employed in the regression analysis.

3.4.2. Data Envelopment Analysis

Following Culliname et al. (2004), in carrying out the data envelopment analysis to investigate the innovative performance of European regions we adopt the *output*-oriented approach, as it is more suitable when the analysis serves as the basis for defining planning and policy strategies, which is commonly the case for geographic units, such as areas, regions or countries. On the other hand, the input orientation is more adequate when operational and managerial objectives are involved.

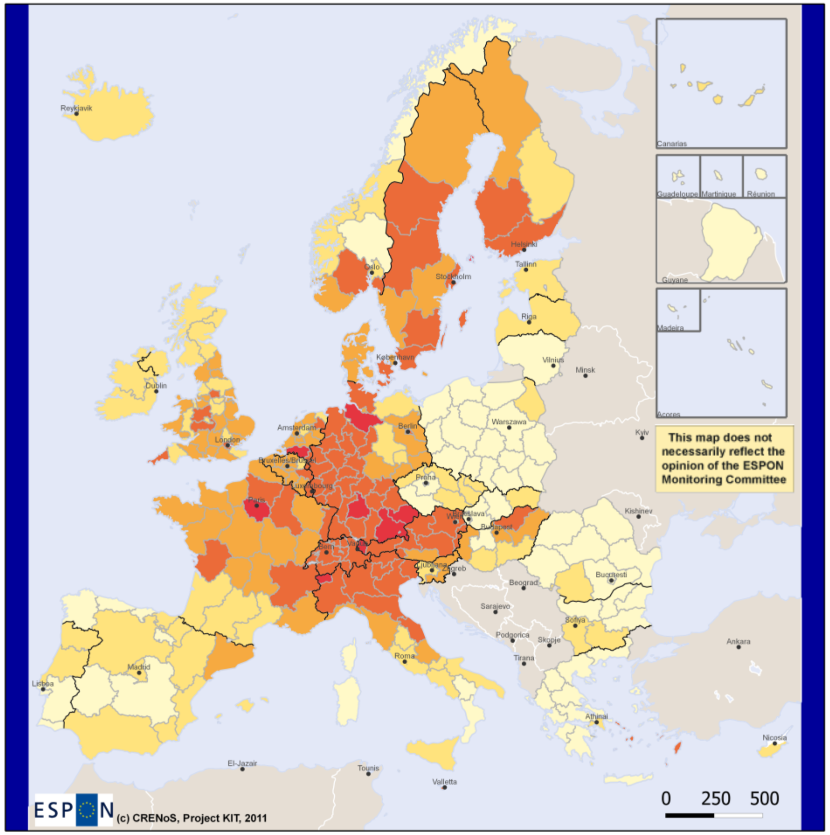
For the European regions included in our sample, the assessment of technical efficiency is carried out by allowing for varying returns to scale[19].

In Maps 3.4 and 3.5 we show the geographical distribution of the regional efficiency measures for the knowledge production function calculated for the initial (2000) and the final (2007) year of the time period considered for the analysis. Fully efficient regions, in terms of converting R&D and human capital inputs into patents, have a technical efficiency score of 100 (red colored in the maps); these are the best performing areas in innovation activity, given their inputs, and therefore they define the production possibility frontier. Comparing the two maps the overall picture does not seem to change appreciably, this is obviously due to the fact that an eight-year period is too limited in time for the pattern of the knowledge creation process to change; it is well-known that such a process is quite persistent as it requires considerable efforts on the investment side, both for R&D expenditure and, especially, for human capital, whose economic returns and effects occur completely only over long run horizons.

Focusing on the maps, the most efficient territories exhibit a great deal of heterogeneity. The majority of the efficient regions are located in the most central or economically strategic areas of the continent, as it is the case for Île-de-France, Stuttgart or the Dutch Noord-Brabant. However, due to the particular features of the DEA methodology, which selects efficient units also at a low scale, we find high efficiency scores also in small and peripheral regions (such as Åland). The most efficient regions are followed by a group of German and North Italian regions, which are pretty close to the frontier as they show high technical scores. On the contrary, the lowest scores are shown by regions located in European peripheral areas, especially in the new accession countries. This analysis confirms the presence of a dualistic – centre *vs* periphery – pattern in the innovation activity. This calls for specific policies, which should target the latter group of regions, in order to support them - not with additional resources - but with the provision of organizational and structural assistance that should enable them to exploit all the potential of their relatively abundant inputs in delivering higher levels of knowledge output, which in turn is expected to ensure better long run economic performance.

[19] The DEAP software by Coelli (1996) is used throughout the analysis.

Map 3.4 Efficiency level of knowledge production by region (DEA methodology, 2000)



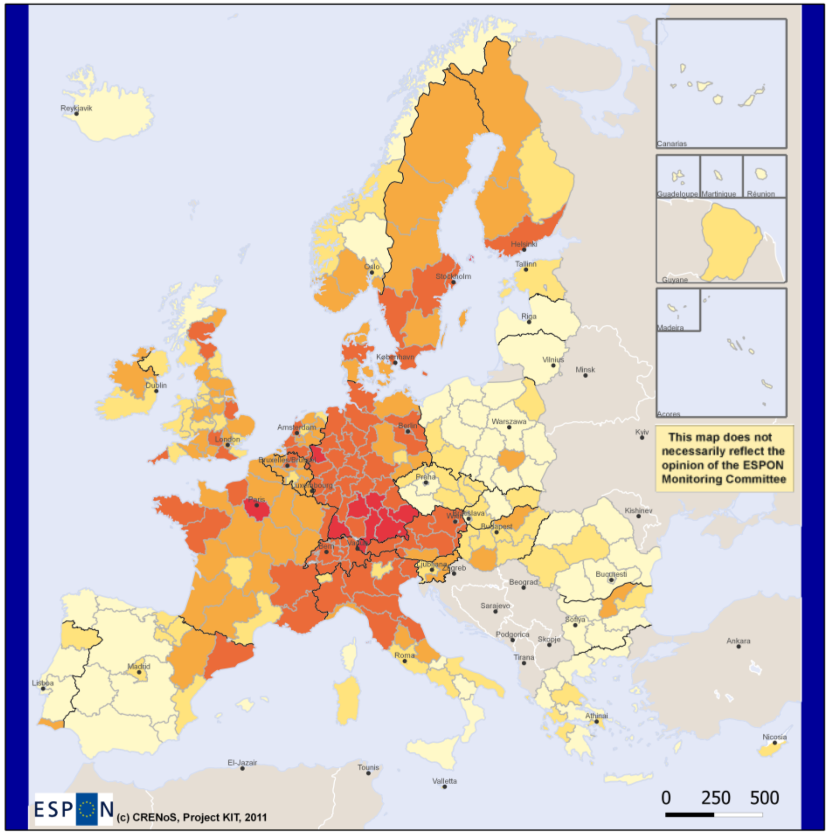
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

(c) EuroGeographics Association for administrative boundaries
Source: CRENoS elaboration, 2011
Origin of data: Eurostat
Regional level: NUTS 2

Legend

- no data
- 0.1 - 5.8: Low efficiency (68)
- 5.8 - 18.6: Medium - low efficiency (69)
- 18.6 - 30.1: Medium efficiency (68)
- 30.1 - 99.9: High efficiency (72)
- 100: Highest efficiency (10)

Map 3.5 Efficiency level of knowledge production by region (DEA methodology, 2007)



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

(c) EuroGeographics Association for administrative boundaries
Source: CRENoS elaboration, 2011
Origin of data: Eurostat
Regional level: NUTS 2

Legend

- no data
- 0.1 - 6.9: Low efficiency (68)
- 6.9 - 15.6: Medium-low efficiency (68)
- 15.6 - 30.2: Medium efficiency (68)
- 30.2 - 99.9: High efficiency (73)
- 100.0: Highest efficiency (10)

3.5. Production function

The aim of this section is to assess whether the knowledge factors, such as technological and human capital, exert a relevant role on regional output levels in addition to the traditional inputs such as physical capital and labor units. Similarly to the previous analysis, we employ both a parametric method by estimating a spatial Cobb-Douglas production function and a non parametric method, i.e. DEA, to measure the efficiency performance. For both methodologies, we consider the level of GDP as the output variable and physical capital, employment, human capital and R&D expenditure as the main determinants of production levels.

3.5.1. Econometric analysis

In Table 3.5 we present the results for the production function estimation. The model is a log-linearized Cobb-Douglas production function where the production level (*gdp*) is explained by the traditional factor endowments, capital stock (*k*) and units of labour (*l*), and by two intangible assets, R&D expenditure (*r&d*) and human capital (*hk*):

$$gdp_{it} = \alpha + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 r\&d_{it} + \beta_4 hk_{it} + \varepsilon_{it} \qquad (2)$$

lower letters indicate log-transformed variables, *i*=1,…287 regions and *t*=2000-2007.[20]

We follow the same empirical strategy as for the Knowledge Production function; we estimate three non-spatial specifications for the basic model (common constant, country dummies and fixed effects, columns 1-3 of Table 3.5), which allow us to test for the presence of spatial dependence. As the evidence provided by the LM tests (bottom panel of Table 5) confirms a considerable degree of spatial autocorrelation we focus the discussion on the main results obtained from the spatial specifications (columns 4-8); note that all of them include a complete set of country dummies to account for institutional factors.

We start from the simple SEM model (column 4), which exhibits significant coefficients for all the variables included. Employment and human capital show the highest coefficient (respectively 0.78 and 0.24). Moreover, also for the production level human capital outperforms R&D (0.13) in enhancing the regional output once the contribution of the traditional inputs is accounted for. The spatial autoregressive coefficient of the error term, as for knowledge production function estimation, turns out to be highly significant and sizeable, signaling a geographical kind of dependence among neighboring regions. Since this is likely to arise as a result of regional interactions, the SAR specification is more adequate to explicitly account for such interactions, especially when they occur in the form of production spillovers.

In column (5) we report results for the first SAR specification and we observe that the human capital coefficient is more than twice the R&D expenditure one (0.30 and 0.13, respectively). Moreover, the significance and magnitude of the coefficient associated with the spatially lagged dependent variable indicates the effectiveness of spillovers: the closer is a region to the most economically advanced areas, the higher the benefits accruing from local externalities moving across borders.

The estimated coefficients for the whole set of production factors, tangible and intangible, have so far been considered as average estimates for all Europe since in regression (5) we constrain the parameters to be the same across all regions. In the next model reported in column (6), we relax this assumption and we assess the hypothesis of heterogeneous coefficients with respect to the two intangible assets, that is human capital and R&D.

We, initially, allow for regionally heterogeneous estimates for R&D expenditure while keeping a common human capital parameter. The evidence found for the R&D regional effects is effectively summarized in Map 3.6, where their spatial distribution is displayed. It is clear that the highest and lowest values are strongly spatially concentrated confirming the intense geographical pattern discussed above. **It is worth noting that the estimated values are not significant for several regions located in the centre of Europe and in the UK.**

Also for the case of the knowledge production function estimation, we make use of the regional taxonomy developed by Capello and Lenzi (chapter 2) in order to check whether there exist

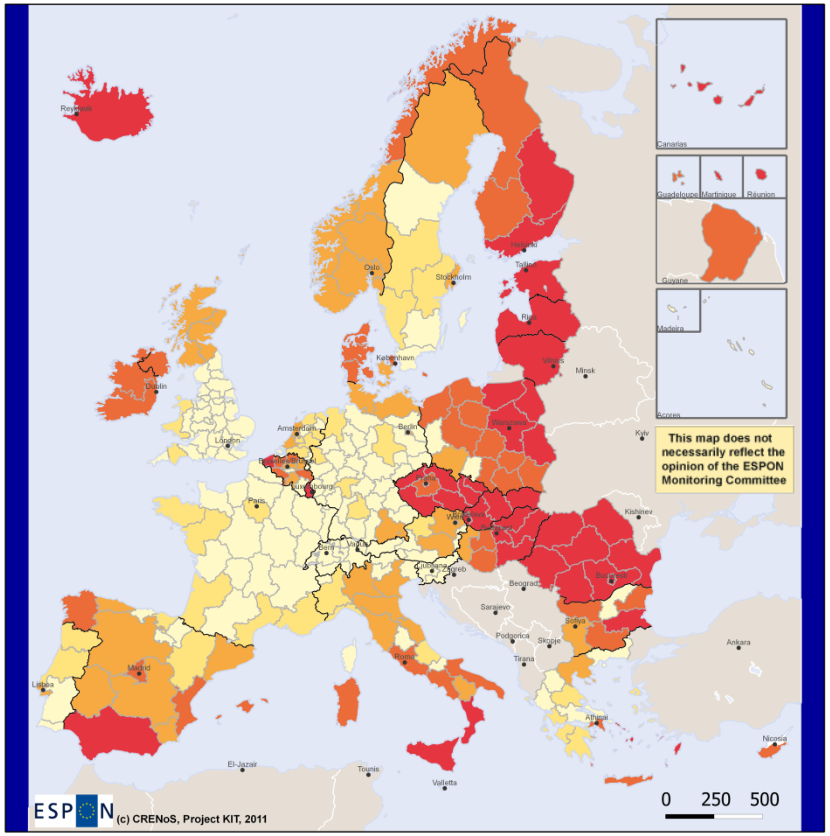
[20] To partly control for endogeneity we have also estimated the basic specification augmented with country dummies with 1 and 2 years lags for the production factors; results are very similar and we, as a consequence, prefer to exploit the full temporal set of information.

significant differences in the estimated impacts for R&D expenditure and human capital when these are allowed to change according to the distinctive innovation pattern of the five groups of regions, detailed in section 3.2. The model for R&D varying coefficients is reported in column (7) and the corresponding model for human capital in the last column (8). It is worth remarking that, as discussed for the case of KPF, the coefficient of human capital in (7), and conversely the one for R&D in (8), is very robust with respect to the inclusion of the interactive terms.

In the case of model (7), as we expected, the highest elasticity values occur for the preeminent groups in knowledge creation, that is European science-based and Applied science territories (respectively 0.15 and 0.12). Whereas, on average, 1% increase in R&D yields 0.13% increase in regional production, this is not the case across all types of regions. In fact, R&D is more efficiently used (i.e. shows a greater elasticity) in those regions which invest considerably in R&D, such as those in the European science-based area. On the contrary, regions characterised by low levels of R&D spending, have little benefit from further investments in R&D to improve their economic performance being their elasticity of innovation to R&D below the European average. The lowest coefficient is shown by the Smart Technological Application group (0.11), which consists of regions which have a strong orientation towards product innovation but are somehow weaker in terms of process innovation. We report these results in Map 3.7 where we can observe that regions with the highest propensity to innovate and the highest R&D elasticity values, are mainly located in the centre of Europe.

Results and interpretation is different when human capital elasticities are allowed to vary with respect to the same five categories. Model (8) shows that the groups with the highest elasticity are the Smart Technological Application (0.31) and the Imitative innovation (0.31). This result highlights that the human capital impact on regional production is quite diversified being high for weak performers in terms of innovation and knowledge. Results for the Smart and Creative Diversification and the Imitative innovation areas are quite similar (0.30 and 0.31, respectively) and also in this case we can interpret this result by arguing that human capital impacts are higher for those territories characterized by a low endowment of knowledge and innovation capabilities. Conversely, the two groups of regions which are the most knowledge and innovation intensive and are also well-endowed with highly educated population and scientific human capital, the European science-based area and Applied science area group, present lower elasticity values (0.17 and 0.25, respectively). In order to have a visual representation of the geographical distribution, results are displayed in Map 3.8 where we can see that regions presenting highest values for human capital elasticity belong to Belgium, Switzerland, Denmark, Spain, France, the north of Italy, Nederland, Sweden and United Kingdom. On the contrary, most of the regions showing the lowest elasticity values belong to Germany.

Map 3.6 Elasticity of GDP level to R&D by region (average 2000-2007)



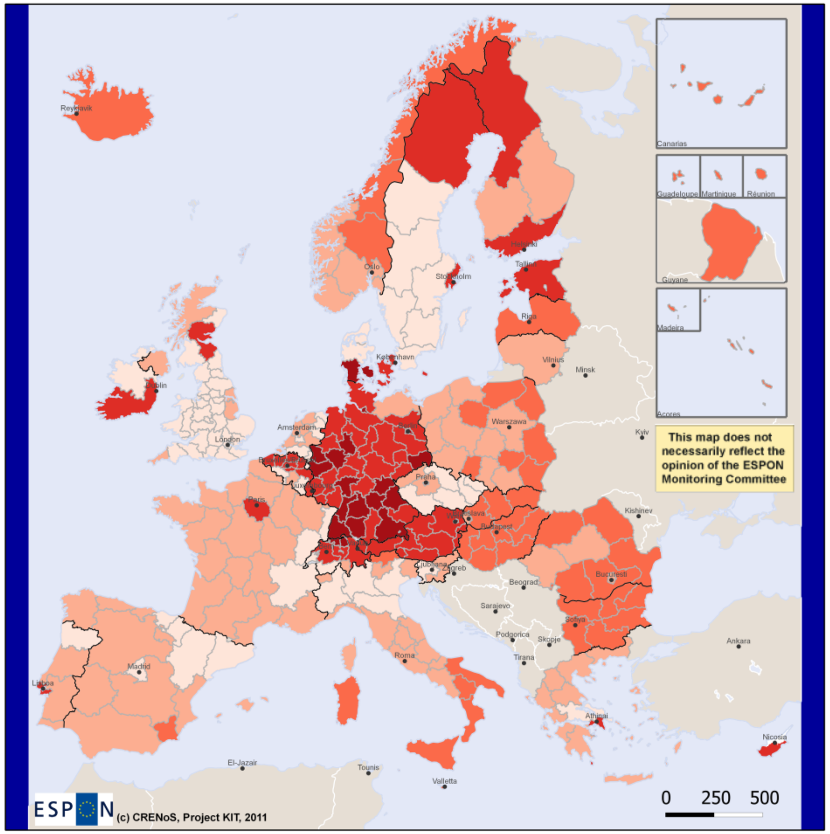
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

(c) EuroGeographics Association for administrative boundaries
Source: CRENoS elaboration, 2011
Origin of data: Eurostat
Regional level: NUTS 2

Legend

- not significant
- no data
- <15.0: Low elasticity
- 0.16 - 0.30: Medium elasticity
- 0.31 - 0.50: High elasticity
- >0.50: Very high elasticity

Map 3.7 Elasticity of GDP level to R&D by territorial patterns of innovation (average 2000-2007)



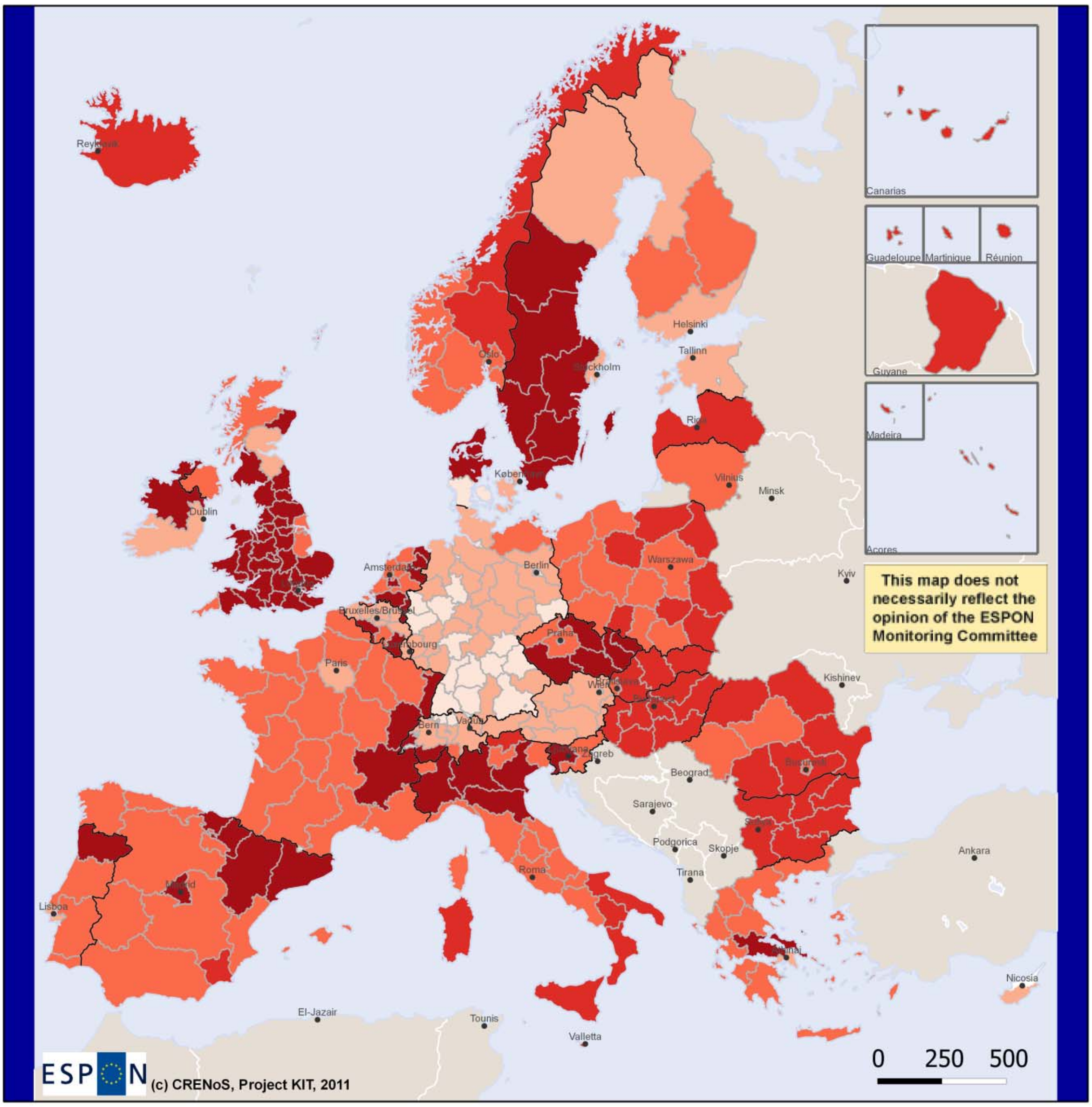
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

(c) EuroGeographics Association for administrative boundaries
Source: EUROSTAT
Origin of data: Author's elaboration
Regional level: NUTS 2

Legend

- no data
- Smart technological application area = 0.108
- Smart and creative diversification area = 0.112
- Imitative innovation area = 0.118
- Applied science area = 0.123
- European science-based area = 0.145

Map 3.8 Elasticity of GDP level to human capital by territorial patterns of innovation (average 2000-2007)



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

(c) EuroGeographics Association for administrative boundaries
Source: EUROSTAT
Origin of data: Author's elaboration
Regional level: NUTS 2

Legend

- no data
- European science-based area = 0.168
- Applied science area = 0.255
- Smart and creative diversification area = 0.303
- Imitative innovation area = 0.309
- Smart technological application area = 0.313

Table 3.5 - Spatial Production Function

Dependent Variable: GDP

	1	2	3	4	5	6	7	8
Model	**Pooled**	**Pooled**	**FE**	**SEM**	**SAR**	**SAR**	**SAR**	**SAR**
Estimation method	OLS	OLS	OLS	ML	ML	ML	ML	ML
Capital	0.017 **	0.045 ***	0.413 ***	0.028 ***	0.035 ***	0.249 ***	0.043 ***	0.042 ***
	(1.967)	(5.277)	(26.543)	(3.376)	(4.128)	(21.746)	(5.136)	(4.955)
Employment	0.396 ***	0.756 ***	0.131 ***	0.775 ***	0.757 ***	0.127 ***	0.764 ***	0.765 ***
	(33.58)	(57.040)	(3.471)	(61.824)	(58.208)	(4.960)	(59.621)	(60.080)
R&D	0.414 ***	0.130 ***	0.227 ***	0.129 ***	0.131 ***			0.113 ***
	(60.256)	(18.605)	(27.709)	(19.747)	(19.178)			(16.609)
Human Capital	0.028	0.313 ***	0.341 ***	0.235 ***	0.297 ***	0.244 ***	0.300 ***	
	(1.397)	(16.428)	(21.716)	(12.069)	(15.759)	(20.096)	(16.021)	
R&D*Imitative Innovation							0.118 ***	
							(15.181)	
R&D*Smart & Creative divers.							0.112 ***	
							(15.927)	
R&D*Smart Techn. Appl.							0.108 ***	
							(15.666)	
R&D*Applied science							0.123 ***	
							(17.382)	
R&D*European science-based							0.145 ***	
							(21.249)	
R&D regional individual terms						Yes		
HK*Imitative Innovation								0.309 ***
								(16.710)
HK*Smart & Creative divers.								0.303 ***
								(16.053)
HK*Smart Techn. Appl.								0.312 ***
								(16.155)
HK*Applied science								0.255 ***
								(11.854)
HK*European science-based								0.168 ***
								(7.525)
Spatial autoregressive coefficient - λ				0.942 ***				
				(65.013)				
Spatial autoregressive coefficient - ρ					0.019 ***	0.376 ***	0.022 ***	0.018 ***
					(7.206)	(22.679)	(7.435)	(6.264)
Constant	Yes	Yes	No	No	No	No	No	No
Fixed effects	No	No	Yes	No	No	No	No	No
Country dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Rbar-squared	0.912	0.971	0.727					
Corr-squared				0.952	0.972	0.997	0.973	0.974
Diagnostics								
Robust LM test - No spatial lag	5.39		0.028					
p-value	0.020		0.867					
Robust LM test - No Spatial err	689		0.159					
p-value	0.000		0.690					
LM test - No Spatial error		645.89						
p-value		0.000						

Panel estimation for the period 2000-2007 and 287 regions; total number of observations 2296

All variables are log-transformed. R&D is total expenditure, Human Capital (HK) are people with tertiary education in per capita te

For the definition of groups of regions see text page 3

For spatial models and tests the weight matrix is the max-eigenvalue normalized matrix of inverse distance in kilometers

Asymptotic t-statistics in parenthesis; significance: ***1%; **5%; *10%

3.5.2. Data Envelopment Analysis

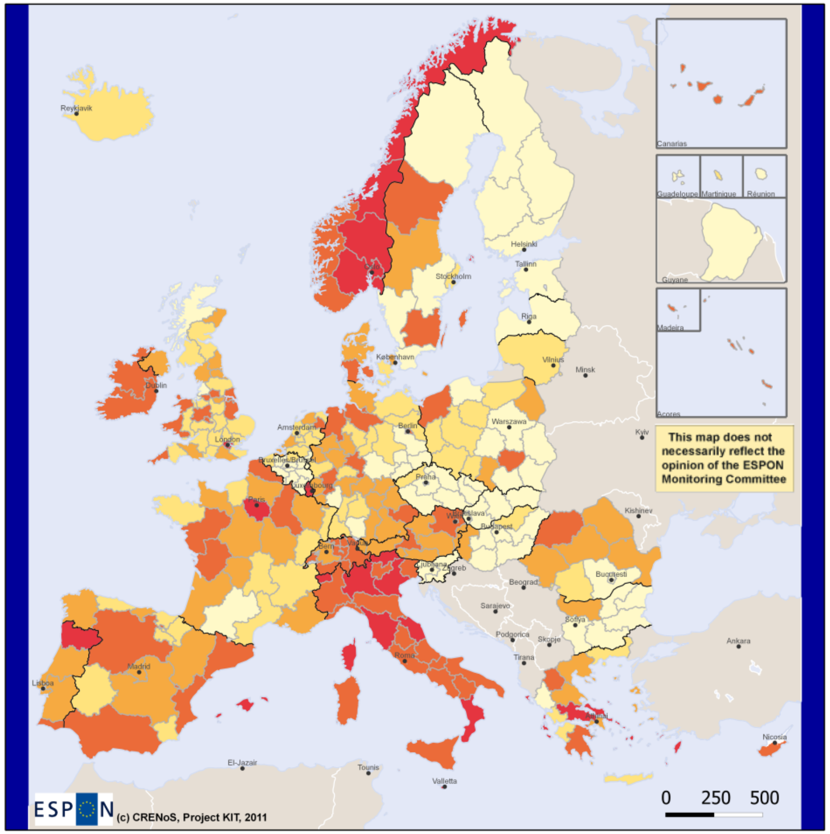
Parallel with the research path taken in section 3.4 for the KPF, we carried out an output-oriented data envelopment analysis also for production, under the assumption of varying returns to scale. The analysis is based on the comparison of the technical efficiency scores in the initial and final year of the period under investigation in order to unveil possible changes in the ability of the European territories to efficiently exploit their resources.

The 2000 efficiency levels are depicted in Map 3.9, whilst Map 3.10 reproduces the frontier in 2007. The production frontier in 2000 is defined by 27 regions (red colored), which exhibit a high degree of heterogeneity in terms of demographic characteristics and geographical location. More specifically, the efficient regions group comprises both small and low densely populated regions, mostly located in peripheral areas (Ciudad Autónoma de Ceuta, Illes Balears, Corse, Malta, Åland or Valle d'Aosta) and large, densely populated central regions, such as Île-de-France, Inner and Outer London. This apparently contradictory picture is expected with the DEA methodology, since it selects efficient units at all possible scales and may therefore reveal high efficiency scores also for small and peripheral regions. Nonetheless, the least efficient territories are, similarly with the case of KPF, mostly located in the Eastern Europe.

In 2007, Map 3.10 shows quite a different picture with a general efficiency gain since the number of efficient regions on the frontier goes from 27 to 32. The spatial distribution of the efficiency scores, however, exhibits a higher degree of dispersion as darker areas now emerge also in Central-Eastern countries, especially in Poland and even in Romania. In general, this analysis points out that the relative average efficiency level has improved for the whole of European regions over the last decade. As a matter of fact, the farthest region from the frontier in 2000 had an efficiency score of 0.20 whilst this value goes up to 0.34 in 2007.

In a tentative comparison of the rankings for KPF and for the production frontier we register, as expected, a much higher level of heterogeneity in terms of innovation efficiency with respect to production efficiency.

Map 3.9 Efficiency level of production function by region (DEA methodology, 2000)



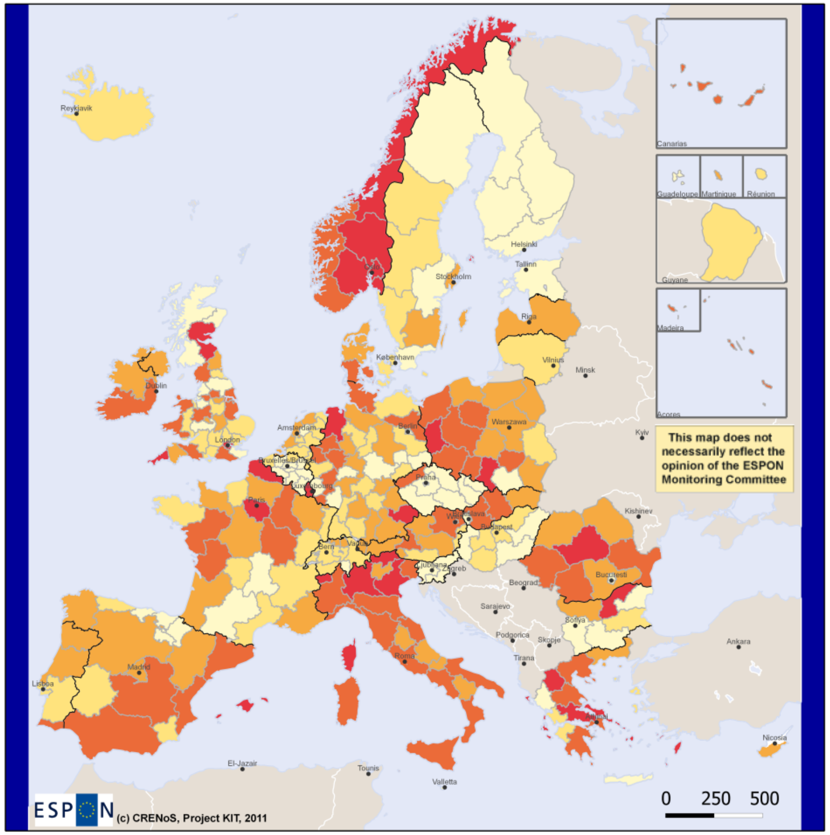
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

(c) EuroGeographics Association for administrative boundaries
Source: CRENoS elaboration, 2011
Origin of data: Eurostat
Regional level: NUTS 2

Legend

- no data
- 19.5 - 53.1: Low efficiency (65)
- 53.2 - 61.9: Medium-low efficiency (65)
- 62.0 - 73.1: Medium efficiency (65)
- 73.2 - 99.9: High efficiency (65)
- 100.0: Highest efficiency (27)

Map 3.10 Efficiency level of production function by region (DEA methodology, 2007)



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

(c) EuroGeographics Association for administrative boundaries
Source: CRENoS elaboration, 2011
Origin of data: Eurostat
Regional level: NUTS 2

Legend

- no data
- 33.4 - 51.9: Low efficiency (62)
- 51.9 - 62.9: Medium-low efficiency (64)
- 62.9 - 74.0: Medium efficiency (64)
- 74.0 - 99.9: High efficiency (65)
- 100.0: Highest efficiency (32)

3.6. Conclusions

The main purpose of this analysis is to investigate the functioning of the knowledge economy at the regional level in Europe. In particular, we assess the impact of intangible assets, such as human capital and research and development activities, on regional economic performances, which is proxied by inventive activity and by production levels. We also evaluate whether this impact is significantly different among regions as a whole and in particular with respect to the characteristics of their innovation behavior, which is synthesized in the classification of the Territorial Pattern of Innovation taxonomy. Finally, we investigate the presence of phenomena of spatial dependence across regions, arising from knowledge and technological externalities which go beyond regional borders.

As far as the returns of R&D expenditures and human capital on regional innovative capacity are concerned, estimated by means of a Knowledge Production Function, there is robust evidence of the strong role played by these inputs in fostering innovation and knowledge creation. Most importantly, the presence of a qualified and skilled labour force proves to be a crucial factor, even more than direct investment in R&D. Both inputs impacts exhibit a high degree of heterogeneity across individual regions and across groups classified according to the Territorial Pattern of Innovation groups. Results also reveal the presence of a strong spatial pattern of innovation activity enhancing spillovers.
According to the DEA results we found evidence of a dualistic (centre vs periphery) pattern in the regional innovation activities, with the highest efficient territories located in the most central or economically strategic areas of the continent, as it is the case for Île-de-France, Stuttgart or Noord-Brabant. Conversely, the lowest efficiency scores are shown by regions located in European peripheral areas, especially in the new accession countries.

As far as the analysis of the regional production function is concerned, the importance of intangible assets is confirmed. The implementation of econometric techniques allows to conclude that the variables measuring knowledge and innovation are significantly related to regional economic performance. Moreover, the relative prevalence of the effect of human capital with respect to R&D is corroborated, providing important indications about public policies for innovation and economic growth. The importance of cross border externalities is also substantiated. This implies that it is not only internal factors which matter for growth but external ones as well and that, as a result, investments in intangible assets are important also for the construction of absorptive capacity to exploit knowledge and ideas coming from other regions and countries. Finally, both econometric and data envelopment analyses suggest the presence of a high level of heterogeneity across regions in terms of impact of intangible factors and in terms of efficiency level in the use of productive resources. Such difference apply also to the classification of Territorial Pattern of Innovation groups.

3.7. References

Autant-Bernard C. and J. LeSage (2010) Quantifying knowledge spillovers using spatial econometric models, *Journal of Regional Science*, 20, 1-26.

Banker P.C., Charnes A. and Cooper W.W. (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*, 30, 1078–1092.

Boschma R.A. (2005) Proximity and innovation. A critical assessment, *Regional Studies*, 39, 61–74.

Capello R. and Lenzi C. (2011) Territorial Patterns of Innovation in Europe, *KIT- ESPON Final Report.*

Charnes A., Cooper W.W. and Rhodes E. (1978) Measuring the efficiency of decision making units, *European Journal of Operational Research*, 2, 429–444.

Coelli T.J. (1996) A Guide to DEAP Version 2.1: A Data Envelopment Analysis Computer Program. Working Papers 8/96, CEPA, The University of New England.

Cohen W.M. and Levinthal D.A. (1990) Absorptive capacity: a new perspective on learning an innovation, *Administrative Science Quarterly*, 35, 128-152.

Colombelli A., Foddi M., Paci R. (2011) The knowledge regions in the enlarged Europe, *Working Paper CRENoS* 2011/10.
Cook W.D. and Seiford L.M. (2009) Data envelopment analysis (DEA) – thirty years on, European *Journal of Operational Research*, 192, 1–17.
Cooper W.W., Seiford L.M. and Tone K. Data Envelopment Analysis, Springer, 2007, second edition.
Crescenzi R., Rodriguez-Pose A. and Storper M. (2007) The territorial dynamics of innovation: a Europe–United States comparative analysis, *Journal of Economic Geography*, 7, 673–709.
Crescenzi R., Rodríguez-Pose A. and Storper M. (2012) The geography of innovation: China, India and USA, *KIT- ESPON Final Report*.
Crescenzi, R., & Rodríguez-Pose, A. (2009). Systems of innovation and regional growth in the EU: endogenous vs. external innovative efforts and socio-economic conditions. In U. Fratesi & L. Senn (Eds.), *Growth and innovation of competitive regions: the role of internal and external connections* (pp. 167-192). Berlin: Springer-Verlag.
Cullinane K., Song D.-W. and Wang T.-F. (2004) An application of DEA windows analysis to container port production efficiency, *Review of Network Economy*, 32, 184–206.
European Commission (2011), REPORT FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS, State of the Innovation Union 2011.
Farrell M.J. (1957) The measurement of productive efficiency, *Journal of the Royal Statistical Society*, Series A, General 120, 253-281.
Greunz L. (2003) Geographically and Technologically Mediated Knowledge Spillovers between European Regions, *Annals of Regional Science*, 37, 657-80.
Griliches, Z. (1979) Issues in assessing the contribution of research and development to productivity growth, *The Bell Journal of Economics*, 10, pp. 92-116.
Jaffe A.B. (1986) Technological Opportunity and Spillovers of R&D: evidence from Firms' Patents, Profits and Market Value, *American Economic Review*, 76, 984-1001.
Jaffe A.B. (1989) Real Effects of Academic Research, *American Economic Review*, 79, 957-70.
Marrocu E., Paci R. and Usai S. (2011a) Proximity, networks and knowledge production in Europe, *WP CRENoS* 2011/09.
Marrocu E., Paci R. and Usai S. (2011b) The complementary effects of proximity dimensions on knowledge spillovers *Working Paper CRENoS* 2011/21.
Moreno R., Paci R. and Usai S. (2005) Spatial spillovers and innovation activity in European Regions, *Environment and Planning A*, 37, 1793-1812.
Usai S. (2011) The geography of inventive activity in OECD regions, *Regional Studies*, 45, 711-731.

Annex A.3.1. Data managing

Source: Eurostat		
Data of extraction: 28/03/2011		
31 Countries (27 EU + Switzerland, Norway, Liechtenstein and Iceland)		
GDP	Millions of euro (from 1.1.1999)/Millions of ECU (up to 31.12.1998)	
	Elaborations:	CH NUTS2 Data 2000-2005: Source ESPON Database 2013
		CH NUTS2 Data 1997-1999: share 2000 (national data available)
		CH NUTS2 Data 2006-2008: share 2003 (national data available)
		NO (NUTS2 data): share on pop distribution (National data available)
POP	Population at 1st January	
	Elaborations:	DE41 and DE42: shares 1999 (NUTS1 available)
		Regional DK data not available: share 2007 (nuts1 available)
		UKM5 and UKM6: share 2000 (nuts1 available)
EMPL	Employment (1000) - 15 years and over	
	Elaborations:	BG nuts2 data: share 2003 (national data available)
		CH nuts2 data: share 2001 (natioanl data available)
		DE41 and DE42: average share 2004-2005 (nuts1 data available)
		DEB1, DEB2 and DEB3: average share 1999-2002 (nuts1 data available)
		DED1,DED2 and DED3: average share 2000-2001 (nuts1 data available)
		DEK01-DK05: average share 2006-2008 (nuts1 data available)
		FR83,FR91,FR92,FR93 and FR94: average share 2001-2003 (national data available)
		FR9: sum of FR91-FR94
		SI01 and SI02: average share 2001-2003 (nuts1 data available)
		UKM5 and UKM6: average share 2000-2001 (nuts1 data available)
		LI: ESPON Database June 2009 (Difference between active population and unemployment)
INV	Gross fixed capital formation (Total of sectors/Current prices/Millions of euro (from 1.1.1999))	
	Elaborations:	BG NUTS1 & NUTS2 data: GDP share (national data available)
		CH NUTS1 & NUTS2 data: GDP share (national data available)
		DE NUTS2 1995-2001: share 2002 (NUTS1 data available)
		DK NUTS2 1995-1999: share 2000 (National data available)
		ES NUTS1 & NUTS2 2005-2007: share 2004 (national data available)
		ES63 and ES64 1995-1999: share 2004
		FR NUTS2 and NUTS1 2006-2007: share 2005 (national data available)
		FR91-FR94 1998: share 2005
		NO NUTS2: GDP share (national data available)
		SI01 and SI02 1995-1997: share 1999 (national data available)
		UK NUTS2 1995-1997: share 1998
		UNM1-UKM5 1995-1997: GDP share 1998
		UKN 1995-1997: share UK 1998
		UK NUTS1 and NUTS2 2001-2007: share 2000 (national data available)
		LI: GDP share
CAPITAL	CRENoS elaborations on Cambridge Econometrics data	
	Elaborations:	IS, LI, PT2 and PT3, FR9, SI: investments share
HK	Economically active population with Tertiary education attainment (levels 5-6 (ISCED 1997)) (15 years and over) (1000)	
	Elaborations:	BG 2000-2002: Active population 15-74 years with tertiary education attainment
		CH 1999-2000: Active population 15-74 years with tertiary education attainment

			DE 1999-2006:Active population 15-74 years with tertiary education attainment
			DK 1999-2006: Active population 15-74 years with tertiary education attainment
			FR 1999-2006: Active population 15-74 years with tertiary education attainment
			SI 1999-2000: Active population 15-74 years with tertiary education attainment
			UK 1999-2000: Active population 15-74 years with tertiary education attainment
			Nuts1 and nuts2 BG data: average share 2003-2005 (National data available)
			CH01-CH02 1999-2000: average share 2001-2003 (national data available)
			DE41-DE42 1999-2003: average share 2004-2006 (national data available)
			DE4 1999-2003: sum DE41, DE42 (National data available)
			DEB, DEB1-DEB3 2000-2001: average share 1999 and 2002 (national data available)
			DED 1999: average share 2001-2002
			DED1-DED3 1999: average share 2001-2002
			DEE and DEE0 1999-2006: average share 2007-2009
			DK01-DK05 1999-2006: average share 2007-2009 (national data available)
			FR9, FR91-FR94 1999-2006: average share 2007-2009 (national data available)
			SI01 and SI02 1999-2000: average share 2001-2003 (nuts1 and natioanal data available)
			UKM, UKM5, UKM6 1999-2000: average share 2001-2003 (national data available)
			Liechtenstein data 2001: Data belong to the Amt für Statistik (Liechtenstein)
			LI: 2000, 2002-2007 share 2001
R&D exp	Total intramural R&D expenditure (All sectors) (Millions of euro (from 1.1.1999)/Millions of ECU (up to 31.12.1998))		
	Elaborations:		AT (nuts1 and nuts2) 1996-1997: share 1998 (natioanl data available)
			AT (nuts1 and nuts2) 1999-2001: average share 1998 and 2002 (national data available)
			AT (nuts1 and nuts2)2003: average share 2002 and 2004 (national data available)
			AT (nuts1 and nuts2)2005: average share 2004 and 2006 (national data available)
			AT (nuts1 and nuts2) 2008-2010: share 2007 (national data available)
			BE1, BE10, BE2 1996-2001: share 2002 (national data available)
			BE1, BE10, BE2 2008-2009: share 2007 (national data available)
			BE21,BE22,BE23,BE24 and BE25: patents share 2006 (NUTS1 and NUTS0 data available)
			BE31,BE32,BE33,BE34 and BE35: patents share 2006 (NUTS1 and NUTS0 data available)
			BG (nuts1 & nuts2) 1996-2001: share 2002 (national data available)
			BG (nuts1 & nuts2) 2009: share 2008 (national data available)
			CH NUTS2 data: patents share 2004 (national data available)
			CZ nuts2 1996-2000: average share 2001-2002 (national data available)
			DE (nuts1 & nuts2) 1996: share 1997 (national data available)
			DE (nuts1 & nuts2)1998: average share 1997-1999 (national data available)
			DE (nuts1 &nuts2) 2000-2002: average share 1997,1999, 2003 (national data available)
			DE (nuts1 & nuts2) 2004: average share 2003-2005 (national data available)
			DE (nuts1&nuts2) 2006: average share 2005-2007 (national data available)
			DE (nuts1&nuts2) 2008-2009: share 2007 (national data available)
			DK nuts2 1996-2006 and 2008-2009: share 2007 (national data available)
			ES63 & ES64 1996-2003: share 2008 (national data available)
			ES (nuts1 & nuts2) 2009: share 2008 (national data available)
			FI (nuts1&nuts2) 1996: share 2000 (national data available)
			FI18&FI19&FI1A 1997-1999: share 2000 (national data available)
			FI (nuts1&nuts2) 2009-2010: share 2000 (national data available)
			FR (nuts1 &nuts2) 2005-2009: share 2004 (national data available)
			FR91,FR92,FR93,FR94: average patents share 1997-2004 (nuts1 data available)
			GR nuts0 1998: average value 1997-1999
			GR nuts0 2000: average value 1999-2001
			GR nuts0 2002: average value 2001-2003
			GR (nuts1 &nuts2) 1998: average share 1997-1999
			GR (nuts1 &nuts2) 2000-2002: average share 1999-2003

			GR (nuts1&nuts2) 2004: average share 2003-2005
			GR (nuts1&nuts2) 2006-2007: share 2005
			HU (nuts1&nuts2) 1996-1998: share 1999
			HU (nuts1&nuts2)2009: share 2008
			IE nuts2 1996-2001: share 2002 (nuts1 &nuts0 data available)
			IE nuts2 2008-2009: share 2007 (nuts1 &nuts0 data available)
			ITD1 & ITD2 1996-2000: share 2007 on national data
			IT (nuts1 & nuts2) 2001-2002 and 2008-2009: share 2007 (national data available)
			IT (nuts1 & nuts2) 2006:average share2005 and 2007 (national data available)
			NL (nuts1 & nuts2) 1996: average share 1997,1998,1999
			NL 12, NL13 1997 and 1998: share 1999
			NL11, NL13, NL34 2000: average share 1999-2001
			NL (nuts1 & nuts2) 2004: average share 2003-2005
			NL (nuts1 & nuts2) 2006: average share 2005-2007
			NL (nuts1 & nuts2) 2008, 2009: share 2007
			NO nuts2 data 2002: average share 2001-2003
			NO nuts2 data 2004: average share 2003-2005
			NO nuts2 data 2006: average share 2005-2007
			NO nuts2 data 2008-2009: share 2007
			PT 1996 and 1998 (nuts1 &nuts2): average share 1997, 1999, 2000 (national data available)
			PT16, PT17 and PT18: share 2000
			PT 2006 and 2007 (nuts1 and nuts2): average share 2005-2008 (national data available)
			PT 2009 (nuts1 and nuts2): share 2008 (national data available)
			RO (nuts1 and nuts2) 1996-2000: share 2001 (national data available)
			RO (nuts1 and nuts2) 2009: share 2008 (national data available)
			SE (nuts1 & nuts2) 1997, 1999, 2001: share 2003 (national data available)
			SE (nuts1 & nuts2) 2004: average share 2003-2005 (national data available)
			SE (nuts1 & nuts2) 2006: average share 2005-2007 (national data available)
			SE (nuts1 & nuts2) 2008, 2009: share 2007 (national data available)
			SI01 and SI02 1996-2002: share 2003 (NUTS1 and NUTS0 data available)
			SI01 and SI02 2009: share 2008 (NUTS1 and NUTS0 data available)
			SK01, SK02, SK03 and SK04 1996-1999: share 2001 (national data available)
			UK (nuts1 and nuts2) 1996-2004: share 2005 (national data available)
			UK (nuts1 and nuts2) 2009: share 2008 (national data available)
			CH (NUTS0, NUTS1 & NUTS2) 1997-1999, 2001-2003, 2005-2007
			IS 2004
			LUX 2001-2002
			MT 2000-2001
			NO 2000
			SE 2000 and 2002
			LI: share GDP

Chapter 4. The Territorial dynamics of innovation in China, India and the US: An explorative analysis and conceptual framework[21]

4.1. Introduction

This chapter of the KIT Final Report provides the in-depth results of our analysis on the comparative analysis of the territorial dynamics of innovation in China, India and the US. The research aims to support the European Union's continued efforts to support knowledge-based economic development across member states.

In 2000, the European Union launched the 'Lisbon Agenda', which aimed to make the European Union the 'most competitive and dynamic knowledge-based economy in the world' by 2010. In 2011, the technological gap with the US appears to have widened (Crescenzi et al 2007). The past decade has also witnessed the dramatic rise to prominence of the BRICS countries, especially India and China: Goldman Sachs suggests that by 2030, the largest three world economies will be USA, China and India (Wilson and Purushothaman 2003). It is therefore critical for European policymakers to understand the dynamics of this shifting, multipolar environment.

This report explores a key aspect of territorial development – namely the geography of innovation in India, China and the USA. The past two decades have seen the globalisation of production *and* the globalisation of R&D (Fu and Soete 2010, Yeung 2009). The USA, China and India have been at the forefront of these shifts (Parayil and D'Costa 2009, Leadbeater and Wilsdon 2008, Popkin 2007).

During the 1970s and 1980s Indian and Chinese firms acted as 'production platforms' for Western firms, largely from the USA, or pursued indigenous innovation strategies with varying degrees of success (Yeung 2009). Since the 1990s, businesses in both countries have been moving up the value chain, engaging in R&D-led innovation and international partnerships (Kikuchi and Tsuji 2010, Bruche 2009). The result has been a number of high-tech urban hubs across South-East Asia, with a complex nexus of relationships between US multinationals, local institutions and domestic firms (Yeung 2009, Saxenian and Sabel 2008).

In most countries innovative activity tends to be spatially clustered, reflecting the 'matching', 'sharing' and 'learning' economies of large urban areas (Duranton and Puga 2003). The resulting 'territorialisation' of innovation is well-observed in mature economies like the USA and EU (Storper 1997). Notably, similar spatial clustering is also present in 'emerging' economies. This means that it is critical to understand the *territorial* aspects of innovation systems in India and China, as well as the USA.

Our analysis is one of the first to present a systematic, cross-country quantitative analysis of territorial innovation systems. We deploy new panel datasests to explore both the geographical patterns of innovative activity, and the range of forces and factors shaping these outcomes. In this way we are able to both explore country-specific factors in detail, and to explore commonalities and differences across China, India and the USA.

Our results show important differences across the three countries. Our descriptive analysis shows that both India and China have spatially concentrated innovation systems. Overall patenting, and patenting in specific technology fields, is far more spatially clustered in India and China than the USA. We confirm other analysis showing that in China innovative activity is concentrated along coastal regions, especially in the South. In India, patent counts are highest in high-tech clusters such as Bangalore, Chennai, Delhi, Hyderabad, Mumbai and Pune.

We also examine key innovation 'inputs', such as R&D intensity and human capital endowments. In contrast with patenting and skilled population bases, R&D spending per capita is significantly more clustered in the USA than in China or India. The distribution of the top-

[21] This chapter has been written by Riccardo Crescenzi, Andrés Rodríguez-Pose and Michael Storper, London School of Economics.

ranked regions across these metrics also varies significantly in India and the USA: much less so in China.

Our quantitative analysis goes on to explore the dynamics of territorial innovation systems in detail. In China, innovative activity appears to be driven by the density-R&D nexus, and more broadly by traditional agglomeration factors – partly reflecting a state-driven economy. India presents a more straightforward 'R&D plus spillovers' story, in a large number of urban cores. The US system combines traditional agglomeration factors and a large number of innovation 'hotspots': the generation of innovation occurs largely in self-contained zones relying on their own R&D inputs, favourable local socio-economic environments and on large pools of skilled individuals.

Our approach adds value for EU policymakers in three ways. First, it enables us to isolate factors shaping innovation and development in different context. In turn, this helps the EU site its own leading and lagging regions. Second, we 'capture' both the emergence of new actors in technological competition as well as existing leaders – helping EU regions identify external competitors and opportunities. Third, our analysis supports policy transfer from the EU to non-EU partners.

The text is organised into sections, as follows. In section 4.2 an in-depth analysis of the spatial distribution of patenting activity, by country, region and key technology fields (ICT, biotech and nanotech) is pursued. Further analysis of R&D, human capital trends and an innovative 'Social Filter' is also provided. Section 4.3 reprises our conceptual framework, which informs the quantitative analysis that follows. Section 4.4 sets out our model and data sources. Section 4.5 gives results of the quantitative analysis. Section 4.6 provides brief conclusions and policy lessons. Details of variables and diagnostics are given in Technical Appendices 4.1 and 4.2.

4.2. Key trends of innovation dynamics in China, India and the USA

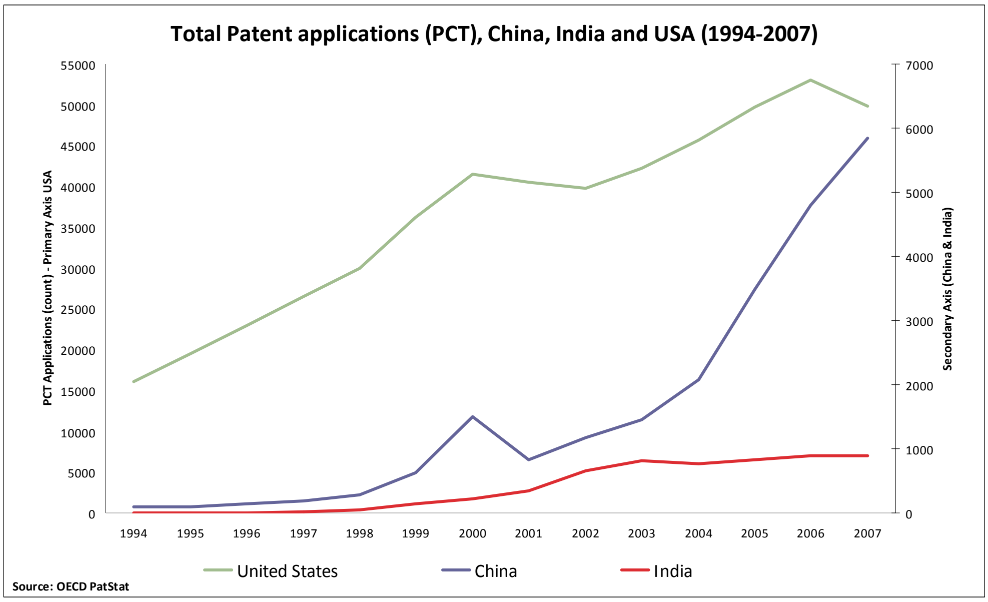
4.2.1 Country-level comparative perspective

We begin with an overview of the comparative 'innovation performance' of the three countries, using the most recently available data across a range of key innovation inputs and outputs.

4.2.1.1. Patenting

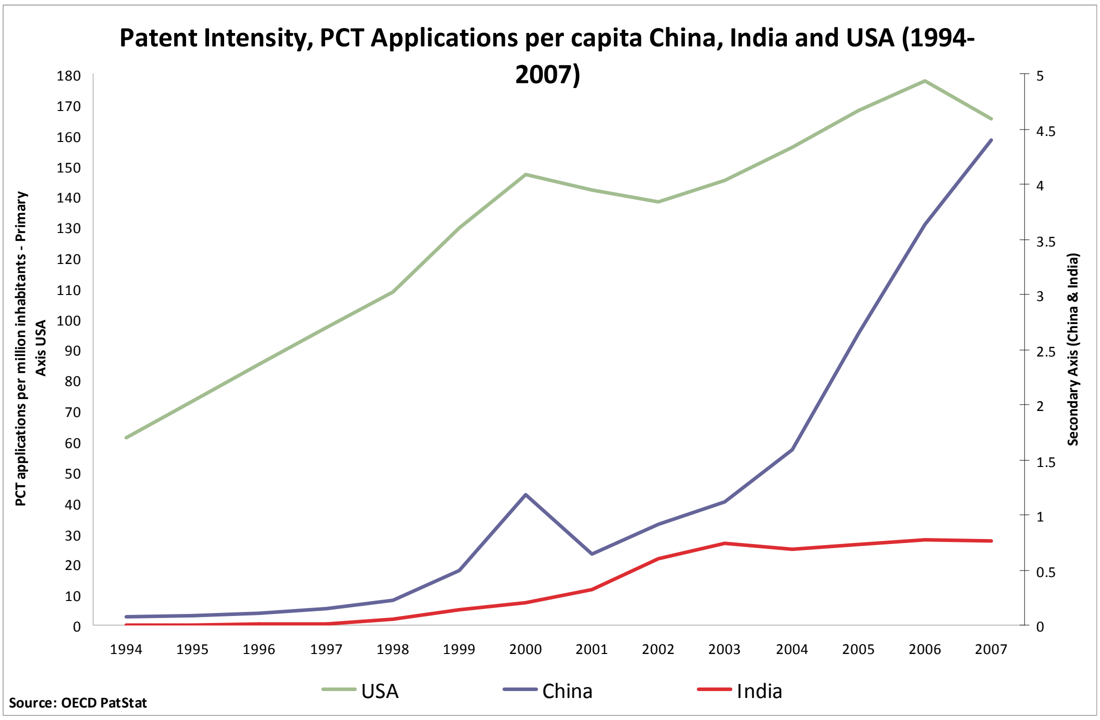
The USA is the acknowledged innovation systems world leader on a range of metrics, including patenting (Crescenzi et al 2007). Figures 4.1 and 4.2 illustrate America's performance on patents per capita over the past two decades. The US has increased its national patenting activity more or less continuously during this time, with counts rising from around 15,000 patents to 55,000.

Figure 4.1. Total patent applications (PCT), China, India and USA 1994-2007



All three countries increased overall patenting and patent intensity during the 1990s. From 2000 onwards India patenting rates rose substantially. However, India's impressive improvements have been dwarfed by the huge jump patenting in China post-2001, shifts which significantly reflect increasing Chinese investments in innovation 'inputs' (see below). Overall patent counts rose from 1,000 to nearly 6,000, with patent intensity (per capita patenting) rising over four-fold.

Figure 4.2. Patent intensity, PCT applications/capita, China, India, USA 1994-2007

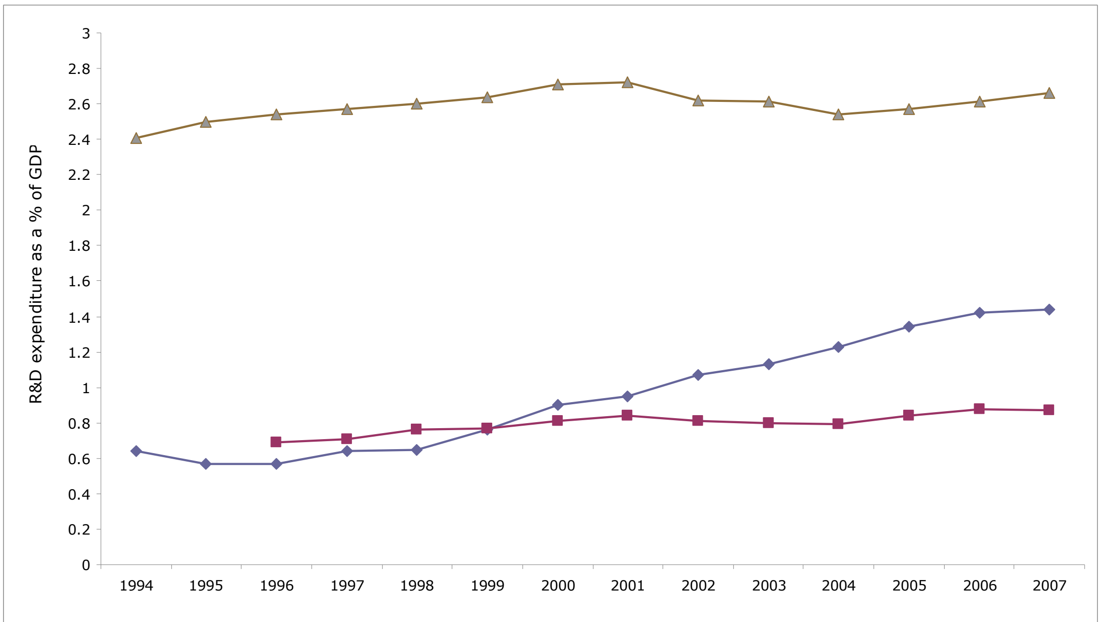


4.2.1.2. R&D / science and technology spending

During the 1990s both India and China invested heavily in innovation 'inputs', particularly China, increasing literacy rates and HE enrolment, raising production of engineering graduates and increasing spend on R&D. Both countries also began to 'globalise' their economies, increasing FDI flows, licensing of foreign technology and moving students abroad (Dahlman 2010). Figure 4.3 shows R&D as a share of GDP in China, India and the USA.

As a share of GDP, R&D spending in the USA has moved slightly upward during this period, but still vastly outstrips the other two countries. China's R&D spending has been on an upwards trend since the late 1990s, with significant climbs since the 2000s. India's R&D share has been more or less in 'steady state'.

Figure 4.3. R&D expenditure as a share of GDP, 1994-2007



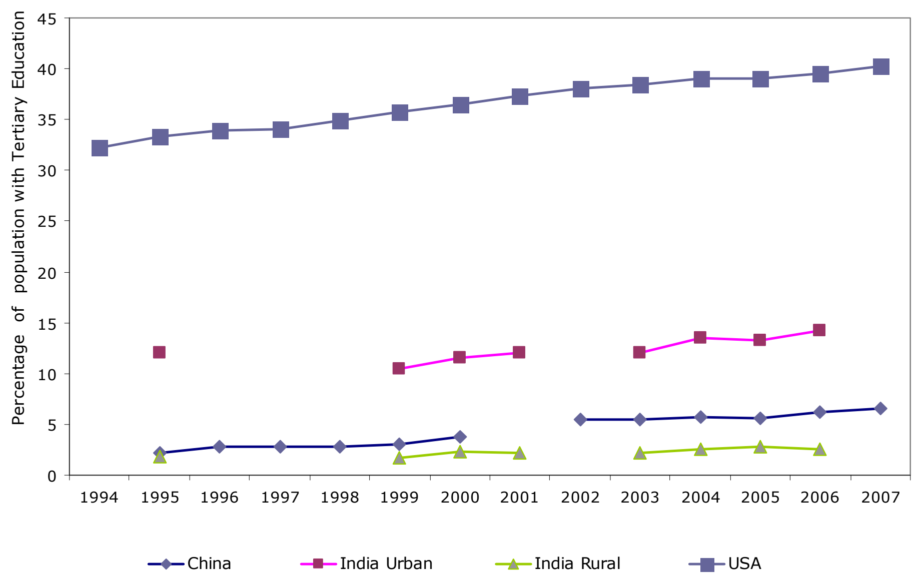
Source: OECD 2010

4.2.1.3 Human capital

Another key innovation input is human capital. As outlined above, in the past two decades both China and India have significantly increased investment in human capital, especially at degree level. Figure 4.4, below, shows country-level population shares with tertiary education or above.

The USA still produces vastly more graduates than India or China. However, in technology-specific fields these countries are catching up with the US. During the 1990s Indian universities significantly increased their production of engineering graduates – from 44,000 per year in 1992 to 184,000 in 2000. This compares with 352,000 per year in China – and just 76,000 per year in the US (Mitra 2007). China has also exploited global knowledge by moving students abroad to study in larger numbers than India – although Indian returnees have had significant impacts on the country's ICT sector (Saxenian 2006). Raising human capital stocks helps build the scientific workforce. With 926 R&D researchers per million people, China now has the second-highest number of researchers world-wide (Schaaper 2009). By contrast, India's R&D worker intensity has actually fallen since the mid-1990s.

Figure 4.4. Population shares with tertiary education, 1994-2007



Source: OECD Factbook, 2009, 2010
China Statistic book, 1996-2008
India National Sample Survey
Note: China: College and higher, aged above 6
India:Diploma/Certificate, Graduate, Post Graduate and Above;
1995 (aged above 15), other years (aged above 7)
USA and EU15:Tertiary attainment for age group 25-64

4.2.1.4 Social and institutional factors shaping innovation systems

Looking deeper into histories and policy choices helps to explain some of these differences. The USA is an established technology leader which comfortably outperforms the EU, as well as India and China, in R&D, R&D workforce, research quality and university-educated workforce population shares (Crescenzi et al 2007). The origins of the US 'national innovation system' date back to the 1945-50 Cold War re-armament period (Mowery 1992). The US system has been built up over time via a series of large scale projects, as well as supportive anti-trust and IP regimes that allow easy commercialisation of ideas. The large venture capital community in the USA has also helped bring new ideas to market (Reed 2010).

India and China manifest a number of similarities, but also some important differences compared to both the USA, and to each other. Historically, both India and China used innovation and technology-led development to pursue national prestige / international positioning, for example via space flight and atomic weapons programmes (Leadbeater and Wilsdon 2007). India and China have also moved from heavily statist models of public policy, towards market-led reforms (Fleischer et al 2010, Fan 2008, Jian et al 1996).

China moved to 'globalise' its economy and innovation system earlier than India, and more comprehensively. China's trade as a share of GDP has been significantly higher than India's since the 1980s; FDI flows and licensing of foreign technology are also higher (Dahlman 2010). China has moved through waves of planned development, with a first phase of market-orientated reforms in 1978. Special Enterprise Zones were introduced in the 1980s to concentrate FDI flows and encourage technology transfer, and 1990s the country joined the WTO (Dahlman 2010, Liu and Buck 2007, Jian et al 1996). A second wave of reforms began in the mid-1990s, with encouragement of private businesses (Fleischer et al 2010).

By contrast, until the 1991 currency crisis forced an acceleration of economic liberalization, India's development strategy had been largely autarkic, based on import substitution (Dahlman 2010). Since then the country has shifted from 'highly regulated, autarkic' development to more market-led models, with a further acceleration in the early 2000s (Fleischer et al 2010, Gajwani et al 2006). More than China, India has since been able to make a virtue of cultural and historical specificities in developing innovative capacity – most obviously the English language and democratic political institutions (Bruche 2009, Bound 2007).

The two countries have developed different overall strengths, partly through conscious policy choices. China has become 'the manufacturing workshop of the world' (Dahlman 2010), although its firms are now climbing up the value chain (Bruche 2009). India has been developing a comparative advantage in pharmaceutical and ICT sectors – a process significantly shaped by partnerships with MNEs and the role of diaspora communities, and by India's English language and human capital bases (Bruche 2009, Mani 2004).

These historical trajectories are shaping current policy priorities. Both countries are developing their domestic innovation capacities, particularly China (Lundin and Schwaag Serger 2007). In 2006 the country announced 'Medium to Long Term Science and Technology Development Programme'. The Programme sets out a 15-year strategy to raise R&D spending from 1.3% of GDP (in 2006) to 2.5% (in 2020): this requires raising annual R&D spending by 10-15% per year. India's model focuses on developing skilled human capital, clustering activity in science parks, and providing financial instruments such as tax incentives, research grants, concessional loans and venture capital (Mani 2004).

As China has switched into investing in domestic capacity, since the 2000s India has taken a more aggressive approach to adopting foreign technology, especially in ICT (Dahlman 2010). A key focus of policy in the 1990s has been to promote co-location of high-tech activity, especially via a network of regional science parks (Mitra 2007). In 2005, Chinese-style Special Economic Zones were also introduced – offering lower tax and less labour regulation in an attempt to attract and grow export-orientated firms.

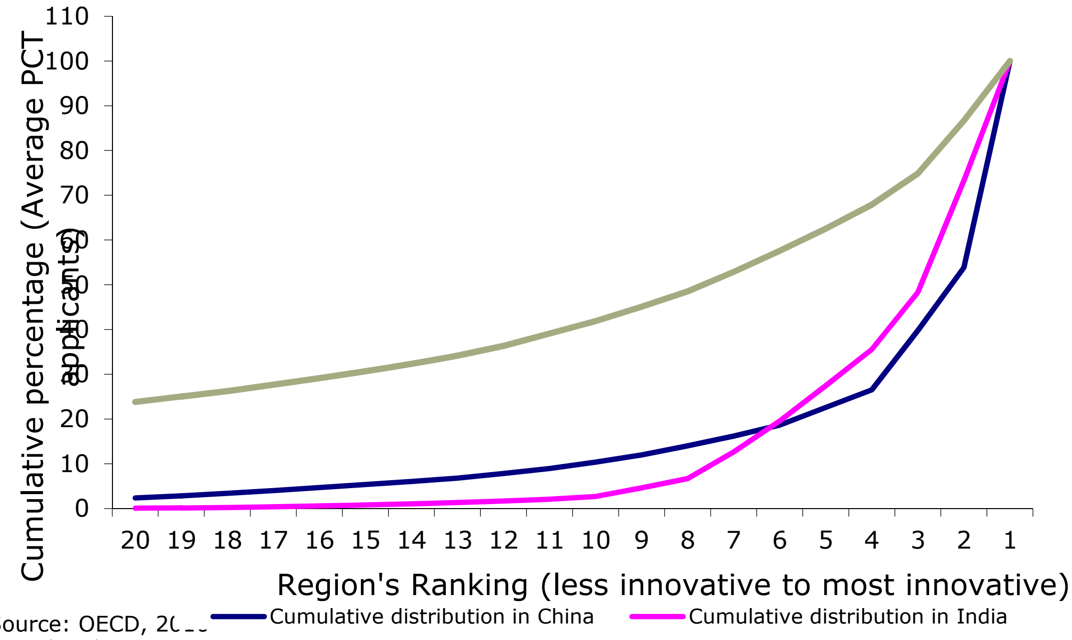
4.2.2 Territorial level comparative analysis

We now move on to consider the territorial aspects of the three countries' innovation systems. Looking at the spatial distribution of innovative activity helps us to understand differences between and within China, India and the USA. First, we know that innovative activity tends to be spatially uneven and reflects agglomeration (see section 3). Second, mature and 'emerging' economic systems will have different territorial dynamics: as noted in the introduction, rapid urbanisation is an important aspect of development in India and China. This suggests different spatial configurations between the three countries – an intuition borne out in the descriptive analysis.

4.2.2.1 Patenting

Figure 4.5 illustrates the cumulative distribution of patenting across space in India, China and the USA from 1994 to 2007, focusing on the 20 regions with the highest patent counts. The graph should be read from right to left. The slope of the curve shows the degree of spatial clustering: the steeper the line, the more clustered. Spatial 'shares' can then be read off points on the line. For example, figure 4.6 shows that the five US regions with the highest shares of patent applications together represent 35% of all US patenting. By contrast, the five most innovative Indian regions cover 75% of Indian patents; in China, the five highest-patenting regions have just under 80% of all patent applications.

Figure 4.5. Generation of innovation in China, India and the US: Cumulative distribution of PCT patent applications. Top 20 most innovative regions



Source: OECD, 20[illegible]

Note: China data 1994-2007, 31 provinces
India data 1994-2006, 24 states
USA data 1994-2007, 179 BEA EA

Two points stand out from the graph. First, there seems to be a clear difference in the spatial features of 'mature' and 'emerging' innovation systems, with patenting in India and China far more spatially agglomerated than in the United States where the distribution of patenting activity is more smoothly distributed across space. Second, differential levels of investment in innovation inputs also appear to influence where innovative activity takes place. The six highest-patenting regions in China account for a bigger share of innovative activity than those in India, although the pattern reverses after that with a long tail of Indian regions.

Figures 4.6-4.8 break down these numbers over time. Sun (2003) finds evidence of increasing spatial agglomeration of innovative activity in China during the 1990s, as measured by patents. The graphs confirm this: in 1994 innovative activity in India is far more concentrated than in China. By the late 1990s the pattern is beginning to change: by 2007 patenting is more clustered in Chinese provinces than in Indian states. Indian patenting remains more concentrated in 2000, so agglomeration of patenting activity in China took place in parallel with the country's overall rise in patenting activity.

Figure 4.6. Cumulative distribution of average PCT applicants: Top 20 most innovative regions, 1994.

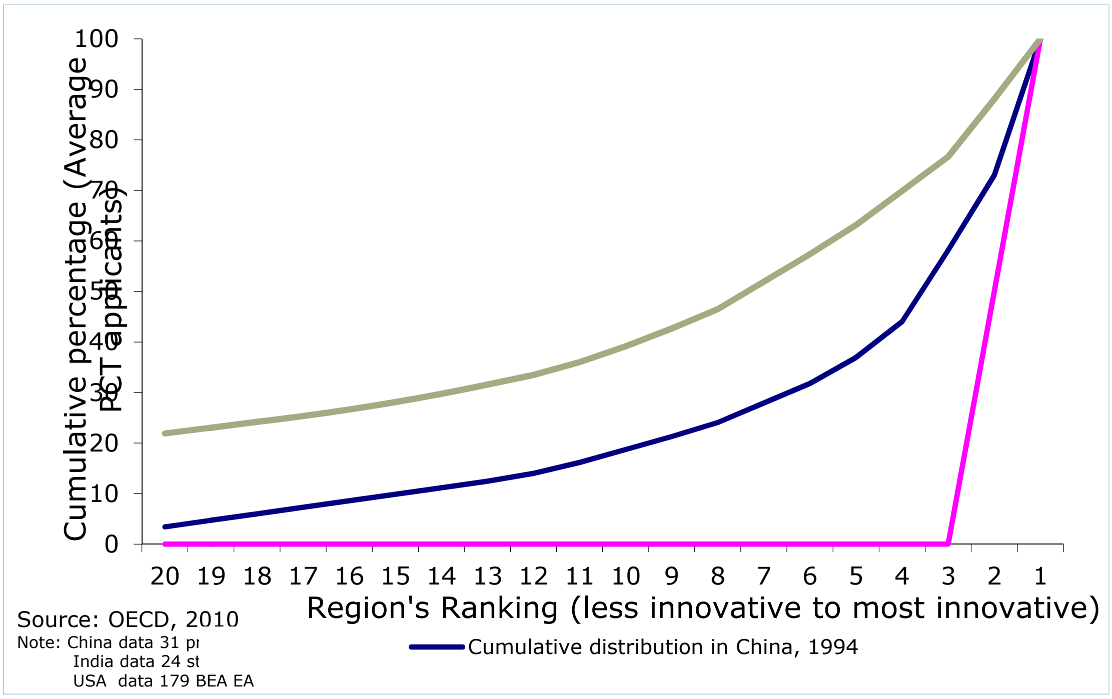


Figure 4.7. Cumulative distribution of average PCT applicants: Top 20 most innovative regions, 1997

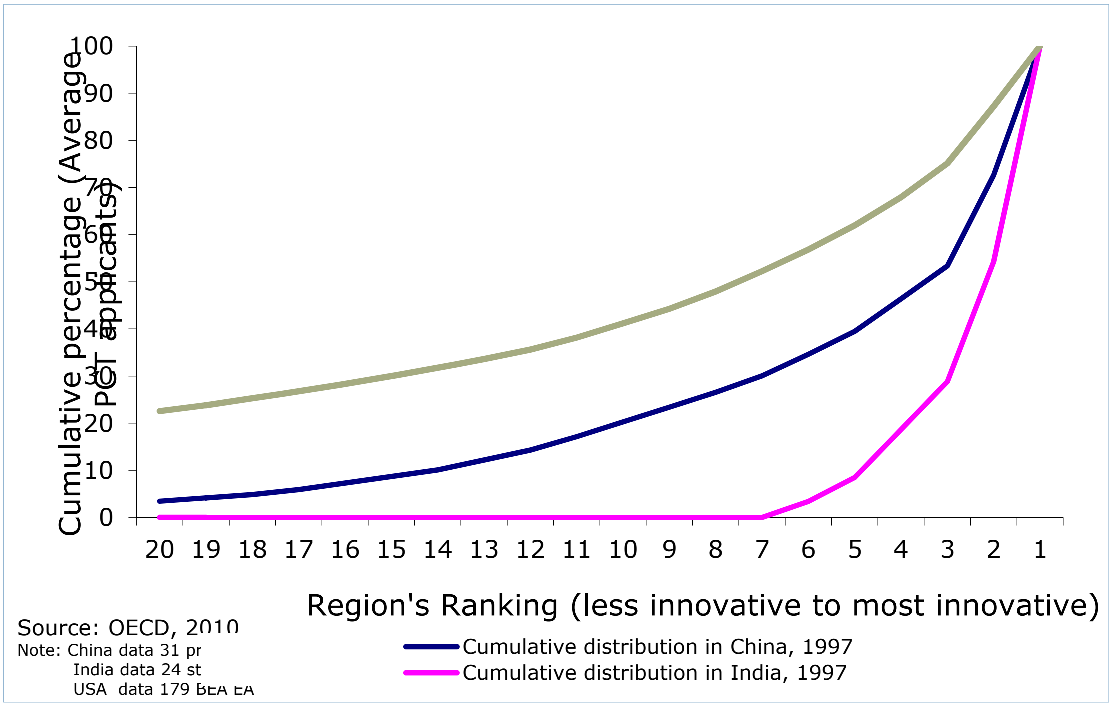
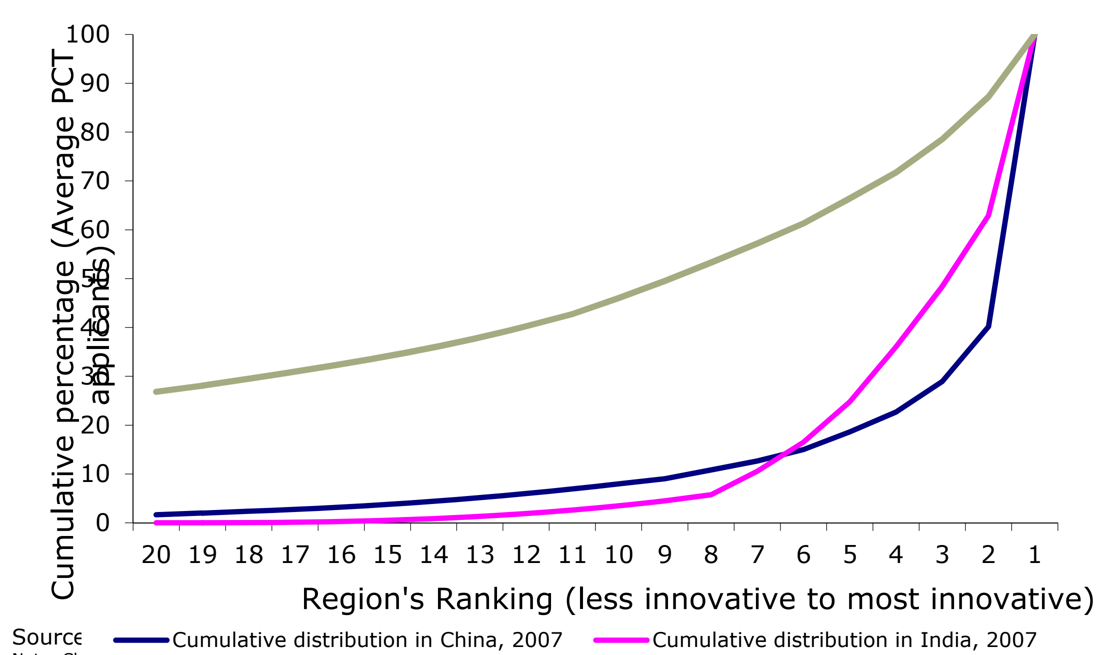


Figure 4.8. Cumulative distribution of average PCT applicants: Top 20 most innovative regions, 2007



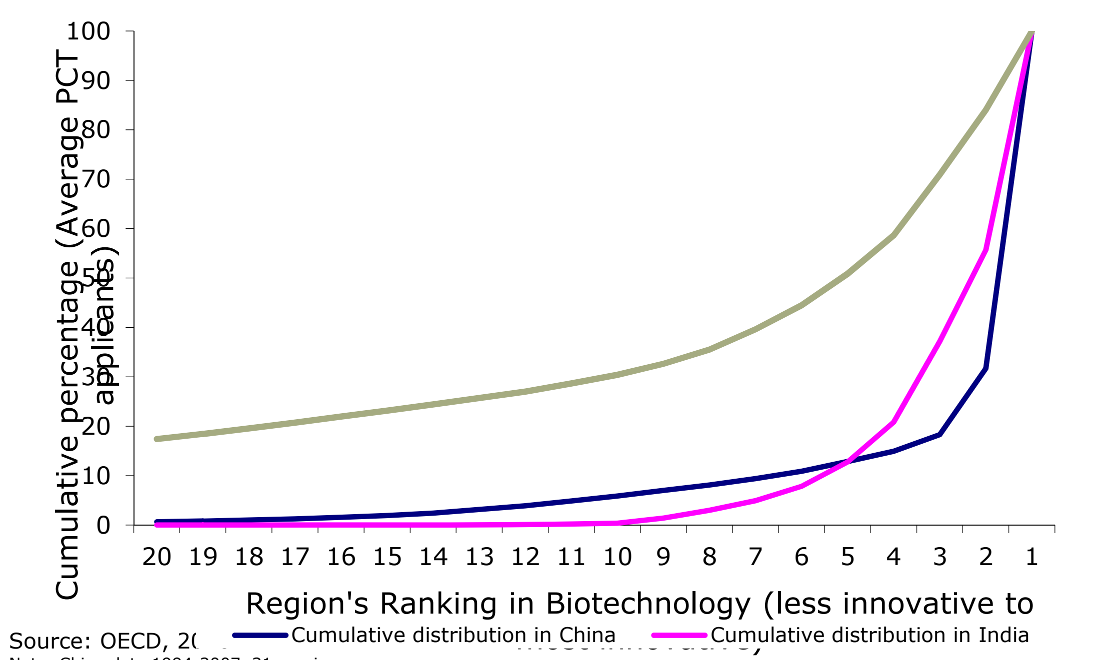
Source

Note: Ch[illegible]
India data 24 states
USA data 179 BEA EA

We next explore patenting trends by more detail by breaking down overall counts into key technology fields. Patent data is organised by 'technology field' rather than industry (as in employment data, for example); OECD data follows standard IPC classifications, from which we explore counts for biotechnology, information and communications technology (ICT) and nanotechnology. Here we present information across the whole period, 1994-2007. Breakdowns across time suggest relatively little change at specific points.

Figure 4.9 shows the spatial distribution of biotechnology patenting across the countries during 1994-2007. Biotechnology patenting is somewhat more spatially agglomerated in China and India than overall patenting; in China, the top three 'biotech regions' account for over 80% of overall patenting in the field. As with overall counts, however, both countries have more concentrated biotech patenting activity than the USA – where the top three regions account for just over 30% of all biotech patents.

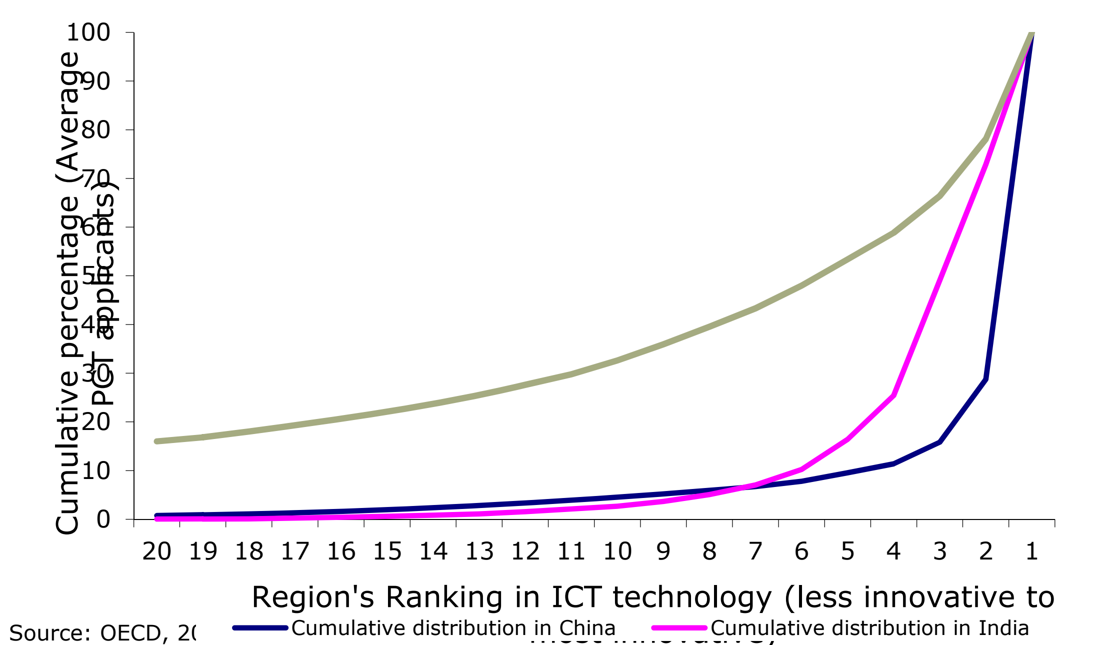
Figure 4.9. Cumulative distribution of average PCT applicants in biotechnology



Source: OECD, 2(
Note: China data 1994-2007, 31 provinces
India data 1994-2007, 24 states
USA data 1994-2007, 179 BEA EA

Figure 4.10 shows the distribution of ICT patents, where similar patterns persist. Sectoral activity is even more agglomerated in China than in India, with both countries having long tails of trailing regions. Again, both countries' ICT patenting is much more spatially clustered than in the USA.

Figure 4.10. Cumulative distribution of average PCT applicants in ICT technology



Source: OECD, 2(
Note: China data 1994-2007, 31 provinces
India data 1994-2007, 24 states
USA data 1994-2007, 179 BEA EA

Figure 4.11. Cumulative distribution of average PCT applicants in nanotechnology

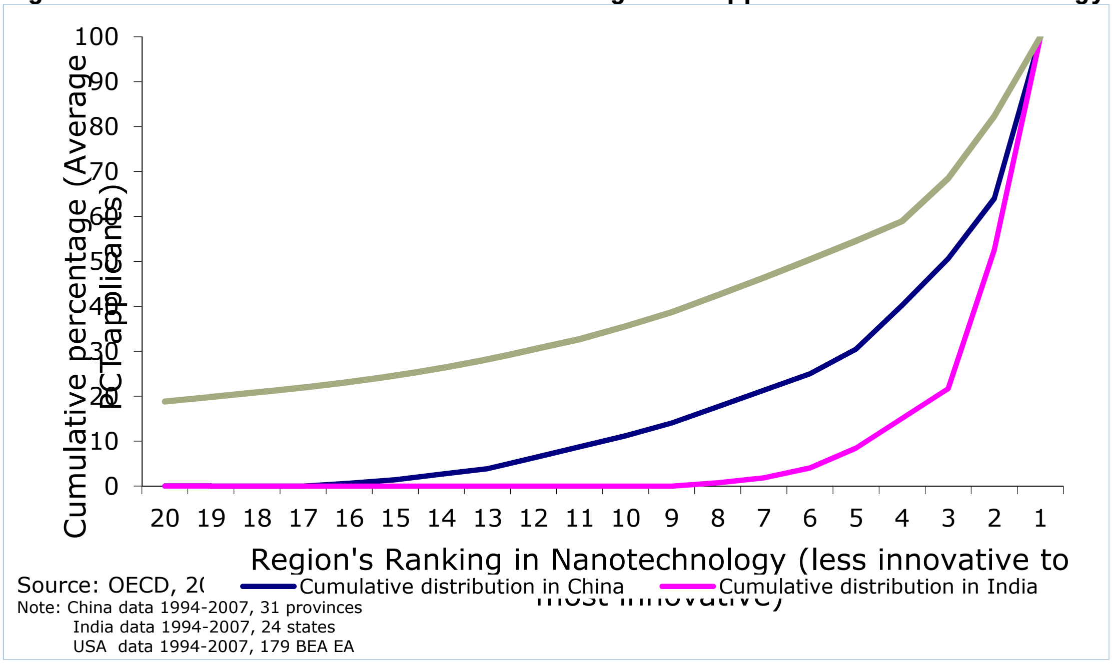
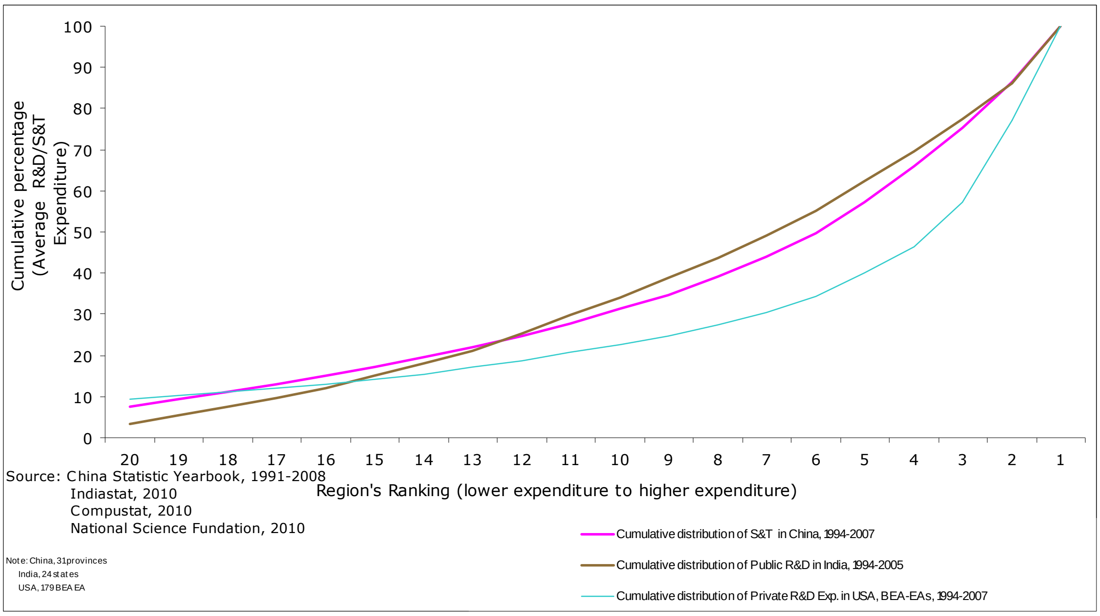


Figure 4.11 gives trends for the <u>nanotechnology patenting</u> field. India has the more agglomerated sectoral innovation system than China, with the top three Indian regions accounting for over 80% of nanotech patenting, against an approximate 60% share for the leading Chinese regions. The USA is rather less agglomerated.

4.2.2.2 R&D spending

We now shift the analysis from patenting, our key innovation 'output', to consider innovation 'inputs'. The first of these is spending on research and development.

Figure 4.12. Cumulative distribution of R&D / science and technology spending



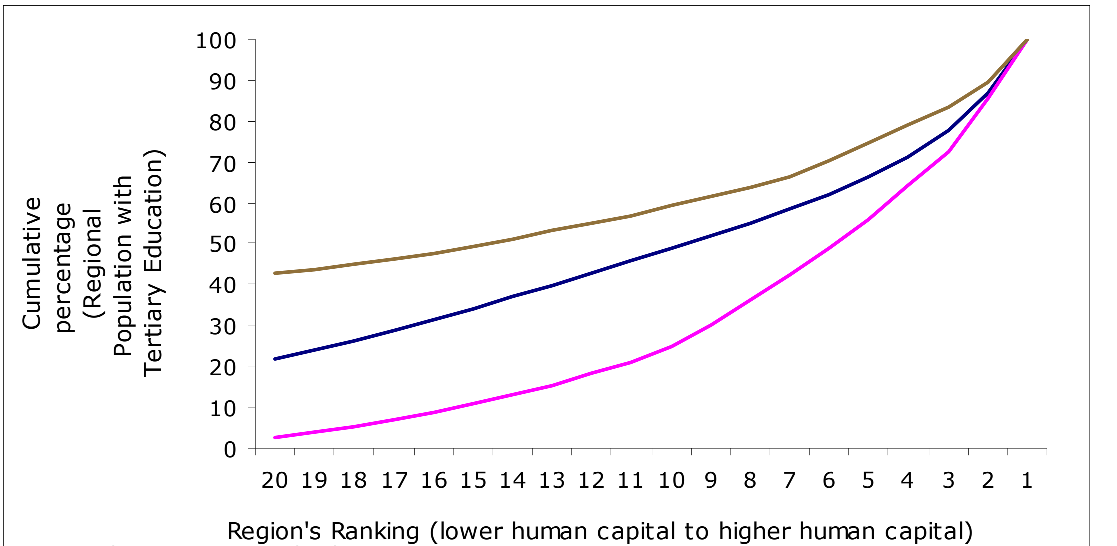
R&D spending patterns are in marked contrast to the spatial distribution of patenting for the three countries (Figure 4.12). R&D is significantly more clustered in the US than China or India, reversing the territorial patterns of patent activity. R&D spending in China is slightly more spatially clustered than that of India.

American patterns largely reflect the existence of large, self-sustaining clusters such as the Boston-Route 128 corridor and Silicon Valley. By contrast, China and India have historically used R&D as an economic development tool, spreading it across several locations.

4.2.2.3 Human capital

Figure 4.13 repeats the territorial analysis for human capital, as proxied by the share of population with degrees. Unlike R&D spending, human capital is considerably more concentrated across space in India than in China and the USA. Much of the variation emerges in the middle of the distribution, with India's top ten regions substantially more spatially clustered than those in China or the USA, where spatial patterns are broadly similar. Patterns in India appear to show significant inter-regional mobility. In China, historic constraints on people movements help to explain the relative lack of concentration of skilled people.

Figure 4.13. Cumulative distribution of human capital



Source: China Statistic Yearbook
India NSS
USA Census, DIGEST
China, above aged 6, 31 provinces
India, above aged 7, 24 states
USA, above aged 25, 179 BEA EA;

4.2.3 Key trends: most / least 'innovative' regions in China, India and the US

Table 4.1 lists the twenty most innovative regions in the three countries over the whole time period, 1994-2007. It usefully complements our graphs and maps.

Table 4.1. Top 20 innovative regions, 1994-2007

	China	India	USA		China	India	USA
1	Beijing	Delhi	San Jose-San Francisco-Oakland, CA	11	Chongqing	Himachal Pradesh	Reno-Sparks, NV
2	Shanghai	Haryana	San Diego-Carlsbad-San Marcos, CA	12	Heilongjiang	West Bengal	New York-Newark-Bridgeport, NY-NJ-CT-PA
3	Guangdong	Chandigarh	Appleton-Oshkosh-Neenah, WI	13	Sichuan	Kerala	Gainesville, FL
4	Tianjin	Maharashtra	Minneapolis-St. Paul-St. Cloud, MN-WI	14	Shaanxi	Punjab	Seattle-Tacoma-Olympia, WA
5	Zhejiang	Andhra Pradesh	Boston-Worcester-Manchester, MA-NH	15	Jilin	Uttar Pradesh	Boise City-Nampa, ID
6	Fujian	Karnataka	Cincinnati-Middletown-Wilmington, OH-KY-IN	16	Hainan	Jharkhand	Chicago-Naperville-Michigan City, IL-IN-WI
7	Jiangsu	Goa	Rochester-Batavia-Seneca Falls, NY	17	Hubei	Rajasthan	Houston-Baytown-Huntsville, TX
8	Liaoning	Gujarat	Austin-Round Rock, TX	18	Shanxi	Madhya Pradesh	Hartford-West Hartford-Willimantic, CT
9	Shandong	Tamil Nadu	Philadelphia-Camden-Vineland, PA-NJ-DE-MD	19	Inner Mongolia	Jammu & Kashmir	Raleigh-Durham-Cary, NC
10	Hunan	Pondicherry	Albany-Schenectady-Amsterdam, NY	20	Xinjiang	Orissa	Santa Fe-Espanola, NM

The USA has a smoother spatial distribution of patents by applicant than either China or India. The three leading regions are San Jose-San Francisco-Oakland (Northern California), San Diego-Carlsbad-San Marcos (Southern California) and Appleton-Oshkosh-Neenah (Wisconsin). These three account for only 32% of all patenting by applicant, compared to 73% and 64% shares for, respectively, the leading Chinese and Indian regions.

Generally, the more innovative regions in the US are located on the Western and Eastern seaboards, or the Great Lakes region (Michigan, Wisconsin). Less innovative areas are located in the Midwest or South, with a couple of exceptions – Houston-Baytown-Huntsville (Texas) and Denver-Aurora-Boulder (Colorado).

In China, as we have seen, the leading regions for innovation tend to be in coastal areas. Outside these regions, the next group of provinces, accounting for 1-3% of total patenting on average are also mainly coastal – only Sichuan (SW) and Hunan (Middle) are not coastal provinces. The middle and West of China are less innovative, such as Tibet, Qinghai and Ningxia, which are far SW or NW provinces.

In India, leading regions tend to be in/around Delhi and the South. The provinces in the next group, which % is above 1%, are generally around Delhi and Mumbai, such as Karnataka (8.7%, close to Mumbai), Haryana (7%, Delhi located) and Tamil Nadu (7%, South). States in north-east India or border states, are less innovative. Some of them do not have any patents applicants until 2007 (for example Assam on the North East border with Bhutan and Bangladesh).

4.2.3.2 R&D spending

Table 4.2 reproduces the ranking analysis for R&D spending (India, USA) and science and technology spending (China). Spend is weighted by population to give comparable measures of intensity for these important innovation inputs.

Patterns of agglomeration for R&D spending differ from those of patenting. For the USA, San Jose-San Francisco-Oakland is top of both league tables, but only three locations (San Jose-San Francisco-Oakland, Seattle-Tacoma-Olympia and Rochester-Batavia-Seneca Falls) remain in the top ten regions. Thirteen locations are shared in the top 20. Noticeably, Detroit-Warren-Flint is the second highest patenting region, but does not feature in the top 20 areas for R&D.

Table 4.2. Top 20 regions in terms of R&D / science and technology intensity

	China, S&T, 1994-2007	***India, R&D, 1994-2006***	***USA, BEA-EAs, Private R&D, 1994-2007***		***China, S&T, 1994-2007***	***India, R&D, 1994-2006***	***USA, BEA-EAs, Private R&D, 1994-2007***
1	Beijing	Uttarancha l	San Jose-San Francisco-Oakland, CA (EA)	**11**	Chongqing	Gujarat	Austin-Round Rock, TX (EA)
2	Shaanxi	Himachal Pradesh	Detroit-Warren-Flint, MI (EA)	**12**	Guangdong	Tamil Nadu	Cincinnati-Middletown-Wilmington, OH-KY-IN (EA)
3	Shanghai	Jammu & Kashmir	New York-Newark-Bridgeport, NY-NJ-CT-PA (EA)	**13**	Ningxia	Andhra Pradesh	Boise City-Nampa, ID (EA)
4	Tianjin	Chandigar h	Davenport-Moline-Rock Island, IA-IL (EA)	**14**	Shanxi	Maharashtra	Minneapolis-St. Paul-St. Cloud, MN-WI (EA)
5	Sichuan	Punjab	Seattle-Tacoma-Olympia, WA (EA)	**15**	Anhui	Madhya Pradesh	San Diego-Carlsbad-San Marcos, CA (EA)
6	Jiangsu	Karnataka	Rochester-Batavia-Seneca Falls, NY (EA)	**16**	Shandong	Orissa	Philadelphia-Camden-Vineland, PA-NJ-DE-MD (EA)
7	Liaoning	Haryana	Boston-Worcester-Manchester, MA-NH (EA)	**17**	Qinghai	Delhi	Hartford-West Hartford-Willimantic, CT (EA)
8	Gansu	Kerala	Indianapolis-Anderson-Columbus, IN (EA)	**18**	Zhejiang	Bihar	South Bend-Mishawaka, IN-MI (EA)
9	Hubei	Assam	Peoria-Canton, IL (EA)	**19**	Hunan	Pondicherry	Richmond, VA (EA)
10	Jilin	Jharkhand	Chicago-Naperville-Michigan City, IL-IN-WI (EA)	**20**	Heilongjiang	Rajasthan	Milwaukee-Racine-Waukesha, WI (EA)

India's top ten also only shares three locations, with substantial movement in the top 20: Delhi, Haryana and Chandigarh, the top three locations for patenting, rank 17th, 7th and 4th for R&D spending respectively. Five of China's top 10 regions for science and technology also feature in the top 10 for patenting applications, and Shanghai and Beijing remain in the top three regions (Guangdong is 3rd for patents but 17th for science and technology intensity).

4.2.3.2 Human capital

Table 4.3, below, gives rankings for human capital inputs – as measured by country population shares with tertiary education or above. The spatial distribution of human capital is different again from patenting and R&D spending. China's territorial system is the most similar across inputs and outputs, with six of its top ten human capital regions also in the most innovative regions list. As with R&D spending, Beijing and Shanghai remain in the top three, in identical positions to their patents rankings.

Four of India's top human capital regions are also in the ten most innovative regions lists, with Delhi and Chandigarh in the top three in both cases. There is substantial change in the rest of the top twenty. In the case of the USA, Washington-Baltimore-Northern Virginia is the economic area with the highest share of graduates, but does not even feature in the top twenty patenting regions. This is largely explained by DC's large community of graduates working in politics and public policy rather than sciences or high-tech manufacturing. Austin-Round Rock is a well-known US tech cluster with a large university, explaining its presence high up patents, R&D and human capital tables. Denver-Aurora-Boulder is the third highest region in terms of graduate population share, but again does not feature in the twenty highest-patenting regions. There is some movement in the rest of the table, but the set of regions is largely the same.

Table 4.3. Top 20 regions in terms of Tertiary Education achievements, 1994-2007

	China,1995-2007	***India, 1995-2006***	***USA, BEA-EAs, 1990 & 2000***		***China,1995-2007***	***India, 1995-2006***	***USA, BEA, 1990 & 2000***
1	Beijing	Chandigarh	Washington-Baltimore-Northern Virginia, DC-MD-VA-WV (EA)	**11**	Shanxi	Jammu & Kashmir	Colorado Springs, CO (EA)
2	Shanghai	Delhi	Austin-Round Rock, TX (EA)	**12**	Zhejiang	Maharashtra	Flagstaff, AZ (EA)
3	Tianjin	Himachal Pradesh	Denver-Aurora-Boulder, CO (EA)	**13**	Jiangsu	Jharkhand	Helena, MT (EA)
4	Xinjiang	Goa	San Jose-San Francisco-Oakland, CA (EA)	**14**	Hubei	Madhya Pradesh	Hartford-West Hartford-Willimantic, CT (EA)
5	Liaoning	Uttar Pradesh	Boston-Worcester-Manchester, MA-NH (EA)	**15**	Guangdong	Punjab	Albuquerque, NM (EA)
6	Jilin	Chhattisgarh	Santa Fe-Espanola, NM (EA)	**16**	Qinghai	Orissa	Chicago-Naperville-Michigan City, IL-IN-WI (EA)
7	Ningxia	Haryana	Burlington-South Burlington, VT (EA)	**17**	Hainan	Andhra Pradesh	Minneapolis-St. Paul-St. Cloud, MN-WI (EA)
8	Inner Mongolia	Assam	Seattle-Tacoma-Olympia, WA (EA)	**18**	Shandong	Karnataka	Cedar Rapids, IA (EA)
9	Heilongjiang	West Bengal	New York-Newark-Bridgeport, NY-NJ-CT-PA (EA)	**19**	Fujian	Gujarat	Tallahassee, FL (EA)
10	Shaanxi	Uttaranchal	San Diego-Carlsbad-San Marcos, CA (EA)	**20**	Hebei	Kerala	Honolulu, HI (EA)

4.2.3.4 Social Filter

Section 4.2.1.4 highlighted the importance of social and institutional factors in shaping the character of innovation systems. We now introduce the 'Social Filter' as a way of capturing some of these features quantitatively. Specifically, the Social Filter is a way of representing the complex set of territorially embedded networks, socio- economic structures and institutions that shape the generation of new knowledge and its diffusion (Crescenzi and Rodriguez-Pose 2009).

Rather than trying to capture the idiosyncratic relational characteristics of individual regions' innovation systems, the Social Filter looks at the structural pre-conditions for their 'successful' development. This approach is particularly helpful when looking at emerging countries in a comparative perspective, as well as comparing 'mature' innovation systems like the USA to 'developing' systems like China and India. Not only the constraints in terms of data availability would make it extremely difficult to operationalize the features of actual regional innovation systems but the comparability between countries at different developmental stages would also be jeopardised by the use of highly context-specific indicators. As a consequence the Social Filter has to be proxied via a set of variables available for China, India and the USA in a consistent and comparable fashion.

As customary in previous empirical work (Crescenzi et al 2007) our Social Filter indicator bears upon three main domains: educational achievement (Lundvall 1992, Malecki 1997) the productive employment of human resources (Fischer and Varga 2003) and demographic dynamism (Rodríguez-Pose 1999).

The first domain of the Social Filter is measured by educational attainment, expressed by the shares of persons with completed tertiary education relative to the overall population (human capital accumulation in the population). We would expect the stock of human capital, an innovation input, to be positive on rates of innovative activity in all three countries.

The second domain, the structure of productive resources, is measured by the percentage of the labour force employed in agriculture and the rate of unemployment. We would expect both to have a negative association with innovation. In the USA's mature urban system, agriculture takes a declining share of economic activity; unemployment is highest in 'struggling' regions. India and China have been experiencing both large scale rural-urban migration and industrialisation, factors linked to improved innovative performance and declining salience of agricultural activity (Dahlman 2010, Gajwani et al 2006). The unemployment rate indicates a lack of local labour demand, and may also indicate poor quality human capital (as opposed to degree-related *quantity* measures) (Gordon 2001).

For the third domain, the percentage of population aged between 15 and 24 is considered as a proxy for new resources entering the labour force, potentially "renewing" the existing stock of knowledge and skills (Crescenzi et al 2007).

We fit the Social Filter both as a set of individual variables, and as a 'Social Filter Index' constructed through Principal Component Analysis (PCA). The Social Filter Index provides us with a multidimensional profile of 'innovation prone' areas. PCA output is shown in Tables A.4.2.1 and A.4.2.2 in Annex A.4.2. The first principal component alone is able to account for around 45 percent of total variance for China and 36 percent for the USA and India (Table A.4.2.1). Scores are computed from the standardised value of the original variables by using the coefficients listed under 'Comp1' in Table A.4.2.2, generating the Social Filter Index.

The Index takes different forms in the three countries. In India, the share of young people and human capital is positive; in China and the USA, by contrast, the unemployment rate and agricultural employment shares take positive values. In the case of the USA, these two components are broadly equal: for China, the coefficient of agricultural employment is almost three times the size of youth unemployment. Because the Filter has positive weightings on components expected to be negative on innovation in the case of China and the USA, scores for these countries are weighted by -1 to make them comparable with those of India.

Table 4.4 provides rankings for the top twenty regions in each of the three countries.

Table 4.4. Top 20 regions in terms of Social Filter conditions

	China,1994-2007	*India, 1994-2006*	*USA, BEA, 1994-2007*		*China,1994-2007*	*India, 1994-2006*	*USA, BEA, 1994-2007*
1	Beijing	Chandigarh	Austin-Round Rock, TX (EA)	**11**	Guangdong	Uttar Pradesh	Seattle-Tacoma-Olympia, WA (EA)
2	Shanghai	Delhi	Washington-Baltimore-Northern Virginia, DC-MD-VA-WV (EA)	**12**	Jiangsu	Assam	New York-Newark-Bridgeport, NY-NJ-CT-PA (EA)
3	Tianjin	Himachal Pradesh	Denver-Aurora-Boulder, CO (EA)	**13**	Hubei	Pondicherry	Tallahassee, FL (EA)
4	Xinjiang	Haryana	Boston-Worcester-Manchester, MA-NH (EA)	**14**	Shaanxi	West Bengal	Hartford-West Hartford-Willimantic, CT (EA)
5	Liaoning	Punjab	Burlington-South Burlington, VT (EA)	**15**	Ningxia	Andhra Pradesh	Albuquerque, NM (EA)
6	Jilin	Jammu & Kashmir	Flagstaff, AZ (EA)	**16**	Zhejiang	Madhya Pradesh	Santa Fe-Espanola, NM (EA)
7	Heilongjiang	Goa	San Diego-Carlsbad-San Marcos, CA (EA)	**17**	Fujian	Tamil Nadu	Richmond, VA (EA)
8	Shanxi	Gujarat	San Jose-San Francisco-Oakland, CA (EA)	**18**	Tibet	Kerala	Helena, MT (EA)
9	Inner Mongolia	Karnataka	Colorado Springs, CO (EA)	**19**	Shandong	Rajasthan	Cedar Rapids, IA (EA)
10	Hainan	Maharashtra	Salt Lake City-Ogden-Clearfield, UT (EA)	**20**	Qinghai	Orissa	Lincoln, NE (EA)

4.2.4 Correlation analysis

We extend the tablular rankings to look at the raw correlations between innovation inputs (R&D, human capital, Social Filter) and our key output, patenting. Figures 4.15 -4.23 represent the main relationships for India, China and the USA in graphical form. In each case, the lines of best fit represent the basic shape of the relationship.

4.2.4.1 Patenting and R&D intensity

Figures 4.14 – 4.16 set out the two-way associations between patenting and R&S intensity in the three countries. Lines of best fit show a strong positive relationship for regions in China and the USA, but no clear relationship for Indian states.

Figure 4.14. China: patent applications and R&D/GDP share, 1994-2007

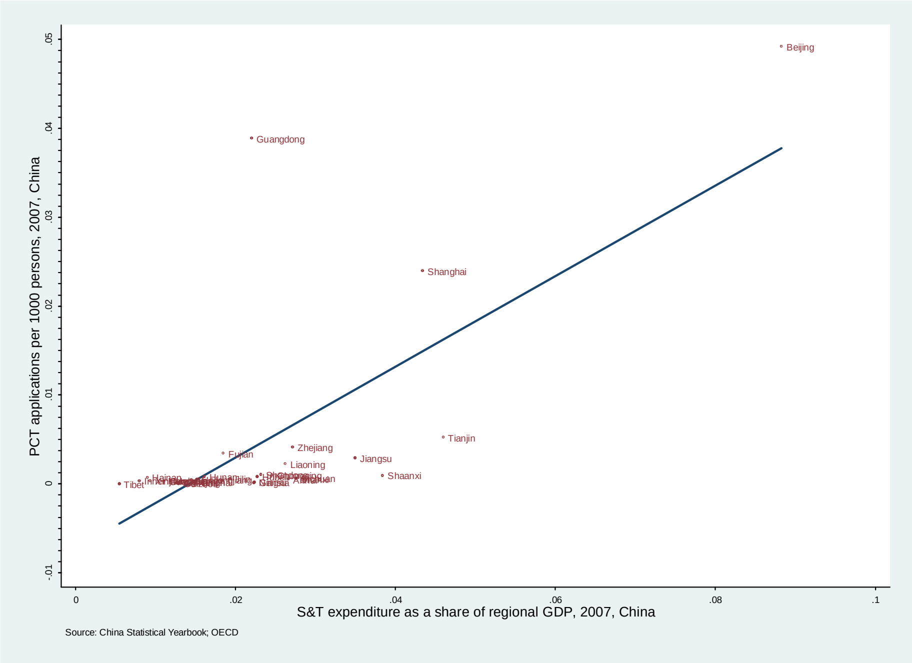


Figure 4.15. India: patent applications and R&D/GDP share, 1994-2007

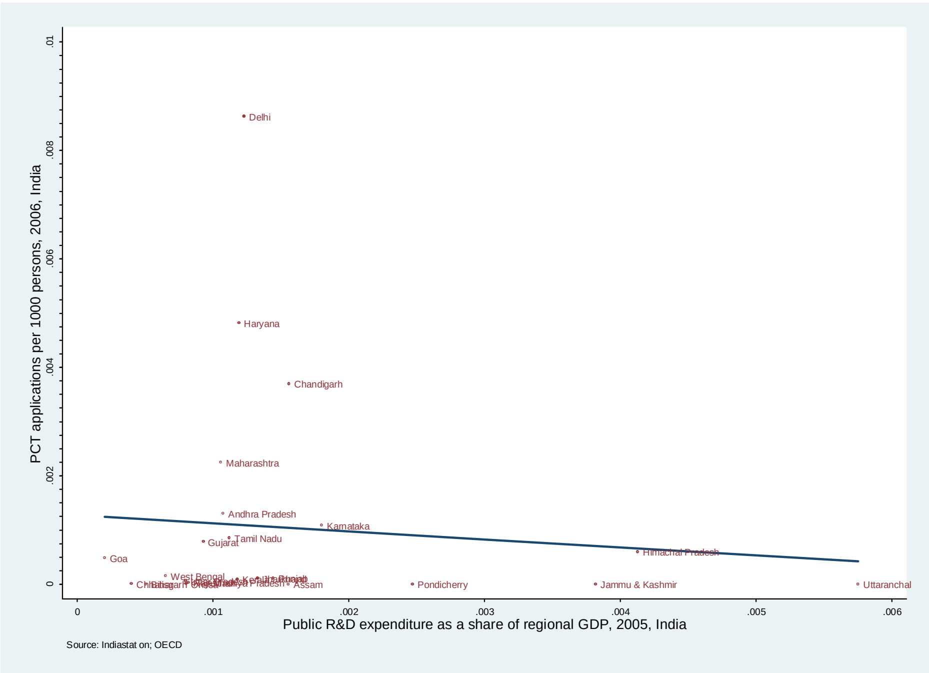
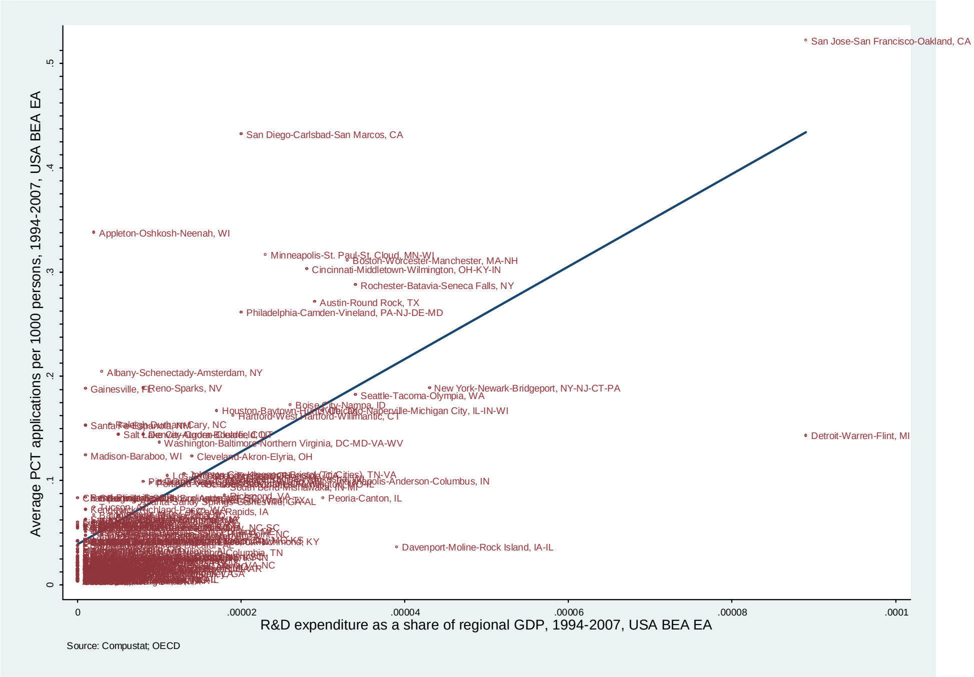


Figure 4.16. USA: patent applications and R&D/GDP share, 1994-2007



The results reflect the territorial characteristics of the three countries: the critical mass of US technological agglomerations (with the San Francisco Bay Area an outlier in the top right-hand corner); China's policies to direct R&D spending to key locations; and a more dispersed system in India. The relatively small number of Indian observations probably also contribute to the result.

4.2.4.2 Patenting and human capital

Figures 4.17-4.19 repeat the analysis for patenting and our human capital measure (share of degree holders in the population).

We see strong positive links between patenting and human capital investment in all three countries, with a rather bigger link in China than in India or the USA. Again, these reflect territorial specificities.

Figure 4.17. China: patent applications and human capital, 1994-2007

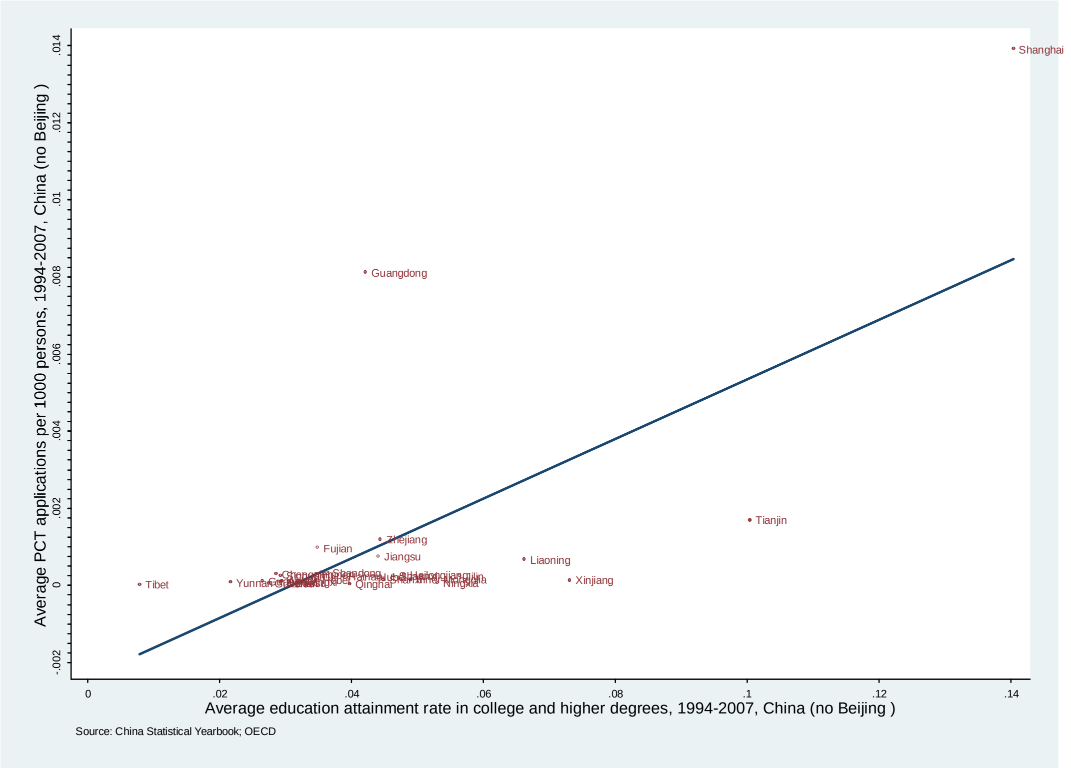


Figure 4.18. India: patent applications and human capital, 1994-2007

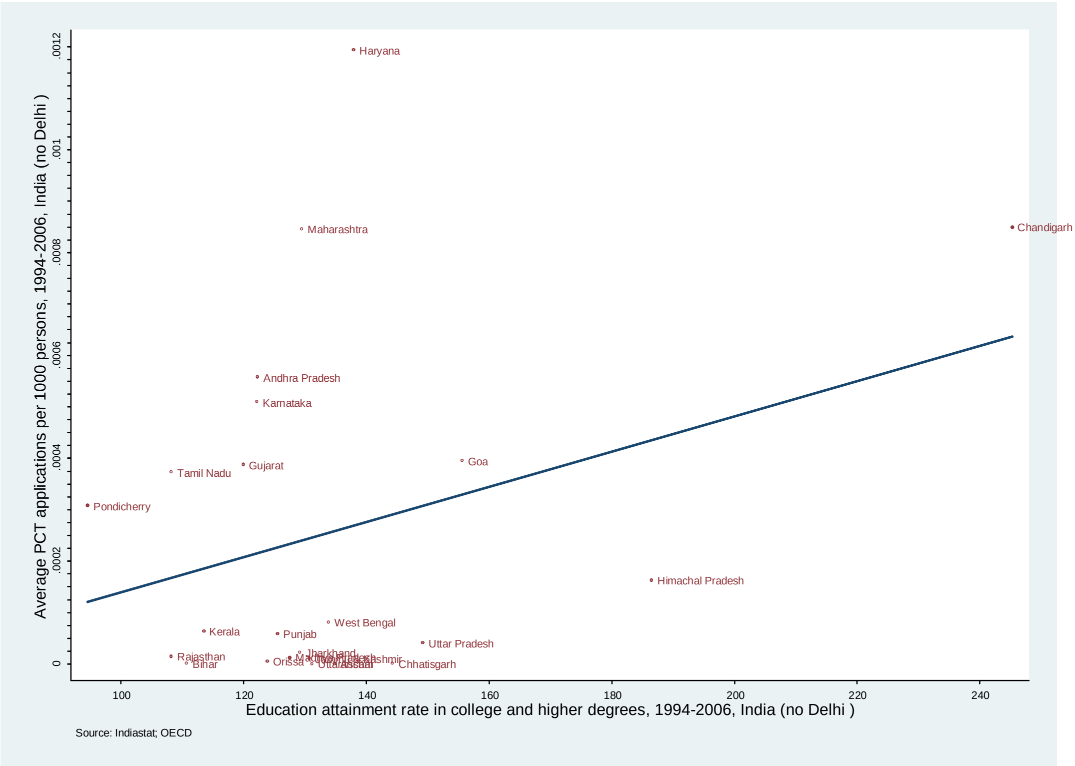
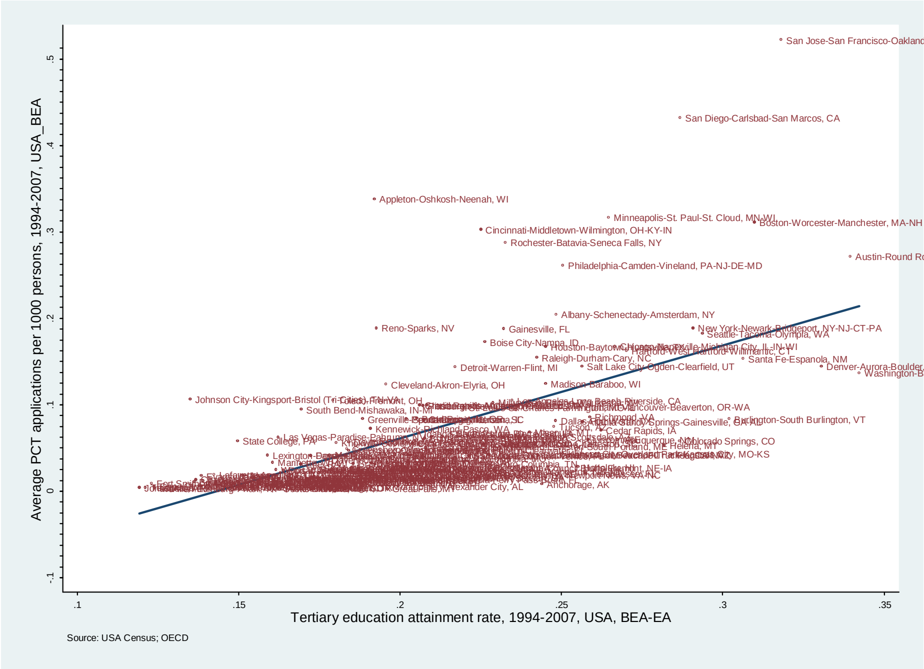


Figure 4.19. USA: patent applications and human capital, 1994-2007



4.2.4.3 Patenting and the Social Filter

Figures 4.20-4.22 illustrate connections between patenting and the Social Filter. Again, we observe a positive relationship in all three countries. Results for China suggest the Social Filter is less important than other conditions, with a few outliers largely driving the relationship. Positive connections are greatest in India, where the filter is associated with human capital and the share of young people in the regional population. The Social Filter seems more important than R&D in explaining patenting. US results suggest a non-linear relationship, rather than linear best fit, is the true link between patenting and the Social Filter. Again, this suggests a critical mass of social and institutional conditions helps to shape innovation outcomes.

Figure 4.20. China: patent applications and Social Filter, 1994-2007

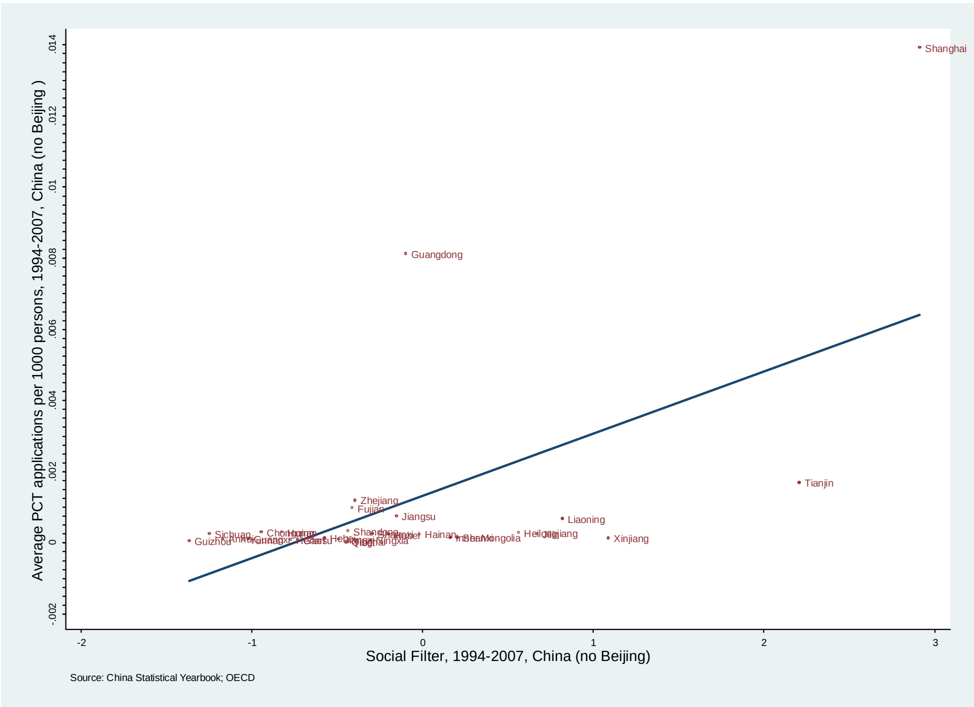


Figure 4.21. India: patent applications and Social Filter, 1994-2006

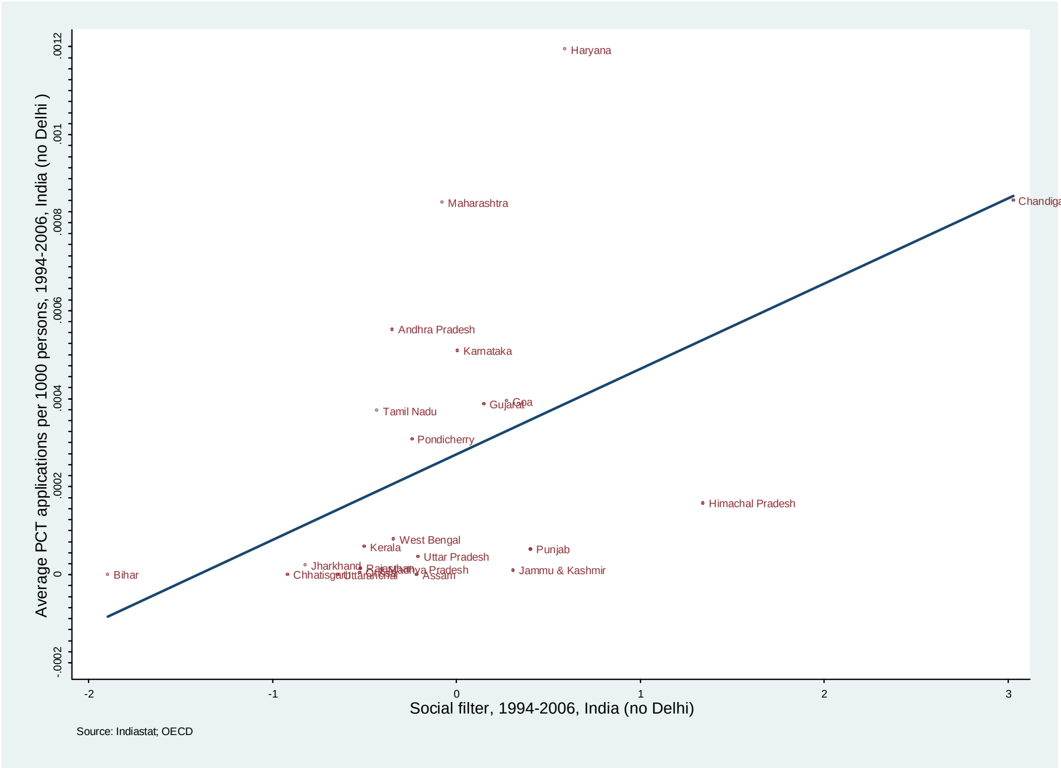
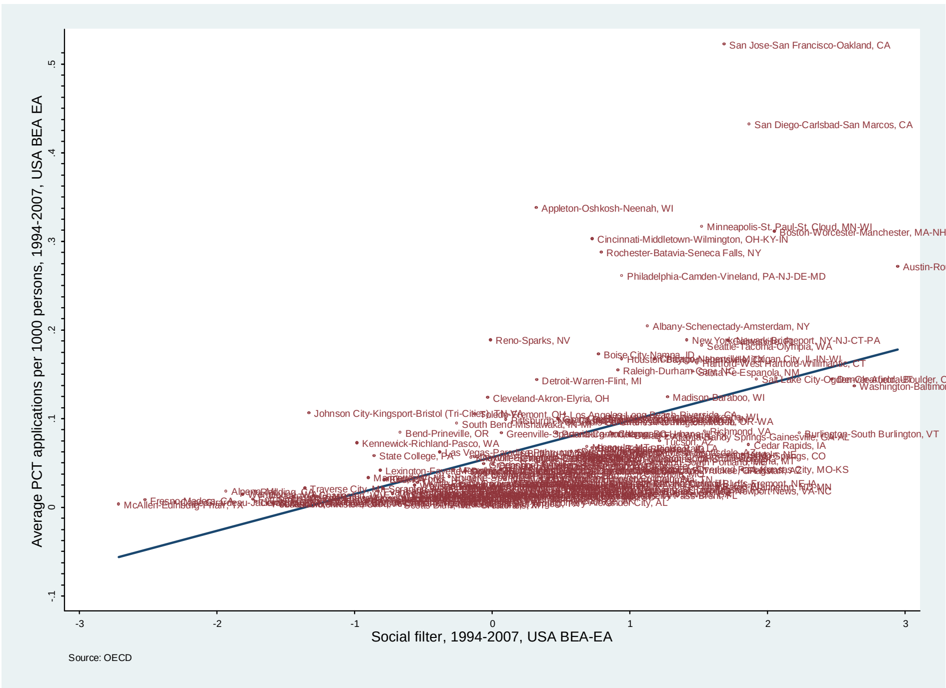


Figure 4.22. USA: patent applications and Social Filter, 1994-2007



Innovation systems in Taiwan and South Korea

This box briefly considers two notable 'Asian Tiger' economies, South Korea and Taiwan in order to better justify and contextualise the comparative analysis presented in this chapter. Both South Korea and Taiwan have developed more rapidly than China and India, and by the 1990s had become leading innovation nations (Mahmood and Singh 2003). Since the 90s a large body of academic literature has explored the genesis and the drivers of their unprecedented technological development. Some contributions (see for example Nelson 1993) adopted a comparative perspective similar to the approach of this chapter that looks at China and India as the new 'raising stars' in international technological competition and important learning 'laboratories' for the EU regions. As will be discussed in the rest of this chapter China and India – for their size and internal territorial dynamics – are certainly the most suitable innovation systems for territorial-level comparisons with the European Union regions. However, it is important to take into account the technological dynamics of other important actors in the area.

During the 1990s and 2000s patent applications in South Korea and Taiwan were significantly higher than in India and China. Using USPTO data, Mahmood and Singh (2003) calculate that Taiwan received 17,367 patents 1990-1999, Korea 14,256, China 571 and India just 442. South Korea's upgrading during the 1990s saw a shift from ship-building and manufacturing patents into electronics and ICT (Mahmood and Singh 2003).

Taiwan, like China has remained more manufacturing-dominated since the 1980s, with gradual upgrading into electronics. Tseng (2009) shows that while South Korea and Taiwan were Asian leaders in ICT patenting during the 1990s, both India and (particularly) China have been catching up in the 2000s.

As in India and China, innovative activity in Korea and Taiwan is spatially concentrated. Taiwan's Taipei-Hsinchu cluster contains all of Taiwan's top 50 ICT firms; both Samsung and LG and located in the Seoul city-region (Yeung 2009).

Yeung (2009) characterises Taiwan's innovation system as a mix of 'international partnerships' and 'indigenous innovation', South Korea's as largely driven by 'indigenous innovation'. China and India have until recently been predominantly 'production platforms'. State policies have been important in all four countries as a means of technological catch-up, but policy choices have also helped shape significant differences in national innovation systems.

For example, multinational firms (MNEs) have been important in India and China during the 1990s, covering 30% of USPTO patents in India and 167.2% in China (Mahmood and Singh 2003). During the same period MNEs scored 0.8% of patents in South Korea and 1.9% in Taiwan. South Korea's innovation system is dominated by large-scale conglomerates, who generate the majority of patents. Patenting in Taiwan, by contrast, involves a mix of private individuals, domestic firms and some international partnerships.

As in India, transnational communities have played an important role in developing Taiwan's innovation capabilities (Saxenian and Sabel 2008). Taiwan has used its ethnic Chinese diasporas to great effect in the USA, where there are now multiple links between Silicon Valley firms and ICT businesses in Taiwan. These diaporic links are now starting to develop on the Chinese mainland, with an emerging 'triangular connection' between the Bay Area, Taipei and the Pearl River Delta (Yeung 2009).

In light of these brief review of the existing literature it is possible to understand how important the analysis of the territorial dynamics of innovation in China and India is for the EU regions, in particular if these countries will show an innovation dynamism similar to that recorded by South Korea and Taiwan over the past two decades.

4.3. A conceptual framework for comparative territorial analysis

The descriptive analysis suggests a very complex story for each of the three countries, and makes initial comparisons between them less than straightforward. In turn, this suggests the need for a clear conceptual framework to delineate conditions and experiences. The framework should be able to explain the *dynamics* of each country's innovation system, including its *territorial components*, and help illuminate the *interactions* between component parts. We develop this framework in what follows.

The economic development literature suggests at least three main ways of thinking about innovation 'systems'. We use the regional innovation systems literature to provide a scalable framework for exploring territorial dynamics of innovation in mature and emerging countries, which allows for the specificities and histories of particular countries and regions.

We also incorporate insights from two other perspectives: endogenous growth models and new economic geography – the importance of R&D and human capital from endogenous growth theories, and the importance of spillovers from NEG models.

4.3.1. The linear model of innovation and traditional knowledge production functions

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

Commonly used in the USA and EU, 'national innovation system' models describe key actors such as businesses, central government, universities and public research institutes (Liu and White 2001) – closely resembling the 'national science systems' explored by David Mowery and others (Mowery 1992, Mowery and Oxley 1995). Analyses focus on countries' performance on key inputs – R&D spending, human capital stock, university investment – and their links to key outputs such as patenting rates and 'gazelle' firms, which approximate ideas generation and diffusion respectively.

These linear, national-level perspectives of innovation systems are relevant to China and India because of both countries' current and historic emphasis on technology-led national growth (Leadbeater and Wilsdon 2008). Both China and India are now investing heavily in 'innovation inputs', such as R&D and HE investment, which both feeds into and feeds from rapid macroeconomic growth (Kjuis and Wang 2006). The main drawback of linear models of innovation activity is that they pay minimal attention to space – and so do not explain why innovative activity is often spatially concentrated.

4.3.2. Bringing 'space' and geography into the picture: the 'New Economic Geography' and knowledge spillovers

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

NEG perspectives are widely used to explain patterns of innovative activity in mature innovation systems such as the EU or USA. A number of studies suggest that proximity-spillover-innovation links also operate in developing country contexts, with strong evidence that urbanisation boosts productive efficiency (Xu 2009, Duranton 2008, Scott and Garofoli 2007). However, these effects may be constrained by the pace of urbanisation and/or institutional capacity. Specifically, rapid or chaotic urbanisation can outstrip governments' ability to provide adequate infrastructure and public services (Cohen 2006, Venables 2005). As such, agglomerations are also strongly correlated with poverty and informal development.

These models offer important insights for China and India. However, NEG models alone do not allow for important country-specific variables – history, institutions, networks and norms – which in practice will significantly influence innovation outcomes.

4.3.3. Institutions, social conditions and (Regional) Systems of innovation

The innovation systems literature helps to fill some of the gaps in NEG models. Originally defined by Freeman (1987) as 'the network of institutions in the public and private sectors whose activities and interactions initiate, import, modify and diffuse new technologies', innovation systems are now viewed broadly as including social institutions, education and communications infrastructures and the norms and rules that regulate economic and social interaction (Lundvall et al 2009). Such frameworks allow incorporation of country-specific factors that NEG models may not include.

'Regional innovation systems' (RIS) localise and spatialise these frameworks to specific regions and clusters (Asheim and Gertler 2005, Cooke 2002, Cooke et al 1997, Storper 1997, Saxenian 1994, Piore and Sabel 1984). The central insight – shared with geographical approaches – is proximity facilitates innovation, or Asheim and Gertler (2005) suggest, 'the geographic configuration of economic agents … is fundamentally important in shaping the innovative capabilities of firms and industries'. RIS analysis is centred on firms' capabilities, and the relationships between these and other institutions. Specifically, business performance is influenced by a number of regional-level factors at the regional level. These include other actors (e.g. universities, public agencies) networks (e.g. public-private partnerships) and institutions (rules, customs and norms). These meso-level factors are also influenced by national-level institutions (such as legal and IPR frameworks, or public spending programmes), and by sectoral factors (industry-specific conditions or technological trends/shocks). Within these systems, critical dynamics are the 'triple helix' of private-university-public sector interactions (Cooke 2002), and the 'untraded interdependencies' that regulate agents' behaviour (Storper 1997).

Synthesising the debate, Storper (1997) famously sees regional outcomes as being governed by three spaces – territory, organizations and technologies. This suggests RIS perspectives usefully complement national and sectoral 'systems' approaches, as well as the endogenous growth and NEG perspectives explored earlier. Recent evolutionary studies also suggest the importance of deep history, path-dependence in explaining regional and national innovation trajectories (Simmie et al 2008, Martin and Sunley 2006). Sectoral perspectives help illuminate the intersections between regional, national and industry factors, and the co-evolution of innovation systems through the interactions of their component parts (Malerba and Mani 2009).

A growing number of researchers are attempting to recalibrate RIS frameworks for developing country perspectives (Lundvall et al 2009, Perez-Padilla et al 2009 and Scott and Garofoli 2007 provide useful overviews). It is important to make these adaptations. First, in both China and India development in the formal economy partly depends on the performance of the broader, informal innovation system – social capital and networks, institutions and governance capacity (Lundvall et al 2009). Second, China and India's 'innovation experiences' need to be understood as part of the globalisation of both production and R&D that has been occurring since the 1970s (Bruche 2009, Mitra 2007). As Yeung (2009) points out, the task is to explain innovation *under globalization*. Third, local, spatial patterns of innovation are linked to these global flows. As Saxenian and Sabel (2008) argue, research needs to explain the specific 'puzzle' of rapid development of high-tech hubs in countries without the consistent quality of institutions generally thought necessary for growth.

Unlike innovation systems in developed countries, formal institutions may be weak in developing countries, especially at regional level, with intellectual property regimes providing only partial coverage and public agencies that may not always be welfare-maximising (Altenburg 2009, Joseph 2009). Capital and finance may be limited, and university-industry collaborations are likely to be limited, with universities mainly providers of human capital (of varying quality) (Perez-Padilla et al 2009).

All of these factors place constraints on firms' ability to develop new products and services – and limits managers' incentives to collaborate with other firms (Altenburg 2009). In this context, multinational enterprises (MNEs) may become important providers of both capital flows (via FDI) and new technologies (via alliances / collaborations and spillovers) (Cantwell 2005). More than half of global R&D is currently done within multinational enterprises; in 2007 Toyota ($8.4bn) and GM ($8.1bn) each spent more on R&D than India (Dahlman 2010). Similarly, export markets become an important source of growth alongside home markets; and the national state (and national policy frameworks) may become more important than regional actors in supporting firms and mediating economic activity (Perez-Padilla et al 2009). 'Discretionary public policies' in national development strategies are critical (Cimoli et al 2009).

These predictions echo the themes of other literatures on the globalization of innovation (Mowery 2001) and its impact on regional economies in developing countries. Archibugi and Iammarino (2002), studying the globalisation of innovation, identify three key processes: international exploitation of locally-generated ideas; 'global generation' of innovations by multi-national enterprises; and global 'techno-scientific collaborations'. Another stream of work focuses on MNE location strategies (Cantwell 2005, Dunning 1998, Dunning 1996), and the behaviour of 'lead firms' (Yeung 2009) which engage in different types of spatially specific 'strategic coupling' with local firms, influencing cluster formation and producing heterogenous patterns of spatial development.

From a different perspective, Saxenian and Sabel (2008) and Saxenian (2006) emphasise the role of migrants and trans-national communities in facilitating innovation, by spreading ideas, developing globalised production systems and influencing institutional reform in 'home' countries. Finally, both Leadbeater and Wilsdon (2008) and Yeung (2009) compare institutional and policy factors in shaping innovation outcomes in South / East Asian countries. They note the importance of more open markets, and public investments in human capital and other 'innovation-enabling' infrastructure.

Taken together, all three approaches – knowledge production functions, geographical perspectives and social / institutional frameworks – help to explain the dynamics and drivers of regional innovation systems. The stylised facts in the previous sections indicate the need to combine approaches. The 'value added' in this report is to assemble such a synthesis and use it to deliver quantitative analysis of each country's territorial innovation system.

4.4. Quantitative analysis: model and data

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

We fit the following empirical model:

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

where:

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

and where *i* represents the region and *t* time.

We assemble panel datasets for Chinese provinces, Indian states and US BEA Economic Areas (see Technical Annex A.4.1 for details). Data for China covers 30 provinces between 1995 and 2007 inclusive. Data for India covers 19 states between 1995-2004. Data for the USA covers 179 BEA Economic Areas, 1994-2007. The choice of empirical variables included in the model is set out below:

Variable	**Internal Factors**	**External Factors**
R&D	Local Investment in S&T/R&D	Investment in S&T/R&D in neighbouring areas
Social Filter	Structural characteristics that would make a region more 'innovation prone', including: • Human Capital • Sectoral composition • Use of resources (unemployment) • Demographics	Same characteristics in neighbouring areas
Specialisation	Krugman Index	
Relative wealth	GDP per capita	
Agglomeration economies	Population Density	
Infrastructure endowment	Kilometres (Kms) of motorways/railways	
Mobility of people	Migration rate	
Fixed effects	Region/Province-specific fixed effect + Time Trends	

4.4.1 Patent intensity

Regional patent applications per capita is the dependent variable and is used as a proxy for the innovative performance of the local economy. Using patent counts to establish geographical patterns of innovation should be done with care, especially in developing country contexts. Our data is from OECD triadic patent families – so avoids problems that might arise using domestic Chinese or Indian data (Li and Pai 2010, Wadhwa 2010). Other innovation metrics for India and China – such as the location of multinational firms – also tend to follow similar spatial patterns to our findings (Bruche 2009) so we can be fairly confident we have identified real trends. There are two important caveats. First, patents measure *invention* and tend to be biased towards particular sectors of the economy where inventions are primarily protected via patenting (OECD 2009). Second, patent *applications* in India and China partly reflect patenting activity by multinational firms (MNEs). MNE patents may be filed in any office around the world, regardless of where the invention actually took place (Li and Pai 2010).

4.4.2 Internal conditions

We fit a number of independent variables covering internal conditions affecting regional innovation performance. These are set out below.

R&D expenditure: The percentage of regional GDP devoted to S&T (China) or R&D (India, USA) is the main measure of economic input used to generate innovation in each region and is also frequently used in the literature as a proxy for the local capability to 'absorb' innovation produced elsewhere (Cohen and Levinthal 1990, Maurseth and Verspagen 1999). In our framework R&D expenditure is a proxy for "the allocation of resources to research and other information-generating activities in response to perceived profit opportunities" (Grossman and Helpman 1991, p. 6) in order to capture the existence of a localised system of incentives (in the public and the private sector) towards intentional innovative activities.
Social Filter: As set out in section 4.3, we use the Social Filter to capture the unique combination 'of innovative and conservative . . . elements that favour or deter the development of successful regional innovation systems' in every space (Rodriguez-Pose, 1999, p. 82). The Social Filter covers three domains: educational attainment, structure of productive resources and population age structure.

4.4.3 Spillovers
In addition to the variables related to the 'internal' characteristics of each territory, the model also includes variables representing the potential spatial-effects from neighbouring regions that may affect innovative performance in the region of interest. These 'spatial' variables are:
WR&D (Extra-Regional Innovation): The innovative success of an area depends both on its internal conditions and on those of neighbouring interconnected regions. The spatially lagged R&D variable captures the 'aggregate' impact of innovative activities pursued in the neighbourhood. Innovative activities pursued in neighbouring regions exert a positive impact on local innovative performance, via inter-regional knowledge exchange channels and complementarities that make localised knowledge flows possible. Conversely, centripetal forces driving the location of innovative activities in pre-designated 'hot-spots' may lead to the generation of negative externalities: proximity to innovative areas may 'absorb' resources from the local economy and limited complementarities/synergies might prevent any market-driven compensation for such distortion. We use a combination of first order contiguity weights and inverse-distance weights to capture localised and far-ranging knowledge spillovers respectively. Weighted measures of both R&D/S&T intensity and the Social Filter are generated. For details, see technical Annex A.4.3.

4.4.4 Wider structural factors
The role of the key drivers for the process of innovation and of their spatial organisation is assessed after controlling for the geography of other key economic variables influencing regional innovative performance (x). These measures include:
Degree of Specialisation (Krugman Index): Following Midelfart-Knarvik et al. (2002) we call the index K the Krugman specialisation index, used to measure the specialisation of local employment by calculating:

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

b) the share of the same industry in the employment of all other regions: $\bar{\nu}_i^k(t)$; and
c) the absolute values of the difference between these shares, added over all industries:

$$K_i(t) = \sum_k abs(\nu_i^k(t) - \bar{\nu}_i^k(t)) \quad \text{with} \quad \nu_i^k(t) = \sum_{j \neq i} x_i^k(t) / \sum_k \sum_{j \neq i} x_i^k(t) \qquad (6)$$

The index takes the value zero if region *i* has an industrial structure identical to the rest of the country, and takes the maximum value of two if it has no industries in common with the rest of the country.

Level of GDP per capita: As customary in the literature on the determinants of regional growth performance, the initial level of GDP per capita is introduced in the model in order to account for the region's initial wealth as proxy for the distance from the technological frontier as customary in technological catch-up literature (Fagerberg 1994). The significance and magnitude of the coefficient associated to this variable will allow us to test the existence of a process of technological catch-up.

Existing stock of transport infrastructure endowment: Transport infrastructure may affect innovative performance through a variety of mechanisms also associated to its influence on the spatial organisation of innovative activities. In order to capture the direct impact of transport infrastructure on regional growth, the model includes a specific proxy for the stock of transport infrastructure proxied by total motorways or railways in region, in kilometres, standardised by regional population (Canning and Pedroni 2004). See Technical Annex A.4.1 for further detail.

Agglomeration: Different territorial configurations of the local economy may give rise to different degrees of agglomeration economies and spillovers. The geographical concentration of economic activity has an impact on innovation (Duranton and Puga 2003, Charlot and Duranton 2006), which needs to be controlled for in order to single out the differential impact of other 'knowledge' assets such us R&D intensity and Social Filter conditions. From this perspective, population is a useful – though very rudimentary – proxy for these factors.

Migration: The degree of internal labour mobility is reflected by the regional rate of migration. A positive rate of migration (*i.e.*, net inflow of people from other regions) is a proxy for the capacity of the region to benefit from external human capital and knowledge by attracting new workers, increasing the size of its labour pool and its 'diversity' in terms of skills and cultural background (Ottaviano and Peri 2005).

4.5. Results of quantitative analysis

We fit the panel data with the model specified in equation (1), which we run as a two-way fixed effects regression.[22] We minimise potential spatial autocorrelation by explicitly controlling for national growth rates. Furthermore, by introducing the 'spatially lagged' variables WR&D and WSF, we take into consideration the interactions between neighbouring regions, minimising any effect on the residuals. Results also use robust standard errors clustered on state (India), province (China) or economic area (USA). We deal with potential endogeneity of the right-hand side variables by fitting these as one-period lags.

Finally, because of different accounting units we express all explanatory variables as a percentage of the respective GDP or population. This is exploratory analysis – so in what follows we focus mainly on the sign and significance of coefficients, rather than the size of specific point estimates.

Results are shown in Tables 4.5-4.7 for China, India and the US respectively. In each case, models (1) through (3) explore 'linear' components of the innovation system, regressing patenting rates on R&D/S&T expenditure and various spatial lags of science spending. Models (4) through (8) introduce the spatial filter and spatially weighted variants. Models (9) to (11) bring in the wider structural factors.

The model generally performs better for Chinese and American data, as we have a longer time period and more observations (because of smaller spatial units). Results for India are more volatile, as we only have state-level 92 observations over 10 years.

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

Table 4.5. China: Social Filter index, no province-specific trends, 1995-2007

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Regional R&D/S&T Expenditure	0.0410	0.0696	0.0349	0.0274	0.00673	0.0249	0.0269	-0.00805	-0.0533	-0.0963	0.492*
	(0.131)	(0.131)	(0.133)	(0.123)	(0.123)	(0.123)	(0.124)	(0.0898)	(0.0601)	(0.0701)	(0.267)
Spatially Weighted S&T (Inverse Dist)		-4.13e-09		-4.64e-09		-4.08e-09	-4.91e-09	-7.93e-10	-1.63e-08***	-7.98e-09***	-7.45e-09***
		(3.64e-09)		(3.36e-09)		(3.44e-09)	(3.42e-09)	(3.01e-09)	(3.85e-09)	(2.56e-09)	(2.28e-09)
Spatially Weighted S&T (First Order Contiguity)			2.37e-10		-4.81e-10						
			(1.13e-09)		(1.06e-09)						
Social Filter				0.00316**	0.00322***	0.00315**	0.00310**	0.00104	2.76e-06	-0.000552	-0.000377
				(0.00123)	(0.00124)	(0.00124)	(0.00123)	(0.000878)	(0.000520)	(0.000564)	(0.000506)
Spatially Weighted Social Filter (Inverse Dist)						-0.00374					
						(0.00366)					
Spatially Weighted Social Filter (First Order Contiguity)							0.000738	-0.00197**	-0.00141*	-0.00210***	-0.00110
							(0.00100)	(0.000985)	(0.000761)	(0.000742)	(0.00100)
Krugman Index								0.0300***		0.0204***	0.0213***
								(0.00566)		(0.00408)	(0.00427)
Railway Density								0.183**		0.134**	0.141***
								(0.0725)		(0.0604)	(0.0496)
Population Density									0.000148***	0.000176***	0.000294***
									(5.52e-05)	(4.91e-05)	(5.86e-05)
Net Migration									-1.81e-05	2.83e-05***	4.57e-05***
									(2.24e-05)	(1.04e-05)	(1.06e-05)
GDP Per Capita									8.27e-07***		
									(2.63e-07)		
Int.Term Exp.S&T*Pop.Density											-0.00111**
											(0.000536)
Constant	-0.000546	1.50e-05	-0.000495	0.00215	0.00145	0.000353	0.00267	-0.0332***	-0.0493***	-0.0798***	-0.121***
	(0.00245)	(0.00246)	(0.00245)	(0.00241)	(0.00235)	(0.00288)	(0.00272)	(0.00590)	(0.0185)	(0.0167)	(0.0215)
Year Dummies	X	X	X	X	X	X	X	X	X	X	X
Observations	390	390	390	390	390	390	390	390	390	390	390
R-squared	0.092	0.099	0.092	0.144	0.136	0.146	0.145	0.312	0.400	0.400	0.570
Number of id	30	30	30	30	30	30	30	30	30	30	30

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

4.5.1 China

The main results for China are given in Table 4.5. Overall, the results suggest a traditional agglomeration story: richer regions with agglomeration activities, good infrastructure endowments and industrial specialisation have higher patenting rates. After controlling for these structural factors in the regional economy, net migration also becomes a force for innovation (although point estimates are much smaller than for structural conditions). Once agglomeration effects are included in our model, spillovers become negative significant, suggesting higher-patenting regions are drawing in resources from neighbouring areas.

Models (1) – (3) explore 'linear' elements of the innovation system. We find that regional R&D spending is not significant on patenting rates, and that spatially weighted science and technology spending is negative insignificant. This echoes other findings for the European Union, where R&D spending tends to be centralised at nation state level (Crescenzi et al 2007). The spillovers result may also reflect effects of a centrally planned economy, in which capital and labour are shifted via policy decisions; or as suggested above, the concentration of innovative activity in a few urban cores.

Models (4) through (8) introduce the Social Filter. As expected, we find the Social Filter is positive significant (at 5%) on innovation rates. However, introducing traditional agglomeration measures removes Social Filter significance. Spatial lags of the Social Filter (using first order contiguity weights) are negative, becoming negative significant when wider structural factors are controlled for. Models (9) to (11) include wider structural factors of regional economies. As noted above, we find traditional agglomeration measures dominate the analysis. The Krugman Index and population density are both positive significant on innovation at 1%. Railway density has a large point estimate but is only marginally significant in full models, perhaps because China has focused on building roads. Net migration is positive significant at 1%, but point estimates are much smaller than for agglomeration measures. To further explore agglomeration processes, we interact science and technology spending with population density. The interaction term is negative significant at 5%, but renders local R&D spending positive significant.

4.5.2 India

In the case of India, our results suggest a rather different and more dispersed configuration of territorial innovation from China and the USA. Here, regional R&D and the Social Filter explain a significant amount of variation in innovative activity. As with China, the interaction of R&D and population density is highly significant – but unlike China, the coefficient is positive and renders simple R&D spending insignificant. Spillover variables are also positive and significant, until net migration is introduced in the analysis. Taken together, the results suggest the importance of a number of several highly dense urban spaces driving innovation, plus wider social and institutional conditions – a finding that tallies with wider evidence reviewed above.

As before, models (1) to (3) explore conventional innovation 'inputs'. Unlike China, we find that regional R&D spending is important for regional innovation. Point estimates are very large, although only significant at 10%. R&D spending maintains its importance as social conditions and structural factors are introduced into the analysis. In contrast with China, spillovers of R&D are positive significant at 5% (although these drop out once net migration are brought in).

Models (4) to (8), exploring social conditions and the Social Filter, also present different results. Unlike China, the Social Filter is positive significant at 5% in most specifications.

Models (9) through (11) introduce wider structural conditions in the regional economy. Compared with China, agglomeration measures generally play a much less important role in innovative activity. The Krugman Index is insignificant, but road density and net migration are both significant at 5%, the latter most salient. As noted above, interacting R&D with population density produces an important result, although in the opposite direction to the Chinese case: suggesting marginal returns to concentrating R&D that are not present in China.

Table 4.6. India: Social Filter index, no state-specific trends, 1995-2004

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Regional R&D Expenditure	1.734*	1.832*	1.787*	1.638	1.657*	1.641*	1.505*	1.456	1.314*	1.545*	0.194
	(0.968)	*(1.064)*	*(0.952)*	*(1.067)*	*(0.963)*	*(0.875)*	*(0.806)*	*(0.885)*	*(0.774)*	*(0.810)*	*(0.321)*
Spatially Weighted R&D (Inverse Dist)		2.14e-09		1.43e-09							
		(4.41e-09)		*(4.36e-09)*							
Spatially Weighted R&D (First Order Contiguity)			2.37e-09**		2.20e-09**	2.04e-09**	1.71e-09*	1.75e-09*	1.04e-09	1.24e-09	1.06e-09
			(1.03e-09)		*(1.05e-09)*	*(9.16e-10)*	*(8.81e-10)*	*(9.07e-10)*	*(8.96e-10)*	*(9.54e-10)*	*(8.19e-10)*
Social Filter				0.000189**	0.000148	0.000246**	0.000261**	0.000255**	0.000253**	0.000210*	0.000194**
				(8.87e-05)	*(8.90e-05)*	*(0.000106)*	*(0.000113)*	*(0.000115)*	*(0.000108)*	*(0.000110)*	*(9.07e-05)*
Spatially Weighted Social Filter (Inverse Dist)						0.00231					
						(0.00158)					
Spatially Weighted Social Filter (First Order Contiguity)							0.00113*	0.00111*	0.000848	0.000694	0.000357
							(0.000580)	*(0.000605)*	*(0.000517)*	*(0.000472)*	*(0.000304)*
Krugman Index								-0.000574		-8.15e-05	-0.000985
								(0.00153)		*(0.00133)*	*(0.000951)*
Road Density								-3.94e-06		-4.53e-05**	-3.69e-05**
								(8.34e-06)		*(2.12e-05)*	*(1.75e-05)*
Population Density									-3.56e-06	1.41e-06	-7.68e-08
									(2.87e-06)	*(1.26e-06)*	*(1.07e-06)*
GDP Per Capita									-6.04e-08		
									(3.80e-08)		
Gross Migration (Inter-State)									1.75e-05***	1.74e-05**	1.30e-05**
									(6.53e-06)	*(7.55e-06)*	*(6.07e-06)*
Int.Term Exp.S&T*Pop.Density											0.000999***
											(0.000276)
Constant	-0.00204*	-0.00385	-0.00443**	-0.00313	-0.00417**	-0.00441**	-0.00354**	-0.00311	0.000568	-0.00622*	-0.00288
	(0.00110)	*(0.00432)*	*(0.00190)*	*(0.00428)*	*(0.00194)*	*(0.00192)*	*(0.00156)*	*(0.00211)*	*(0.00438)*	*(0.00348)*	*(0.00211)*
Year Dummies	X	X	X	X	X	X	X	X	X	X	X
DelhiTrend	X	X	X	X	X	X	X	X	X	X	X
Observations	92	92	92	92	92	92	92	92	92	92	92
R-squared	0.903	0.904	0.911	0.906	0.912	0.919	0.923	0.923	0.935	0.938	0.964
Number of id	19	19	19	19	19	19	19	19	19	19	19

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

Table 4.7. USA, BEA: Social Filter index, no BEA-specific trends, 1995-2007

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Regional R&D Expenditure	2769***	2792***	2757***	2782***	2745***	2737***	2787***	2586***	2441***	2334***	739.0
	(668.4)	*(672.0)*	*(666.3)*	*(671.5)*	*(665.9)*	*(661.4)*	*(665.6)*	*(580.0)*	*(574.3)*	*(527.2)*	*(906.9)*
Exp_rd_compustat_percentage											
Spatially Weighted R&D (Inverse Dist)		-1846		-2065		-570.9	-1882	-1362	428.6	458.3	1137
		(1580)		*(1584)*		*(1603)*	*(1588)*	*(1551)*	*(1538)*	*(1525)*	*(1608)*
Spatially Weighted R&D (First Order Contiguity)			489.0		454.2						
			(454.8)		*(449.1)*						
Social Filter				0.00582***	0.00566***	0.00624***	0.00822***	0.00627***	0.00738***	0.00642***	0.00668***
				(0.00129)	*(0.00130)*	*(0.00131)*	*(0.00150)*	*(0.00148)*	*(0.00143)*	*(0.00144)*	*(0.00147)*
Spatially Weighted Social Filter (Inverse Dist)						0.0384***					
						(0.00923)					
Spatially Weighted Social Filter (First Order Contiguity)							-0.0119***	-0.00891***	-0.00587*	-0.00433	-0.00513
							(0.00358)	*(0.00341)*	*(0.00322)*	*(0.00313)*	*(0.00323)*
Krugman index								-0.0868***		-0.0253	-0.0373*
								(0.0239)		*(0.0225)*	*(0.0224)*
Road Density								4.31e-05***		3.29e-05**	3.20e-05**
								(1.58e-05)		*(1.42e-05)*	*(1.36e-05)*
Population Density									0.000589***	0.000466***	0.000359***
									(0.000157)	*(0.000162)*	*(0.000130)*
Net Domestic Migration									-1.50e-07**	-8.07e-08	-2.40e-08
									(6.37e-08)	*(5.75e-08)*	*(5.94e-08)*
GDP Per Capita									5.77e-06***	5.30e-06***	4.95e-06***
									(9.60e-07)	*(9.24e-07)*	*(8.11e-07)*
Int.Term Exp.R&D*Pop.Density											7.904*
Constant	0.0217***	0.0267***	0.0189***	0.0260***	0.0179***	0.0165**	0.0266***	0.00743	-0.159***	-0.189***	-0.161***
	(0.00495)	(0.00592)	(0.00578)	(0.00591)	(0.00577)	(0.00673)	(0.00591)	(0.0452)	(0.0321)	(0.0469)	(0.0404)
Year Dummies	X	X	X	X	X	X	X	X	X	X	X
Observations	2327	2327	2327	2327	2327	2327	2327	2327	2327	2327	2327
R-squared	0.252	0.253	0.253	0.256	0.256	0.261	0.260	0.296	0.312	0.330	0.340
Number of beaeacode	179	179	179	179	179	179	179	179	179	179	179

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

4.5.3 USA

Table 4.7 gives the main results for the USA. As the only 'mature' urban and innovation system in our country set, we expect the results to be different from India and China. Overall, the USA results indicate a stable geography of innovation organised around large, specialised spatial clusters.

As before, models (1) – (3) explore linear components of the US innovation system. The results suggest a consistently strong connection between regional R&D expenditure and patenting activity – a relationship that holds throughout the specifications (except for model (11), or which more below). Unlike China and India, we find no significant effects of R&D spillovers in any specification. This reflects wider analysis that knowledge spillovers within US regions exhibit considerable distance decay, tending to die out within the economic area in which ideas are generated (Ács 2002).

As with China and India, social and institutional factors exhibit a robust positive influence on innovation. Models (4) through (7) indicate that the Social Filter is significant on patenting at 1%, a relationship that persists in further specifications. Social Filter spillovers exhibit a mixed effect: inverse distance weights are positive significant, while first order contiguity weights are negative significant, and become progressively less important as wider structural factors are introduced.

Models (9) through (11) bring in wider structural factors. These confirm what is already apparent from models (1) to (3): that traditional agglomeration factors play important roles in explaining the geography of innovation. Population density and GDP per capita are both strongly positive on patenting. Interacting R&D spending with population density (model (11)) helps explore the relative role of linear and structural factors: the interaction term and population density are both significant, while R&D spending becomes insignificant. This suggests the joint effect of agglomeration is driven by structural factors.

As in India (but not China), the Krugman Index is weakly significant or insignificant. Net inter-BEA migration is rather less important in the US than in China or India, reflecting the relative stability of the country's innovation geography.

4.5.4 Comparisons: China, India and the USA

Overall, the China analysis suggests that the country's regional innovation systems are driven by the density-R&D nexus, and more broadly by traditional agglomeration factors. Patenting activity is concentrated in richer regions with big urban cores and good infrastructure networks. This may be because of China's sharper density gradient, plus the role of the state-directed economy – which appears to limit spillovers between regions. The Social Filter is positively linked to innovation, but the relationship has no statistical significance.

By contrast, India presents a more straightforward 'R&D plus spillovers' story, especially in a number of dense urban cores. Agglomeration measures play a less important role than in China; conversely, spillover variables are positive and (mostly) statistically significant as a driver of patenting. The results for India also highlight the importance of migration: there appears to be a very dynamic spatial matching of talent across regions, perhaps reflecting freer movement of labour. Also unlike China, the Social Filter is positive and significantly linked to innovation.

Overall, the US system shares some superficial similarities with both China (a traditional agglomeration story) and India (a number of innovation 'hotspots'). The generation of innovation occurs largely in self-contained zones relying on their own R&D inputs, favourable local socio-economic environments and on large pools of skilled individuals. However, we know from the previous territorial analysis that innovative activity in both China and India is far more spatially clustered than in the US. Knowledge spillovers in the US are largely localised: but the large number of innovation 'sites' helps raise the country's overall innovation performance.

4.6. Conclusions and policy lessons

Our analysis has explored the dynamics and drivers of innovative activity in the USA, China and India. The USA is widely considered as the world's technological leader. Both China and India have experienced significant jumps in national innovation outputs in recent years; more broadly, both countries are now key locations in increasingly globalised sectoral innovation systems. Many of these sectoral networks have been led by MNEs originating in the USA, via complex outsourcing and collaborative ventures. We are interested in how these national and pan-national forces are shaping the evolution of innovative activity across space, and their interaction with country-specific social, institutional and historical factors.

Our analysis has a number of useful features for policymakers. We deliver rich, detailed descriptive analysis on key innovation inputs and outputs across the three countries. We site these results within an analytical framework which allows us to identify individual components of innovation systems and their interaction. We then apply this framework in regression modelling, in order to explore key relationships in more detail.

How does this type of comparative analysis add value to EU policymakers, especially at regional level? First, it enables us to isolate the factors that shape the genesis of innovation and economic dynamism at the territorial level at different stages of the process of technological development. In turn, this helps develop a better understanding of these processes for EU leading and lagging regions at the same time.

Second, the territorial approach allows us to 'capture' the emergence of new actors in the international technological competition arena as well as to situate existing leading regions. This is important for EU regions to understand their 'competitors' as well as for EU-based firms and institutions (e.g. universities) to identify new opportunities in 'distant' markets. In this respect our analysis should be read alongside other territorial studies such as the World Bank World Development Report 2009.

Third, it supports 'policy transfer' where the EU aims to provide support to non-EU partners wishing to learn from the EU experience: comparative analysis provides a systematic framework for policy development work, for example the European Commission's 2010 China Regional Policy report.
With this in mind, what does our comparative analysis tell us? Overall, that there is no single 'best practice' or 'optimal model' for EU innovation, as territorial specificities are of crucial importance for regional/local economic development/innovation policies. Factors behind successful outcomes in China, India and the USA cannot be easily replicated in different contexts. For example, Americanising EU innovation systems is not helpful. Policies need to be tailored to local conditions.

The country-specific findings throw out a number of important lessons for policymakers. First, in the US tighter functional integration (when compared to Europe) is fostering concentration and specialisation by means of factor mobility. The EU should carefully consider how integration policies – and mobility in particular – impact on innovation and its geography. A narrow focus on innovation-inputs may cover-up crucial framework conditions. This is particularly important for leading regions but also for emerging territories as shown for China and, even more so, for India.

Second, at this initial stage of technological development only a very few 'hotspots' emerged in China and India, but new 'localities' are now developing with new opportunities and challenges for EU actors:

- New territories in international competition (increased competition for both EU leading and lagging regions). Our research provides EU firms, Institutions and policy-makers with an invaluable analytical/critical picture of their external competitors

- The EU clearly faces competition from 'below' (China and India) and from 'above' (USA). But the picture is more complex when analysed at the sub-national level

- There are new opportunities for EU firms/actors, which are highly localised but the situation is constantly changing/evolving. Our research clearly showed where this is happening and what forces are driving the process of change

- The growing development of 'global networks' involving new emerging actors might reinforce ability of EU firms, institutions and regions to benefit from the new global scenario. Further research is needed on this

- The level of internal disparities in emerging countries still very high (even when compared with the US). This might produce social and/or political tensions in the future possibly threatening further evolution of these economies if appropriate development policies are not implemented. This risk should be carefully taken into account by EU firms for its impact on investments and import/export.

4.7. References

Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy, 31*(7), 1069-1085.

Altenburg, T. (2009). Building Inclusive Innovation Systems in Developing Countries: Challenges for IS Research In B.-A. Lundvall, J. Vang, K. J. Joseph & C. Chaminade (Eds.), *Handbook of Innovation Systems in Developing Countries* Cheltenham: Edward Elgar.

Archibugi, D., & Iammarino, S. (2002). The globalization of technological innovation: definition and evidence. *Review of International Political Economy, 9*(1), 98–122.

Asheim, B., & Gertler, M. (Eds.). (2005). *The Geography of Innovation: Regional Innovation Systems*. Oxford: OUP.

Audretsch, D., & Feldman, M. (1996). Innovation in Cities: Science-Based Diversity, Specialisation and Local Competition R&D Spillovers. *European Economic Review 43*, 409-429.

Bound, K. (2007). *India: The uneven innovator*. London: Demos.

Bruche, G. (2009). *A New Geography of Innovation - China and India rising* New York: Vale Columbia Center, Columbia University.

Cantwell, J. (2005). MNCs, local clustering and science-technology relationships. In G. Santangelo (Ed.), *Technological Change and Economic Catch-Up: The Role of Science and Multinationals*. Cheltenham: Edward Elgar.

Carlino, G., Chatterjee, S., & Hunt, R. (2007). Urban Density and the rate of invention. *Journal of Urban Economics, 61*(3), 389-419.

Charlot, S., & Duranton, G. (2004). Communication externalities in cities *Journal of Urban Economics, 56*(3), 581-613.

Cimoli, M., Dosi, G., Nelson, R., & Stiglitz, J. (2009). Institutions and policies in developing economies. In B.-A. Lundvall, C. Chaminade, K. J. Joseph & J. Vang (Eds.), *Handbook of Innovation Systems and Developing Countries: Building Domestic Capabilities in a Global Context*. Cheltenham: Edward Elgar.

Cohen, B. (2006). Urbanization in developing countries: Current trends, future projections, and key challenges for sustainability *Technology in Society, 28*, 63–80.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly, 35*(1), 128-152.

Cooke, P. (2002). Regional Innovation Systems: General Findings and some new evidence from biotechnology clusters *Journal of Technology Transfer, 27*, 133-145.

Cooke, P., Urange, M., & Extebarria, G. (1997). Regional Innovation Systems: Institutional and Organizational Dimensions. *Research Policy, 26*, 475-491.

Crescenzi, R., & Rodríguez-Pose, A. (2009). Systems of innovation and regional growth in the EU: endogenous vs. external innovative efforts and socio-economic conditions. In U.

Fratesi & L. Senn (Eds.), *Growth and innovation of competitive regions: the role of internal and external connections* (pp. 167-192). Berlin: Springer-Verlag.

Crescenzi, R., Rodriguez-Pose, A., & Storper, M. (2007). *The Geographical Processes Behind Innovation: A Europe-United States comparative analysis*. Madrid: IMDEA.

Crescenzi, R., Rodríguez-Pose, A., & Storper, M. (2007). The territorial dynamics of innovation: a Europe–United States comparative analysis. *Journal of Economic Geography, 7*(6), 673-709.

da Motta e Albuquerque, E. (2003). *Immature systems of innovation: introductory notes about a comparison between South Africa, India, Mexico and Brazil based on science and technology statistics*. Cedeplar: Universidade Federal de Minas Gerais.

Dahlman, C. (2010). Innovation Strategies of Three of the BRICS: Brazil, India and China-What Can We Learn From Three Different Approaches. In X. Fu & L. Soete (Eds.), *The Rise of Technological Power in the South*. Basingtoke: Palgrave MacMillan.

Duan, Y., & Kong, Y. (2008). *The role of R&D offshoring in explaining the patent growth of China and India at USPTO.* Paper presented at the 2008 IEEE INTERNATIONAL CONFERENCE ON MANAGEMENT OF INNOVATION AND TECHNOLOGY, Bangkok.

Dunning, J. (1996). The geographical sources of competitiveness in firms: Some results of a new survey. *Transnational Corporations, 5*(3), 1-21.

Dunning, J. (1998). Location and the Multinational Enterprise: a neglected factor? *Journal of International Business Studies, 29*(1), 45-66.

Duranton, G. (2008). Viewpoint: From cities to productivity and growth in developing countries. *Canadian Journal of Economics/Revue canadienne d'économique, 41*, 689–736.

Duranton, G., & Puga, D. (2003). *Micro-Foundations of Urban Agglomeration Economies*. Cambridge, Mass.: NBER.

Fan, P. (2008). *Innovation Capacity and Economic Development China and India*. Helsinki: UNU World Institute for Development Economics Research.

Fischer, M., & Varga, A. (2003). Spatial knowledge spillovers and university research. *Annals of Regional Science, 37*, 303-322.

Fleischer, B., Li, H., & Zhao, M. Q. (2010). Human capital, economic growth, and regional inequality in China. *Journal of Development Economics, 92*(2), 215-231.

Freeman, C. (1987). *Technology Policy and Economic Policy: Lessons from Japan* London: Pinter.

Fu, X., & Soete, L. (Eds.). (2010). *The Rise of Technological Power in the South*. Basingstoke: Palgrave MacMillan.

Gajwani, K., Kanbur, R., & Zhang, X. (2006). *Comparing the evolution of spatial inequality in China and India: a fifty-year perspective*. Washington DC IFPRI.

Gordon, I. (2001). Unemployment and spatial labour markets: strong adjustment and persistent concentration. In R. Martin & P. Morrison (Eds.), *Geographies of Labour Market Inequality*. London: Routledge.

Griliches, Z. (1979). Issues in assessing the contribution of R&D to productivity growth. *Bell Journal of Economics, 10*(92-116).

Griliches, Z. (1986). Productivity, R&D, and basic research at the firm level in the 1970s. *American Economic Review, 76*(141-154).

Grossman, G. M., & Helpman, E. (1991). Quality Ladders in the Theory of Growth. *The Review of Economic Studies, 58*(1), 43-61.

Jaffe, A. (1986). Technological Opportunity and Spillovers of R&D: Evidence from firms' patents, profits and market value. *American Economic Review, 76*(5), 984-1001.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics, 108*(3), 577-598.

Jian, T., Sachs, J., & Warner, A. (1996). Trends in regional inequality in China. *CHINA ECONOMIC REVIEW, 7*(1), 1-21.

Joseph, K. J. (2009). Sectoral innovation Systems in Developing Countries: The Case of India's ICT Industry. In B.-A. Lundvall, C. Chaminade, K. J. Joseph & J. Vang (Eds.), *Handbook of Innovation Systems and Developing Countries: Building Domestic Capabilities in a Global Context*. Cheltenham: Edward Elgar.

Kuchiki, A., & Tsuji, M. (Eds.). (2010). *From agglomeration to innovation: upgrading industrial clusters in emerging economies*. Palgrave Macmillan: Basingstoke.
Leadbeater, C., & Wilsdon, J. (2007). *The Atlas of Ideas: How Asian innovation can benefit us all*. London: Demos.
Li, X., & Pai, Y. (2010). The Changing Geography of Innovation Activities: What do Patent Indicators Imply? In X. Fu & L. Soete (Eds.), *The Rise of Technological Power in the South*. Basingstoke: Palgrave MacMillan.
Liu, X., & Buck, T. (2007). Innovation performance and channels for international technology spillovers: Evidence from Chinese high-tech industries. *Research Policy, 36*(3), 355-366.
Liu, X., & White, S. (2001). Comparing innovation systems: a framework and application to China's transitional context. *Research Policy, 30*, 1091–1114.
Lundin, N., & Schwaag Serger, S. (2007). *Globalization of R&D and China – Empirical Observations and Policy Implications*. Stockholm: Research Institute of Industrial Economics.
Lundvall, B.-Ã. (1992). *National systems of innovation. Towards a theory of innovation and interactive learning.* . London: Pinter.
Lundvall, B.-A., Joseph, K. J., Chaminade, C., & Vang, J. (Eds.). (2009). *Handbook of innovation systems and developing countries : building domestic capabilities in a global setting*. Edward Elgar: Cheltenham.
Mahmood, I. and J. Singh (2003). "Technological dynamism in Asia." Research Policy **32**(6): 1031-1054.
Malecki, E. (1997). *Technology and economic development: The dynamics of local, regional and national competitiveness.* Cambridge: Addison-Wesley, Longman.
Malerba, F., & Mani, S. (Eds.). (2009). *Sectoral systems of innovation and production in developing countries : actors, structure and evolution*. Edward Elgar: Cheltenham.
Malmberg, A., Solvell, O., & Zander, I. (1996). Spatial Clustering, Local Accumulation of Knowledge and Firm Competitiveness. *Geografiska Annaler Series B: Human Geography, 78*(2), 85-97.
Mani, S. (2004). Institutional support for investment in domestic technologies: An analysis of the role of government in India. *Technological Forecasting and Social Change, 71*(8), 855-863.
Martin, R., & Sunley, P. (2006). Path dependence and regional economic evolution. *Journal of Economic Geography, 6*(4), 395-437.
Maurseth, P. B., & Verspagen, B. (2002). Knowledge Spillovers in Europe: A Patent Citations Analysis. *Scandinavian Journal of Economics, 104*(4), 531-545.
Midelfart-Knarvik, K. H., Overman, H., Redding, S., & Venables, A. (2002). *The Location of European Industry*. Brussels: European Commission
Mitra, R. (2007). *India's Emergence as a Global R&D Center - an Overview of the Indian R&D System and Potential*. Ostersund: Swedish Institute for growth Policy Studies.
Mowery, D. (1992). The U.S. national innovation system: Origins and prospects for change. *Research Policy, 21*(2), 125-144.
Mowery, D. C. (2001). Technological Innovation in a Multipolar System: Analysis and Implications for U.S. Policy. *Technological Forecasting and Social Change, 67*(2-3), 143-157.
Mowery, D. C., & Oxley, J. E. (1995). Inward technology transfer and competitiveness: the role of national innovation systems. *Cambridge Journal of Economics, 19*(1), 67-93.
Nelson R. (1993), National Innovation Systems: A Comparative Analysis, Oxford: OUP
O hUallachain, B., & Leslie, T. F. (2007). Rethinking the regional knowledge production function. *Journal of Economic Geography, 7*(737-752).
OECD. (2009). *OECD Patent Statistics Manual*. Paris: OECD.
Padilla-Perez, R., Vang, J., & Chaminade, C. (2009). Regional innovation systems in developing countries: integrating micro and meso-level capabilities In B.-A. Lundvall, J. Vang, K. J. Joseph & C. Chaminade (Eds.), *Handbook of Innovation Systems and Developing Countries*. Cheltenham: Edward Elgar.
Parayil, G., & D'Costa, A. (2009). *The new Asian innovation dynamics: China and India in perspective*. Basingstoke: Palgrave Macmillan.
Piore, M. J., & Sabel, C. (1984). *The second industrial divide: possibilities for prosperity*. New York: Basic Books.

Ponds, R., van Oort, F., & Frenken, K. (2010). Innovation, Spillovers and university-industry collaboration: an extended knowledge production function approach. *Journal of Economic Geography, 10*, 231-255.
Popkin, J. M., & Iyengar, P. (2007). *IT and the East : how China and India are altering the future of technology and innovation*. Boston, Mass.: Harvard Business School Press.
Reed, H. (2010). *Reinventing Venture Capital: Towards a new economic settlement*. London: Demos.
Rodríguez-Pose, A. (1999). Innovation Prone and Innovation Averse Societies: Economic Performance in Europe. . *Growth and Change, 30*(1), 75-105.
Romer, P. (1990). Endogenous Technological Change. *Journal of Political Economy, 98*(5), 71-102.
Santangelo, G. (Ed.). (2005). *Technological Change and Economic Catch-Up: The Role of Science and Multinationals*. Cheltenham: Edward Elgar.
Saxenian, A.-L. (1994). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128* Cambridge, MA: Harvard University Press.
Saxenian, A.-L. (2006). *The New Argonauts: Regional Advantage in a Global Economy*. Cambridge, MA: Harvard University Press.
Saxenian, A.-L., & Sabel, C. (2008). Venture Capital in the 'Periphery': The New Argonauts, Global Search and Local Institution-Building. [Roepke Lecture in Economic Geography]. *Economic Geography, 84*(4), 379-394.
Schaaper, M. (2009). *Measuring China's Innovation System: National Specificities and International Comparisions*. Paris: OECD.
Scott, A., & Garofoli, G. (Eds.). (2007). *Development on the Ground: Clusters, Networks and Regions in Emerging Economies*. Oxford: Routledge.
Simmie, J., Carpenter, J., Chadwick, A., & Martin, R. (2008). *History Matters: Path dependence and innovation in British city-regions*. London: NESTA.
Storper, M. (1997). *The Regional World: Territorial Development in a Global Economy*. New York: Guilford.
Sun, Y. (2003). Geographic patterns of industrial innovation in China during the 1990s. *TIJDSCHRIFT VOOR ECONOMISCHE EN SOCIALE GEOGRAFIE, 94*(3), 376-389.
Tseng, C. (2009). "Technological innovation and knowledge network in Asia: Evidence from comparison of information and communication technologies among six countries." Technological Forecasting and Social Change **76**(5): 654-663.
UN Population Division. (2010). *United Nations World Urbanisation Prospects: The 2010 Revision Population Database*: United Nations.
Venables, A. J. (2005). Spatial disparities in developing countries: cities, regions, and international trade. *Journal of Economic Geography, 5*(1), 3-21.
Wadhwa, V. (2010). Chinese and Indian Entrepreneurs are Eating America's Lunch. *Foreign Policy*, 28 December.
Wang, C., & Lin, G. (2008). The growth and spatial distribution of China's ICT industry: New geography of clustering and innovation. *ISSUES & STUDIES, 44*(2), 145-192.
Wilson, D., & Purushothaman, R. (2003). *Dreaming with BRICS: The Path to 2050*: Goldman Sachs.
Xu, Z. (2009). Productivity and Agglomeration Economies in Chinese Cities. *Comparative Economic Studies, 51*(3), 284-301.
Yeung, H. (2009). Regional Development and the Competitive Dynamics of Global Production Networks: An East Asian Perspective. *Regional Studies, 43*(3), 325-351.

Annex A.4.1. Geographical coverage and description of the variables

A.4.1.1 China: Geographical Coverage

For **China** data are available for the Provincial-level administrative subdivisions: 22 Provinces, 4 Autonomous Regions, 4 Municipalities. Two Special Administrative Regions (Hong Kong and Macau) and One Autonomous Region (Tibet) have been excluded from the analysis due to the lack of data for the selected variables.

Table A.4.1.1. Geographical Coverage for China

Provincial Subdivisions	**DATA AVAILABLE**
Anhui	YES
Beijing	YES
Chongqing	YES
Fujian	YES
Gansu	YES
Guangdong	YES
Guangxi	YES
Guizhou	YES
Hainan	YES
Hebei	YES
Heilongjiang	YES
Henan	YES
Hubei	YES
Hunan	YES
Inner Mongolia	YES
Jiangsu	YES
Jiangxi	YES
Jilin	YES
Liaoning	YES
Ningxia	YES
Qinghai	YES
Shaanxi	YES
Shandong	YES
Shanghai	YES
Shanxi	YES
Sichuan	YES
Tianjin	YES
Xinjiang	YES
Yunnan	YES
Zhejiang	YES
Hong Kong□(SAR)	NO
Macau□(SAR)	NO
Tibet□(AR)	NO

A.4.1.2. India: Geographical Coverage

For **India** data are available for 18 States and 3 Union Territories that are covered in the analysis. Bihar and Rajasthan are included in descriptive statistics but not in the regression analysis due to limited number of observations available over time.

Table A.4.1.2. Geographical Coverage for India

States of India	**DATA AVAILABLE**
Andhra Pradesh	YES
Arunachal Pradesh	
Assam	
Bihar	Limited Availability / Excluded from regression analysis
Chhattisgarh	
Goa	YES
Gujarat	YES
Haryana	YES
Himachal Pradesh	YES
Jammu and Kashmir	YES
Jharkhand	YES
Karnataka	YES
Kerala	YES
Madhya Pradesh	YES
Maharashtra	YES
Manipur	
Meghalaya	
Mizoram	
Nagaland	
Orissa	YES
Punjab	YES
Rajasthan	Limited Availability / Excluded from regression analysis
Sikkim	
Tamil Nadu	YES
Tripura	
Uttar Pradesh	YES
Uttarakhand	
West Bengal	YES
Union Territories	
Andaman and Nicobar Islands	
Chandigarh	YES
Dadra and Nagar Haveli	
Daman and Diu	
Lakshadweep	
National Capital Territory of Delhi	YES
Puducherry	YES

A.4.1.3. USA: Geographical coverage

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

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

Regional definitions from BEA:
http://www.bea.gov/regional/definitions/#P

Definitions of GDP vs. Personal Income and their availability:
http://www.bea.gov/regional/about.cfm

The Bureau prepares GDP-by metropolitan area estimates only beginning with 2001. Conversely Local area personal income is the only detailed, broadly inclusive economic time series for local areas that is available annually beginning with 1969 (BEA Website 2011 http://www.bea.gov/regional/about.cfm). Only the latter is also available for the 179 BEA Economic Areas.

A.4.1.4. Definitions of Variables

Table A.4.1.3. Definitions of Variables for China

Variable	Definition	Source(s)	Notes
Patenting indicator (Dependent Variable)			
PCT applications per capita (per 1000 persons)	Number of Provincial PCT applications (count) / total regional population	OECD.Stat	Patents filed under the Patent Co-operation Treaty (PCT), at international phase, that designate the EPO. Indicator based on fractional count.
Innovation efforts			
Regional S&T Expenditure	Intramural expenditure on Science and Technology (S&T) as a share of total regional GDP .	China Statistical Yearbook on Science and Technology, 1991-2008	Data on Intramural expenditure for S&T activities cover innovative activities pursued in (1) independent research and science institutions under government control, (2) higher learning education and (3) large and medium enterprises. In line with UNSECO guidelines this item includes expenditure for (1) research and experimental development (R&D), (2) R&D applied services (3) scientific and technological services (STS) and (4) S&T popularization activities. Disaggregated provincial-level R&D data are only available since 1998 and with a limited geographical coverage
Social Filter			
Agricultural Employment	Agricultural employment as a share of total provincial employment	China Statistical Yearbook, 1991-2008	
Unemployment rate	Unemployment rate at the provincial level (in Urban areas only)	China Statistical Yearbook, 1991-2008	
Young Population (15-24)	People aged 15-24 as share of total population in the province	China Population Census Data	
Human Capital Accumulation (Tertiary Education)	People with college-level or higher degrees as a share of total provincial population (aged 6 and above)	China Statistical Yearbook, 1991-2008	
Structure of the local economy			
GDP per capita	Total regional GDP/ total provincial population (units)	China Statistical Yearbook, 1991-2008	
Population density	Calculated as average population (units) in year t /surface of the province (Sq kms)	China Statistical Yearbook, 1991-2008	

Krugman Index	Provincial-level Krugman Index calculated on the basis provincial employment in 15 major sectors defined by the 1990 official statistical classification of industrial sectors.	China Statistical Yearbook, 1991-2008	Break-down of GDP by sector not available (only industrial)
Railway Density	Length of railways in operation (Kms) in the province / total surface of the province (Sq km)		
Net Migration	Net inter-provincial migration per 1000 persons, calculated as the difference between total migratory inflows minus total migratory outflows	China Population Census Data	Very high correlation between Net and Gross migration rate (0.9483). Regression results qualitatively identical if Net Migration replaced by Gross Migration to match India data availability.

*China statistical Yearbook and Population Census data can be accessed through China Data Online (http://chinadataonline.org/) and National Bureau of Statistics of China website (http://www.stats.gov.cn/). For the years not covered by these websites, we relied on paper-based editions of these publications.

For more information about how China collect R&D/S&T data and the definition of R&D/S&T statistics, please refer to the website: China Science and Technology Statistics (Chinese only) (http://www.sts.org.cn/), which is under the Ministry of Science and Technology, China.

Table A.4.1.4. Definitions of Variables for India

Variable	Definition	Sources**	Notes
Patenting indicator (Dependent Variable)			
PCT applications per capita (per 1000 persons)	Number of State PCT applications (Count) / total regional population	OECD.Stat	Patents filed under the Patent Co-operation Treaty (PCT), at international phase, that designate the EPO. Indicator based on fractional count.
Innovation efforts			
Regional R&D Expenditure	Combines Central Government Extramural and State total expenditure in R&D as a share of regional GDP	Research and development statistics 2004-05 & 2007-08; Research and Development in Industry 2000-01, Ministry of Science and Technology, Govt. of India; Planning Commission, India	Extramural R&D: 12 major scientific agencies/ department. Institutions receiving support from funding agencies classified into five categories: Universities/Colleges and Universities, Institutes of National Importance, National Laboratories and other Institutions under State Governments, Voluntary Agencies, Registered Societies. No data are available for Private R&D expenditure at the State-level.
Social Filter			
Unemployment rate	Rate of unemployment at the state level (urban areas)	Planning Commission, Govt. of India.	
Agricultural employment	Agricultural employment as a share of total employment at the state level.	Census of India 1991, 2001	
Human Capital Accumulation (Tertiary Education)	People with college, diploma or higher degrees (in urban areas) as a share of total state population (aged 7 and above)	National Sample Survey	
Young people	People aged 15-24 as a share of total state population	Census of India 1991, 2001	
Structure of the local economy			
Population density	Calculated as average population (units) in year t /surface of the state (Sq-kms)	Central Statistics Office	
GDP per capita	Calculated as regional gross domestic	Central Statistics Office	

	product/regional population (units)		
Krugman Index	Statel-level Krugman Index calculated on the basis State GDP in 13 major sectors	Central Statistics Office	
Gross Migration	Inter-state migratory in-flows per 1000 persons	Census of India 1991, 2001	Net Migration not available (no information on outflows)
Religious Fractionalization Index (R_index)	The index is calculated on the basis of 7 major religious groups $1-\sum_{k=1}^{K} p_k^2$, K≧2 K is different religious group, and p_k indicates the share of group k in the total state population	Census of India 1991, 2001	
Road Density	Calculated as the length of state roads (Kms) /surface of the state (Sq kms)	Basic Road Transport Statistics of India, Ministry of Transport and Highways	All categories of roads (no breakdown available)

** The data sources listed in the table have been accessed through Indiastat.com (http://www.indiastat.com/). Additional data have been collected from the Central Statistic Office (http://mospi.gov.in/) including India key economic and survey data. Census data have been collected from the Census of India (http://ww.censusindia.net/). In addition Science & Technology Management Information System (NSTMIS), under the responsibility of the Department of Science and Technology, provides R&D statistic reports (http://www.nstmis-dst.org/index.asp). For some state-level census data not available on line we relied upon paper-based publications.

Table A.4.1.5: Definitions of Variables for USA, BEA Economic Areas

Variable	Definition	Sources	Notes
Patenting indicator (Dependent Variable)			
PCT applications per capita (per 1000 persons)	Number of State PCT applications (Count) / total regional population	OECD.Stat	Patents filed under the Patent Co-operation Treaty (PCT), at international phase, that designate the EPO. Indicator based on fractional count.
Innovation efforts			
Regional R&D Expenditure	Regional Private R&D Expenditure as a percentage of Regional Total Personal Income	Compustat from Standard & Poor's - Wharton Research Data Services (WRDS), available in LSE library	This variable accounts for ALL costs incurred by private firms listed in S&P Compustat during the year that relate to the development of new products or services.*** No data are available at the BEA EA level for Public and/or University R&D expenditure.
Social Filter			
Unemployment rate	Rate of unemployment at the BEA EA level.	U.S. Bureau of Labour Statistics, Local Area Unemployment Statistics	1990-2009
Agricultural employment	Agricultural employment as a share of total employment at the BEA EA level.	USA Census Bureau Counties Data Files	1990-2007
Human Capital Accumulation (Tertiary Education)	People with Bachelor's degree and higher as a share of total BEA EA population (aged 25 and above)	USA Census Bureau Counties Data Files	1991-1999 is calculated by averaging 1990 and 2000 data. 2001 onwards uses 2000 data as proxy
Young people	People aged 15-24 as a share of total BEA EA population	USA Census Bureau Counties Data Files	1990, 2000-2008. 1999 interpolated with CAGR
Structure of the local economy			
Population density	Calculated as average population (units) in year t /surface of the BE EA (Sq-kms)	USA Census Bureau, USA Counties Data files/Bureau of Economic Analysis	1990-2008

Personal Income per capita	This is used as a proxy for GDP per capita (see note) as is calculated as Total Personal Income on the BEA EA /regional population (units)	USA Census Bureau, USA Counties Data files/Bureau of Economic Analysis	1990-2008 The Bureau prepares GDP-by metropolitan area estimates only beginning with 2001. Conversely Local area personal income is the only detailed, broadly inclusive economic time series for local areas that is available annually beginning with 1969 (BEA Website 2011) Only the latter is also available for the 179 BEA Economic Areas.
Krugman Index	Economic Areas-level Krugman Index calculated on the basis BEA-EA Employment in 10 major sectors	USA Census Bureau, USA Counties Data files/Bureau of Economic Analysis	1990-2007
Net Migration	Domestic Inter-EA net migratory in-flows per 1000 persons	USA Census Bureau, USA Counties Data files/Bureau of Economic Analysis	Data available for 2000-2008 only. 1990-1999 imputed using 2000 values
Road Density	Calculated as the length of highways (Kms) /surface of the Economic Area (Sq kms)	USA Bureau of Transport Statistics, National Transportation Atlas Database.	USA highway data are available from 1996 to 2010 only. Data for 1994 and 1995 have been imputed using 1996 data.

*** This amount includes the company's contribution only. This item includes: 1) Software expenses, 2) Amortization of software costs. This item excludes: 1) Customer or government-sponsored research and development (including reimbursable indirect costs) 2) Extractive industry activities, such as prospecting, acquisition of mineral rights, drilling, mining, etc. 3) Engineering expense routine, ongoing efforts to define, enrich, or improve the qualities of existing products 4) Inventory royalties 5) Market research and testing. This item is not available for banks and utilities.

Annex A.4.2. PCA results

Table A.4.2.1. Principal Component Analysis: Eigen analysis of the Correlation Matrix

China				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.78367	0.607117	0.4459	0.4459
Comp2	1.17655	0.390576	0.2941	0.7401
Comp3	0.785977	0.532178	0.1965	0.9366
Comp4	0.2538	.	0.0634	1
India				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.42679	0.397231	0.3567	0.3567
Comp2	1.02956	0.140551	0.2574	0.6141
Comp3	0.889012	0.234381	0.2223	0.8363
Comp4	0.654631	.	0.1637	1
USA, BEA				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.4628	0.380224	0.3657	0.3657
Comp2	1.08258	0.107053	0.2706	0.6363
Comp3	0.975522	0.49642	0.2439	0.8802
Comp4	0.479102	.	0.1198	1
USA, State				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.76773	0.678858	0.4419	0.4419
Comp2	1.08887	0.137143	0.2722	0.7141
Comp3	0.951726	0.760046	0.2379	0.9521
Comp4	0.191679	.	0.0479	1

Table A.4.2.2. Principal Component Analysis: Principal Components' Coefficients

China					
Variable	Comp1*	Comp2	Comp3	Comp4	Unexplained
Young Population (15-24)	-0.0159	-0.7543	0.6441	0.1262	0
Population with Tertiary Educ.	-0.6743	0.2201	0.1046	0.6971	0
Unemployment Rate (Urban)	0.2586	0.6176	0.7407	-0.0559	0
Agricultural Employment	0.6915	-0.0337	-0.1602	0.7036	0
India					
Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
Young Population (15-24)	0.5725	-0.2819	0.5164	-0.571	0
Population with Tertiary Educ.	0.6567	0.1375	0.15	0.7262	0
Agricultural Employment	-0.4901	-0.1991	0.786	0.3184	0
Unemployment Rate (Urban)	-0.0285	0.9284	0.3033	-0.2127	0
USA, BEA					
Variable	Comp1*	Comp2	Comp3	Comp4	Unexplained
Young Population (15-24)	-0.1487	0.4121	0.8939	-0.095	0
Population with Tertiary Educ.	-0.727	-0.0067	-0.045	0.6852	0
Unemployment Rate	0.4163	-0.6588	0.4222	0.4631	0
Agricultural Employment	0.5254	0.6294	-0.1439	0.5542	0

*For the calculation of the Social Filter Index the score for Comp1 in China, USA (BEA) and USA (State) has been pre-multiplied by -1 to match the interpretation of the index computed for India (proxy for ‘innovation prone-ness’)

Annex A.4.3. Spillover measures

Extra-regional innovative activity is proxied by the average of R&D/S&T intensity in neighbouring regions is calculated as:

$$WR\&D_i = \sum_{j=1}^{n} R\&D_j w_{ij} \qquad \text{with } i \neq j \qquad (1)$$

Where *R&D* is our proxy for regional innovative efforts of the *j*-th region and w_{ij} is a generic 'spatial' weight. In order to test for the spatial scope of the processes discussed above alternative definitions for the 'spatial weights' have been adopted in our analysis: highly localised spatial processes have been proxied by means of first-order contiguity weights (w^{FC}) while far-ranging flows have been captured with inverse-distance weights (w^{ID})[23]:

$$w^{FC}{}_{ij} = \begin{cases} 1 & \text{if j directly shares a border or a vertex with i} \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

$$w^{ID}{}_{ij} = \begin{cases} 0 & \text{if } i = j \\ \dfrac{\frac{1}{d_{ij}}}{\sum_j \frac{1}{d_{ij}}} & \text{if } i \neq j \end{cases} \qquad (3)$$

where d_{ij} is the linear straight-line distance between region *i* and *j* and *w* the corresponding weight.

WSF (Extra-Regional Social Filter Conditions): The measure of extra-regional Social Filter conditions is calculated in the same way as that of the extra-regional innovation presented in equation (2). For each region *i*:

$$WSF_i = \sum_{j=1}^{n} SF_j w_{ij} \qquad \text{with } i \neq j \qquad (4)$$

Where *SF* is our proxy for regional Social Filter Conditions (Social Filter Index) and *w* is as above.

[23] Alternative definitions for the spatial weights matrix are possible: distance weights matrices (defining the elements as the inverse of the distances) and other binary matrices (rook and queen contiguity matrices).

Chapter 5. Knowledge spillovers and regional knowledge creation[24]

5.1. Introduction

This chapter builds upon the long tradition of the regional Knowledge Production Function (KPF hereafter) within the geography of innovation literature (Audretsch and Feldman, 2004), and try to take on board the multiple criticisms this approach has received, both from a methodological viewpoint, as well as from an interpretative perspective. Specifically, the goal of this chapter is to analyse the contribution made by research networks and the labour and geographical mobility of inventors to the process of knowledge creation. To this end, we extend the typical regional KPF to the inclusion of such features of the local labour market, which are likely to explain the spatial heterogeneity in patent production across 287 European regions, in a multivariate econometric model. To the best of our knowledge, the contribution of these features to spatial differences in regional innovation is still poorly understood.

Our motivation is based upon two strands of criticisms. On the one side, we take on board those claims against the linear perspective of regional innovation production, which states that all kind of R&D efforts will systematically lead to a larger number of inventions. We argue that this argument overlooks the importance of a set of factors that actually account for how innovation is generated at the regional level (Rodriguez-Pose and Crescenzi, 2008). Hence, we aim to estimate disproportionate levels of patent production that are attributable to the aforementioned features –mobility and networks, above and beyond regional R&D endowments and other control variables. On the other side, we take into account those criticisms to the localization of knowledge diffusion and claim that, indeed, it is not enough by ‘being there’ to access private pools of knowledge within regions. Rather, knowledge diffuses within the region by means of structured and defined channels, such as networks and labour mobility of human capital, whose spatial distribution explains a non negligible part of patent production heterogeneity across regions.

The second part of the chapter focuses its attention on the external dimension of regional innovation production. As it has been argued in the literature, we claim that cross-regional research networks and movements of skilled workers across regions act as main channels through which knowledge is transferred throughout the space (Fratesi and Senn, 2009). As stated by Bathelt et al. (2004) and Owen-Smith and Powell (2004), firms in regions build ‘pipelines’ in the form of alliances to benefit from knowledge hotspots around the world. In a similar vein, as Breschi et al. (2010) put it, ‘knowledge always travels along with people who master it. If those people move away from where they originally learnt, researched, and delivered their inventions, knowledge will diffuse in space. Otherwise, access to it will remain constrained in bounded locations’. In consequence ‘crucial extra-regional exchanges of knowledge take place beyond firm networks, in particular through the migratory patterns of different types of mobile individuals embodying tacit knowledge’ (Coe and Bunnell, 2003). With these ideas in mind, we examine in detail the role of external-to-the-region research alliances in the likelihood to patent at the regional level, as well as the influence exerted by the geographical mobility patterns of knowledge workers.

The motivation of the present inquiry is also strongly based on latest policy developments at the European level. That is to say, our study perfectly fits the rationale around the Smart Specialisation strategy, recently launched by the European Commission (Foray et al., 2009). As McCann and Ortega-Argilés (2011) recently put it, in order to work out how the Smart Specialisation concept could be applied to regional policy, the concepts of *embeddedness* of the local networks and the local labour force, as well as the idea of *connectedness* to global knowledge hotspots, by means of learning-linkages in the form of cross-regional alliances and spatial mobility of human capital, are pivotal. To the best of our knowledge, few empirical analyses have tried to give empirical content to the conceptual rationale behind the Smart Specialisation strategy, and therefore we aim to fill in this gap.

[24] This chapter has been written by Ernest Miguelez, Rosina Moreano and Jordi Surinach – AQR, Barcelona University.

Contrary to what is customary in this literature, we make use of a longitudinal dataset and estimate a fixed-effects model which allows us to control for a number of unobservable time-invariant confounders that might bias our results if not included. We extend previous empirical works by including a large sample of 287 regions of 31 European countries. In addition, by drawing on patent data and computerized algorithms to identify individual inventors, a large dataset of individuals containing information regarding their personal address(es), their patenting history, the owners of their patents, and the co-authors of their patents –among other details, was constructed. To the best of our knowledge, very few studies have examined the influence of these features on regional innovation and therefore it constitutes a main contribution of the present analysis.

The rest of the chapter is organized as follows: section 5.2 reviews the literature on knowledge diffusion, space, and innovation, as well as inventor networking and mobility, and their relationship with the former phenomena. In section 5.3 we present a testable empirical model; section 5.4 presents the data; whilst section 5.5 includes the results. Finally, section 5.6 presents the conclusions and identifies certain limitations in the approach.

5.2. Theoretical and empirical background

The KPF has been widely used to empirically test the relationship between technological inputs (such as R&D and human capital investments) and innovation outputs. First used in the seminal studies of Griliches (1979) and Hausman et al. (1984) at the firm level, this framework was subsequently extended by Jaffe (1986, 1989) to the regional level. The regional setting was claimed to be more apposite to appraise the aforementioned relationships, since it better takes on board potential direct and indirect effects of R&D and human capital efforts of firms and institutions on firms' innovation rates. Among other things, this approach was strongly based on the belief that knowledge –specially that of tacit nature- is difficult to appropriate in its totality by its creator and therefore may spill over to third parties, on the one hand; and on the evidence that knowledge spills over, but its diffusive patterns are subjected to strong spatial decays (Jaffe et al., 1993). This logic chain gives raise during the nineties and still now to a flourishing literature claiming that, by being co-located and sharing the same geographical space, agents are exposed to a ceaseless amount of information flows, knowledge transfers and learning opportunities that take place continuously in both organized and accidental meetings (Bathelt et al., 2004). That is to say, knowledge flows are more or less automatically received by those who share the same physical space (op. cit.).

The first set of criticisms stems from the evidence that the passage from R&D efforts to innovation is not always straightforward. As Rodriguez-Pose (1999) puts it, different social and institutional local conditions may lead to marked spatial differences in the returns to innovation (Rodriguez-Pose, 1999). In spite of the widespread wisdom of technology as the engine of economic growth (Romer, 1986, 1990), the relationship between innovation efforts and knowledge outputs is far from being linear and overlooks the importance of a set of factors that actually account for how innovation is generated at the regional level (Rodriguez-Pose and Crescenzi, 2008). Rather, countries and regions do enormously differ in their socioeconomic background, which may explain a sizeable part of the spatial heterogeneity in patent production, above and beyond local R&D and human capital endowments. It follows from this appreciation that certain features of the local labour market for inventors, such as their job-to-job mobility, as well as the configuration of their networks of research collaboration, may influence regional innovation rates.

A parallel strand of criticisms relates to the widespread logic chain of the localized knowledge spillovers story. During the nineties, empirical analysis from the geography of innovation (Feldman and Audretsch, 1999; Jaffe 1986, 1989; Jaffe et al., 1993) and new economic geography models (Martin and Ottaviano, 1999) indicated the localized pattern of knowledge spillovers and their role in explaining both the high spatial concentration of economic activity as well as marked spatial differences in economic growth. Central to this reasoning is the assumption that corporate and public R&D investment spills over to third parties in the form of an externality, but 'the ability to receive knowledge spillovers is influenced by distance from the knowledge source' (Audretsch and Feldman, 1996, p. 630). After all, 'intellectual breakthroughs must cross hallways and streets more easily than oceans and continents' (Glaeser et al., 1992, p. 1127).

Against this widely accepted tradition, some studies consistently argue that co-location is not a sufficient condition for accessing private pools of local knowledge, but the active participation in meaningful networks such as the collaboration patterns between inventors and their job-to-job mobility across firms and institutions. As Zucker et al. (1998) or Breschi and Lissoni (2009) put it, in the absence of large levels of local labour mobility of super-skilled labour and research networks of formal collaboration, informal linkages and serendipitous encounters explain only a relatively minor part of the localization of knowledge flows. Thus, knowledge flows might be a powerful agglomeration force and might basically occur at the regional level, but not in the form of a spillover, but through well-regulated knowledge exchanges deliberated on a market basis (Breschi and Lissoni, 2001). As far as we know, few quantitative studies have attempted to disentangle the effect of these features as mechanisms of local knowledge diffusion and innovation.

Broadly speaking, the literature on collaborative research networks, and their impact on knowledge diffusion and innovation, has expanded greatly in recent years.[25] This is particularly true in the case of networks of co-inventors thanks to the availability of relevant data (co-patent data). Part of this literature has been devoted to explaining the determinants of these collaborative patterns (Hoekman et al. 2009; Maggioni and Uberti, 2008), while a further important line has focused on networks as mechanisms for inter-regional R&D spillovers (Kroll, 2009; Ponds et al., 2007, 2010), and, in particular, networks as the means by which knowledge diffuses between individuals and across firms (Breschi and Lissoni, 2004, 2006; 2009; Gomes-Casseres et al., 2006; Singh, 2005).

Singh (2005) finds strong evidence in the US that the existence of interpersonal ties in the form of co-patents increases the probability of knowledge flows, as measured by patent citations. Singh claims that geography matters especially because interpersonal networks tend to be regional in nature (Op. cit.). Similar results are found by Breschi and Lissoni (2004) for Italy. In the same line, recent findings by Breschi and Lissoni (2009), using patent applications to the European Patent Office (EPO), similarly suggest that networking activity across firms is in large part responsible for the localisation of knowledge flows, indicating that the residual effect of non-market externalities is not as great as was previously believed.

All these studies stress the importance of networks as knowledge transmission, and hence creation, mechanisms. Co-location and shared space are reported as being neither necessary nor sufficient for knowledge flows, but rather it is social distance, or social connectivity, which appears to be critical for the effective diffusion of knowledge (Boschma, 2005). If this were to be the case, the features of the inventors' network structure at any given location should play a significant role in regional innovation outcomes. In this sense, a number of macro-level empirical analyses have recently been conducted in a knowledge production function framework by Bettencourt et al. (2007a,b), Fleming et al. (2007) and Lobo and Strumsky (2008) for the case of US metropolitan statistical areas. These studies have shown that the agglomeration of inventors is much more critical in explaining regional innovation rates than structural properties of inventors' networks, such as the 'small world' configuration –which combines low average path length among individuals in a network and high levels of clustering coefficient, and which has been identified to be innovation-prone (Watts and Strogatz, 1998; Cowan and Jonard, 2004). Breschi and Lenzi (2011), by contrast, find 'small world' properties to be positively correlated with MSA's rates of innovation. The present chapter's aim is rather

[25] Recent special issues on the subject include: "Spatial knowledge diffusion through collaborative networks" Guest editors: Corinne Autant-Bernard, Jacques Mairesse and Nadine Massard, *Papers in Regional Science* 2007, 86(3): 341-525; and, more specifically on the subject of networks of co-inventors, the special issue, "Embedding network analysis in spatial studies of innovation". Guest editor: Edward M. Bergman, *The Annals of Regional Science*, 2009, 43(3): 559-833.

different, though, since it does not attempt to appraise 'small world' properties' influence on European regional innovation, but the general degree of connectivity through networks of research collaboration as well as the strength of these networks.

Similarly, earlier studies have examined how the labour mobility of inventors acts as key mechanism in the diffusion of knowledge (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Saxenian, 1994). One strand of this literature has shown the relationship between mobility and the flow of knowledge as measured by patent citations, as well as the knowledge gain by a firm hiring an inventor from another firm. For example, in a pioneering study, Almeida and Kogut (1999) show that inter-firm mobility of patent holders in the semiconductor industry of the US influences the local transfer of knowledge across firms. Similar findings are reported in the aforementioned study conducted by Breschi and Lissoni (2009) for US inventors in selected technological fields making patent applications to the EPO. In a similar vein, Agrawal et al. (2006) stress the idea that once inventors leave their workplace, they will maintain interpersonal ties with their former colleagues which can translate into a citation of their work by these co-workers. In addition, several studies (Crespi et al., 2007; Corredoria and Rosenkopf, 2006; Kim et al. 2006; Singh and Agrawal, 2009; Song et al., 2003) have stressed the role of mobility insofar as it increases the hiring firm's use of a hired inventor's prior knowledge.

Parallel to these studies, another line of research has studied mobility by focusing its attention on inventors' performance itself. For instance, mobility-productivity relationships have been studied by Hoisl (2007, 2009) for German, by Lenzi (2009) for Italian, and by Shalem and Trajtenberg (2008) for Israeli inventors. Broadly speaking, it has been shown that mobility may in fact enhance productivity (Hoisl, 2007), although results in that direction are not as robust as one would expect (Shalem and Trajtenberg, 2008), which has been attributed to what have been identified as the short-term costs of mobility.

If an individual's innovative output on moving increases and the new host firms acquire more knowledge and are more efficient in their innovative activities, the innovative capacity of a region as a whole should increase as the degree of inventors' mobility rises across firms within a region. To the best of our knowledge, there have been few empirical attempts at quantifying how this feature of the local labour market for inventors –in other words, the degree of job-to-job mobility of inventors – impacts on regional innovation outcomes, and as such constitutes one of the main contributions of this chapter.

The second part of this chapter aims to put to the forefront an important debate within the geography of innovation literature that has emerged recently, that is, the role of external knowledge linkages in the process of regional knowledge creation. Indeed, an increasing number of academics have called into question the widely accepted assumption that knowledge flows are localized. This assumption, they argue, might have limited our understanding of the ways in which knowledge flows across space (Coe and Bunnell, 2003). Certainly, recent empirical evidence casts doubts on the orthodox viewpoint outlined above and some studies have extensively explored the influence of extra-local knowledge sources on firms' innovative performance and knowledge acquisition (Owen-Smith and Powell, 2004; Gittelman, 2007; Gertler and Levite, 2005; Giuliani and Bell, 2005; Rosenkopf and Almedia, 2003; Simonen and McCann, 2008; Boschma et al., 2009).

Besides, several scholars have lately stressed the need for firms to network with extra-local knowledge pools to overcome potential situations of regional 'entropic death', 'lock-in' or 'over-embeddedness' (Boschma, 2005; Camagni, 1991; Grabher, 1993). These claims have contributed to a lively current debate among research streams about the conditions in which tacit knowledge can be transmitted at a distance and go beyond a region's confines, as well as the extent of such transmission. Indeed, it has been argued that two very close actors may have little knowledge to exchange whereas innovative production usually requires the combination of dissimilar, but related, complementary knowledge (Boschma and Frenken, 2010; Boscham and Iammarino, 2009).[26] Thus, as time passes and local interactions lead to the combination and recombination of the same pieces of knowledge, organizations end up stuck in strong social structures that tend to resist social change (Boschma and Frenken, 2010; Morrison et al., 2011) and prevent them from recognizing opportunities in new markets and technologies (Lambooy and Boschma, 2001). Thus, **'**distant contexts can be a source of novel ideas and expert insights useful for innovation processes (…). Firms therefore develop global pipelines not only to exchange products or services, but also in order to benefit from outside knowledge inputs and growth impulse' (Maskell et al., 2006, p. 998). This way, the analysis of the role of extra-regional formal linkages in the process of knowledge creation is the second main contribution of this paper.

5.3. Research design

In order to meet the goals identified in the previous sections, the KPF framework at the regional level is used. For the sake of simplicity, the local/non-local dimensions are analysed separately and the multivariate analysis is divided in two parts. Thus, we first suggest an empirical model where local mobility and networks are included as main explanatory variables under scrutiny. In the second part, extra-regional linkages are included as regressors.

Our point of departure is the simplest specification of this model:

$$Y = f(RD, HK, Z), \qquad (1)$$

where Y is the innovative output of a given region, which depends on regional R&D expenditures (RD) as well as the stock of human capital (HK). To capture a variety of returns that might affect innovation outcomes, Z are a number of time-variant controls that account for specific features of the region i at time t. Among them, the level of inventors' labour mobility within a given region, as well as the scale and density of its collaborative research networks are included. Population of the regions (POP) is also included in order to control for size and market potential. As it is customary in the related literature, it is assumed that the KPF follows a multiplicative functional form:

$$Y_{it} = e^{\theta} \cdot RD_{it}^{\beta} \cdot HK_{it}^{\gamma} \cdot POP_{it}^{\rho} \cdot Z_{it}^{\alpha} \cdot e^{\delta_i}, \qquad (2)$$

where e^{θ} is a constant term capturing the impact of all common factors affecting innovation. In additional, e^{δ_i} stands for 287 regional time-invariant fixed-effects, that allow us to capture unobserved time-invariant heterogeneity that might importantly bias our estimates if they are not considered. In particular, we refer to institutional features that may affect innovation, technology-oriented regional policies, inherited skills of the local community, prestige of research and higher education institutions, inherited innovation culture, social capital and, in general, all the historical path-dependent features that may importantly affect spatial differences in innovation rates.

5.3.1. Labour mobility, research networks and innovation

In the present chapter, social network analysis (SNA) tools are employed to investigate empirically the quantitative relationship between inventors' collaborations and levels of inventiveness.[27] We are interested in measuring some particular aspects of inventors'

[26] Note that, as stressed in Boschma and Iammarino (2009, p.295), 'extra-regional knowledge that is complementary, but not similar, to existing competences in the region will particularly enhance interactive learning. (…). If the external knowledge is unrelated, the industrial base of the region cannot absorb it and is unlikely to benefit from it. When the external knowledge is the same (…), it can be absorbed locally, but the new knowledge will not add much to the existing local knowledge base'. As we will show later on, our empirical application does not consider this distinction, which is left for future extensions.

[27] SNA has been widely applied to collaboration in research and innovation studies, although a review of detailed methodological contributions falls outside the scope of this paper. In fact, in recent years many contributions have been made to economics and economic geography using SNA tools, most notably Balconi et al. (2004), Breschi and

networks. First of all, the scale of these networks, i.e., whether a greater number of social ties are beneficial for inventive intensity. A positive effect on creativity is expected. Second, the extent of the local network is also of interest, i.e., whether a large number of local inventors involved in co-innovations is beneficial for regional innovation. Finally, we are concerned with the strength of the inventors' community ties, measured as the network density. The naïve, expected effect of density on innovation is positive. However, we should bear in mind Granovetter's (1985) warning that overly strong interpersonal ties might well hamper innovation because of the fact that, at some point, the information flowing across those ties becomes redundant and less valuable. In consequence, the scale and extent of research networks, as well as their intensity within the region, are included as additional regressors. Besides, the degree of labour mobility within the region is also included. Thus,

$$Z_{it} = g(MOB_{it}, DEGREE_{it}, CONN_{it}, DENS_{it}, X_i), \tag{3}$$

where MOB is the measure of mobility, $DEGREE$ stands for the average degree centrality of skilled workers, that is, the average 'popularity' of inventors in regions, $CONN$ stands for the overall connectivity of the local network, i.e., the inclusiveness of the local network, and $DENS$ is a measure of the density of the regional network. Finally, X controls for the existence of specialization and concentration economies. Assuming that (3) also follows a multiplicative functional form and inserting it into the logarithmic transformation of (2) yields to:

$$\begin{aligned} \ln Y_{it} &= \theta + \beta \cdot \ln RD_{it-1} + \gamma \cdot \ln HK_{it-1} + \rho \cdot POP_{it-1} + \omega_1 \cdot MOB_{it-1} + \\ &\omega_2 \cdot \ln DEGREE_{it-1} + \omega_3 \cdot CONN_{t-1} + \omega_4 \cdot \ln DENS_{it-1} + \omega_n \cdot \ln X_{it-1} + \delta_i + \varepsilon_{it} \end{aligned} \tag{4}$$

Note that the subscript t-1 is now introduced in all the explanatory variables in order to make clear that they have been time lagged one period in order to lessen endogeneity problems. Section 4 includes further details regarding the construction of all the variables used in the present analysis and a brief summary is provided in Annex 5.1.

5.3.2. Spatial heterogeneity of labour mobility and networks impacts on innovation

As labour mobility and research networks are assumed to be a fundamental factor in the creation of knowledge, an unequal distribution of such mechanisms in the territory could be a cause of regional differences in knowledge levels and economic development in general. Knowledge can therefore be considered to be a causal factor in regional disparities and it can be thought that the policies aimed at encouraging the mobility of high skilled workers or the fact of enhancing the participation in research networks (as promoted by the European Commission through Marie Curie programs or the Framework Programs) in less productive regions can constitute a key factor in the creation of knowledge, and as a consequence in development, or at least a necessary condition for it. However, the effectiveness of this policy depends in large part on each region's capacity to give returns to labour mobility and the participation in research networks. One would expect these returns to be homogeneous in all regions if they were also homogeneous in other aspects, such as industrial mix, propensity to generate and adopt innovations and technological specialisation, among others. When this is not the case, returns to labour mobility and research networks may differ between regions. Any appraisal of the value of this policy as a tool for use in regional development would therefore be particularly useful if information about the regional distribution of such returns were available.

The aim of this subsection is to analyse the existence of regional variations in the returns to labour mobility and networking, indicating that development policies based on stimulating these mechanisms of knowledge diffusion differ in effectiveness. In order to do it, we have initially introduced a cross-effect of the corresponding focal variable, both labour mobility and

---

Catalini (2009), and Ter Wal and Boschma (2009). For a more complete theoretical discussion of the methods and applications of SNA, see Wasserman and Faust (1994).

the different proxies for research networks, with a dummy for each region. This way we are able to compute a specific elasticity for each regional economy in Europe. However, with the idea of providing more general patterns of heterogeneity in the returns to labour mobility and networks, we give a step forward and obtain different elasticities according to a set of typologies of the European regions. Specifically, we consider the following six typologies:

- Type and moment of accession of the corresponding country to the EU: EU15, EU New Entrants 12, EFTA 4
- The development level of the regions: Convergence regions, Transition regions, Competitive regions
- The territorial innovation patterns across European regions: European Science-based area, Applied science area, Smart Technological specialisation area, Smart and Creative diversification area, Imitative innovation area
- The presence of science-based or high-technology sectors: Technologically advanced regions, High-tech manufacturing regions, High-tech services regions and Low-tech regions
- The importance of function like R&D and high education: Scientific regions, Research intensive regions, Human capital intensive regions and Regions with no specialisation in knowledge
- The ability to use external sources of knowledge: Knowledge networking regions, Globalising regions, Clustering regions and Non-interactive regions.

5.3.3. Labour mobility, networks and knowledge diffusion

We turn now to investigate the specific role of our foci variables, not only as an innovation creation mechanism, but also as knowledge diffusion mechanisms. It is commonplace in the related literature that close network links should prove more useful in transferring complex knowledge (Cowand and Jonard, 2004), especially that with a high component of "tacitness" (Singh, 2005). Similarly, individuals connected within a collaborative framework are more willing to learn from each other than is the case of isolated inventors. Additionally, participating in networks reduces the degree of uncertainty and provides fast access to different kinds of knowledge. All this would signal to the fact that belonging to a research network may imply higher returns of knowledge endowments, such as R&D and human capital investments, on regional innovation.

On the other hand, mobility may favour knowledge diffusion as well. Knowledge, especially that of tacit nature, is mostly embedded in individuals. Moving themselves means moving the knowledge capital they accumulate. Their movement across firms must therefore contribute to knowledge exchange between firms (Boschma et al., 2009). Skilled workers take their knowledge with them and share it in a new workplace with their new colleagues, at the same time as they provide their new employer with this knowledge. In return, they acquire new knowledge from their new colleagues, establish new links and social networks for future collaborations based on trust and, in general, promote new combinations of knowledge (Laudel, 2003; Trippl and Maier 2007). Therefore, the return obtained from the investments in R&D and human capital may increase with the level of mobile workers.

To address this issue, we allow now the coefficient of both R&D and human capital in equation (4) to be a function of a constant part, which can be identified as the direct impact on innovation, and an additional element which is a function of one of the characteristics of the local labour market (we are reluctant to include the resulting interactions in the same equation in order to minimize collinearity problems). Thus,

$$\beta = \lambda_0 + \lambda_1 \cdot F_{it-1} \text{ and } \gamma = \tau_0 + \tau_1 \cdot F_{it-1} \qquad (5)$$

where F stands for each of the variables included in the main model, that is, labour mobility, two measures of research networks, and network density. Therefore, (4) includes now interaction effects between R&D and each of the 4 variables foci in the main model, running 4 different estimations for each of the interactions included, as well as interactions between human capital and again our 4 variables under analysis.

$$
\begin{aligned}
\ln Y_{it} &= \theta + \lambda_0 \cdot \ln RD_{it-1} + \lambda_1 \cdot (F_{it-1} \cdot \ln RD_{it-1}) + \tau_0 \cdot \ln HK_{it-1} + \tau_1 \cdot (F_{it-1} \cdot \ln HK_{it-1}) \\
&+ \rho \cdot \ln POP_{it-1} + \omega_1 \cdot MOB_{it-1} + \omega_2 \cdot \ln DEGREE_{it-1} + \omega_3 \cdot CONN_{it-1} + \omega_4 \cdot \ln DENS_{it-1} + \\
&+ \omega_n \cdot \ln X_{it-1} + \delta_i + \varepsilon_{it}
\end{aligned} \tag{6}
$$

5.3.4. Cross-regional collaborations and inter-regional mobility

As stated in the previous section, a second aim of this chapter is the analysis of extra-local linkages, in the form of skilled labour mobility and spatial networks, on the innovative performance of European regions. Regions are not isolated entities not interacting with the rest of the world; rather, an increasing number of studies have identified that firms in regions source more and more their innovations in non-local knowledge interactions.

First, as it has been stated elsewhere, local knowledge diffusion is favoured by the labour mobility of skilled workers (Breschi and Lissoni, 2009; Almeida and Kogut, 1997, 1999). However, to the extent that knowledge travels along with people who master it (Breschi et al., 2010), what happens when highly-skilled individuals move in the space? Geographical mobility of knowledge workers has been regarded to be a source of knowledge diffusion across areas and, on top, is responsible for the recombination of previously unconnected pieces of knowledge that may lead to increased innovation rates. In order to analyse the role of skilled geographical mobility on the innovative performance of regions, we correlate two different measures proxying inflows of skilled migration with regional patent production. Again, within the KPF framework, where typical innovation inputs, as well as structural controls, are included as regressors, the rate of incoming skilled individuals, as well as the net rate, are included among the r.h.s. variables, running two different models in order to avoid collinearity problems. Positive and significant coefficients are expected for both variables.

Recently, several authors pinpoint at outward migration of skilled individuals as an alternative source of knowledge flows and interactions back to the home location of the left skilled employee, reverting the 'brain drain' phenomenon into 'brain gain' or 'brain circulation' (Saxenian, 2006). Thus, for instance, Agrawal et al. (2006) and Oettl and Agrawal (2008) report disproportionate knowledge flows from inventors leaving a region or a country back to their former colleagues. Kerr (2008) and Agrawal et al. (2008, 2011) do likewise and estimate disproportionate knowledge flows from ethnic inventors in the US to their origin countries, stressing the role of Diasporas in accessing frontier knowledge. Following these ideas, we also test the role of the gross migration rate (inflows plus outflows) of skilled individuals, as well as the outward migration rate, as patent production predictors in regions.

Next, we also hypothesize that the more inventors collaborate with fellow inventors outside the region, the greater are the returns on innovation. As it is for the case of geographical mobile inventors, spatial networks formation is also likely to be conducive to knowledge diffusion, knowledge recombination and innovation. At the level of European regions, Ponds et al. (2010) and Maggioni et al. (2007) show the importance of cross-regional networks to the process of knowledge diffusion. Following these ideas, we conjecture that higher amounts of patents co-authored with fellow inventors outside the region are expected to explain spatial differences in innovation.

As an extension of this hypothesis, we take on board insights from the literature on 'related variety' (Boschma and Iammarino, 2009) and break down our variable into cross-regional linkages with different areas of the world, that is, Europe, US, East-Asia, and rest of the OECD countries. The underlying logic states that when the external knowledge is the same to existing competences in the region, it can be absorbed locally, but the new knowledge will not add much to the existing local knowledge base (op. cit.). Logically, a follow-up analysis would require breaking down knowledge linkages by sectors. This type of analysis goes however beyond the scope of the present study.

5.4. Data

In order to meet the goals identified in previous sections, the KPF is estimated for 287 NUTS2 European regions of 31 countries (EU-27 plus Iceland, Liechtenstein, Norway and Switzerland). Thanks to data availability, we are in position to estimate a panel fixed-effects model of 6 periods (2001 to 2006). Again, the use of longitudinal data and the inclusion of fixed effects in our regressions allow us to improve previous estimates in a KPF framework, to the extent that these fixed effects account for a number of time-invariant unobservable characteristics of the regions that might bias our results if not included.

Next, innovation is measured by patent applications (PAT), a variable widely used in the literature to proxy innovation outcomes. As well known, this proxy presents serious caveats since not all inventions are patented, nor do they all have the same economic impact, as they are not all commercially exploitable (Griliches, 1991). In spite of these shortcomings, patent data have proved useful for proxying inventiveness as they present minimal standards of novelty, originality and potential profits, and as such are a good proxy for economically profitable ideas (Bottazzi and Peri, 2003). Patent data come from the KIT database, collected from the OECD REGPAT database. Since these data are prone to exhibit lumpiness from year to year, we have averaged out patent figures. Thus, a three-year moving average is computed for every observation, thereby mitigating the effects of annual fluctuations in this variable, especially in those less populated areas.

As for the explanatory variables, R&D expenditures data also come from the KIT project and again figures are averaged out from the same reason. Specifically, all the data were collected from EUROSTAT and some National Statistical Offices, with some elaboration for regions in specific countries (Belgium, Switzerland, Greece, Netherlands). Human capital is measured as the absolute population with tertiary education (Population aged 15 and over by ISCED level of education attained) and is extracted again from the KIT records, collected from EUROSTAT. Annual figures are considered in this case. Both variables, as well as the remaining regressors, are time-lagged one period in order to lessen endogeneity problems. Thus, for instance, the average R&D expenditures in time t are computed using data from t-3 to t-1, whereas data from t-1 is used to compute human capital figures in the t period. Population data is computed used a single (lagged) year as well, and retrieved from Eurostat databases.

The data for constructing the mobility and network variables are based on individual inventor information retrieved from EPO patents, taken from the REGPAT database (January 2010 edition). However, in spite of the vast amount of information contained in patent documents, a single ID for each inventor and anyone else is missing. In order to draw the mobility and networking history of inventors, it is necessary to identify them individually by name and surname, as well as via the other useful details contained in the patent document. The method chosen for identifying the inventors is therefore of the utmost importance in studies of this nature. In line with a growing number of researchers in the field, we apply several algorithms squeezing patent data information for singling out individual inventors (Miguélez and Gómez-Miguélez, 2011).

Once each inventor has been assigned an individual identification, mobility and network data can be calculated for each region. Note that, in line with related studies (Schilling and Phelps, 2007; Breschi and Lenzi, 2011), a 1-year lagged 5-year moving window is adopted to compute all the mobility and network variables, as well as for the case of the control variables. Thus, mobility or network measures of the period t include data from t-5 to t-1.

A "mobile" inventor is broadly defined as an individual who moves across different organisations offering his/her services (Breschi and Lissoni, 2009). Therefore, mobility can refer either to labour mobility understood in its strictest sense (an employee leaving a firm to take up a position in a new one), or to that demonstrated by consultants, freelance workers, university inventors, and the like. We assume that both constitute sources of knowledge flows to the extent that in the two instances knowledge is transferred from former employers or customers to new ones. Mobility is then proxied as the share of mobile inventors to the absolute number of inventors per region, as is usually done in the labour literature.

The design of the network variables is built upon the theory of SNA. Thus, the inventors form the nodes in the network, and these are grouped via edges or ties (in this instance, co-patents) into different components.

Two different, though complementary, variables measure the scale of network connectivity among inventors in regions. Average degree centrality is calculated by averaging out the degree centrality of the nodes (inventors) by region. The degree centrality of a node is the number of linkages it has to other nodes. That is to say, it measures how well connected, how popular, is each of the nodes. Thus, it measures the extent to which inventors in regions are prone, on average, to be connected with other inventors through networks of research collaboration. On its side, connectivity goes a little bit further and tries to take on board the scope of the local network by computing the share of inventors with at least one tie in the form of co-patent. That is, the number of connected nodes of the whole network minus the number of isolated nodes, as a proportion of the total number of nodes (inclusiveness, in SNA terms). Formally,

$$\mathrm{CONN}_{it} = \frac{\mathrm{Q}_{it} - \mathrm{NQ}_{it}}{\mathrm{Q}_{it}}, \tag{7}$$

where Q_{it} stands for the total number of inventors in region i and time t, and NQ_{it} stands for the number of isolated inventors.

The strength of these ties is proxied by the network density, which is the number of ties between inventors within the region divided by the possible number of ties within that region. Formally,

$$\mathrm{DENS}_{it} = \frac{\mathrm{T}_{it}}{\mathrm{Q}_{it}(\mathrm{Q}_{it} - 1)/2}, \tag{8}$$

where T_{it} stands for the number of edges (ties) within a given region, and Q_{it} is again the total number of inventors within that region. As stressed earlier, the expected effect (be it positive or negative) of innovation density is not so clear a priori.

As regards the variables proxying meaningful linkages across regions, the 1-year lagged 5-year moving window criteria is also adopted. The Net Migration Rate (NMR) is computed as the inflows minus outflows of inventors to the current number of inventors, for each time window. The Inward Migration Rate (IMR) corresponds only to the inflows of inventors to the current number of inventors, whereas the Outward Migration Rate (OMR) computes the outflows of inventors to the current number of inventors, again within each time window. Finally, Gross Migration Rate (GMR) measures inflows plus outflows of inventors to the current number of inventors. Note, importantly, that spatial mobility is computed through observed changes in the reported region of residence by the inventor in patent documents. Note also that we compute each movement in between the origin and the destination patent, but only if there is a maximum lapse of 5 years between them. Otherwise, the exact move date is too uncertain.

Cross-regional networks of research collaboration are computed as the sum of local patents, fractional count, co-authored with inventors from outside, to the total number of inventors of the region, within each 5-year time window. Extra-regional inventors include both European and non-European ones. In this way, as we will show later on, we are in position to estimate also the influence of extra-regional linkages broken down according to the geographical scope of these ties. Thus, cross-regional networks are computed both as a whole and broken down into: (i) linkages with other European regions (of 31 countries); (ii) linkages with the US; (iii) linkages with singular East-Asian countries (Japan, China and India); and (iv) linkages with remaining OECD countries (Australia, Brazil, Canada, Chile, Croatia, Israel, South Korea, Mexico, New Zealand, Russia, Turkey, and South Africa).

As explained in the methodological section, several variables were also included in our regressions to control for other regional time-variant features that may affect spatial differences in patent production. Thus, a specialization index and a concentration index of industries constructed using patents from 30 IPC[28] technological sectors –OST subdivision- are also included, in order to control for the influence of specialization and concentration economies on innovation (Feldman and Audretsch, 1999). To calculate the technological specialization index, we employ the following formula

$$\mathrm{SpIn}_{it} = \frac{1}{2}\sum_{j}\left|\frac{\mathrm{PAT}_{ijt}}{\mathrm{PAT}_{it}} - \frac{\mathrm{PAT}_{Cjt}}{\mathrm{PAT}_{Ct}}\right|, \qquad (9)$$

where PAT is the number of patents in each region i for each sector j, expressed as a difference for the whole sample of regions (C). The concentration index is built as follows:

$$\mathrm{ConIn}_{it} = \sum_{jt}\left(\mathrm{PAT}_{ijt}/\mathrm{PAT}_{jt}\right)^{2}. \qquad (10)$$

Three additional controls capture differences in technological content across regions: the shares of biotechnology (BIOTECH), organic chemistry (CHEM), and pharmaceuticals (PHARMA) in their patenting activity, according to the IPC classification - since these three sectors tend to be more research intensive.[29,30]

5.5. Results of the econometric specifications

5.5.1. Results on the role of research networks and labour mobility on knowledge: Evidence on the direct impact

Column (1) of Table 5.1 presents the results of the fixed effect estimation of the KPF once labour mobility of inventors as well as the scale and density of the research networks in which they participate are included as additional variables. In principle, the coefficients can be interpreted as elasticities, since the variables in the regression are either expressed in natural logarithmic form or as in percentage terms: the proportional increase in patenting activity in response to a 1% increase in a given explanatory variable. Note also that Hausman tests (Hausman, 1978) have been also computed for all the models and the null hypothesis that individual effects are uncorrelated with the independent variables is always rejected, so the fixed-effects model is preferred to the expense of the random-effects.

Some specific results are worth highlighting. In general, the KPF holds in the European regional case for the period under consideration. The elasticity of patents with respect to R&D expenditures when the FE estimation is carried out presents a significant value of 0.19, which is in line with the value obtained in the literature although in the lower limit. In fact, the elasticity goes from 0.2 to 0.9 in the USA (Jaffe, 1989; Acs et al, 1994; Anselin et al., 1997), and from 0.24 to 0.8 in the European case (Bottazzi and Peri, 2003; Moreno et al, 2005). It should be noted that with respect to these three previous contributions we exploit a more disaggregated and updated database for the European regions, covering more countries and in a panel data set. In fact, our parameter resembles more the ones obtained in the study by Moreno et al (2005), with an elasticity of 0.25, where a vector of control variables are

[28] International Patent Classification

[29] Although overall employment in these sectors would be a better proxy, these data are not available.

[30] We added a small value, 0.01, to all the explanatory variables presenting zero values in at least one observation to allow for a logarithmic transformation.

included, as in our case. Additionally, the human capital parameter is, in general, strongly significant and with the expected positive sign, with similar values to those reported elsewhere in the literature when a similar indicator is used (as in Bottazi and Peri, 2003, with values between 0.4 and 0.5).

Table 5.1. Baseline estimations. Regional networks and regional mobility

Dep. Var.: ln(Patents)$_t$‡	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
ln(RD)$_{t-1}$	0.19***	0.20***	0.16**	0.19**	0.40***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.13)
ln(HK) $_{t-1}$	0.50***	0.50***	0.46***	0.50***	0.50***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
ln(POP) $_{t-1}$	-0.19	-0.16	-0.45	-0.19	-0.02
	(0.81)	(0.82)	(0.81)	(0.81)	(0.82)
(Mobility) $_{t-1}$	0.01***	0.01*	0.01***	0.01***	0.01***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
ln(Average Degree) $_{t-1}$‡	0.04*	0.04*	-0.13***	0.04*	0.04*
	(0.02)	(0.02)	(0.05)	(0.02)	(0.02)
(Connectivity Degree) $_{t-1}$	0.02***	0.02***	0.01***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Network Density) $_{t-1}$‡	-0.18***	-0.18***	-0.17***	-0.18***	-0.32***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)
ln(SpecIn) $_{t-1}$‡	0.02	0.02	0.00	0.02	0.03
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
ln(ConIn) $_{t-1}$‡	-0.03	-0.03	-0.04	-0.03	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
(Chemistry) $_{t-1}$	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(Biotechnology) $_{t-1}$	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(Pharmaceuticals) $_{t-1}$	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(RD)$_{t-1}$* (Mobility) $_{t-1}$		-0.00			
		(0.00)			
ln(RD)$_{t-1}$* ln(Average Degree) $_{t-1}$			0.06***		
			(0.02)		
ln(RD)$_{t-1}$*(Connectivity Degree) $_{t-1}$				0.00	
				(0.00)	
ln(RD)$_{t-1}$* ln(Network Density) $_{t-1}$					0.05*
					(0.03)
Constant	1.56	1.10	5.42	1.58	-1.34
	(11.21)	(11.26)	(11.20)	(11.23)	(11.31)
Observations	1,722	1,722	1,722	1,722	1,722
Number of Regions	287	287	287	287	287
R2 within	0.1408	0.1409	0.1500	0.1408	0.1429
R2 between	0.7706	0.7639	0.7686	0.7704	0.7019
R2 overall	0.7474	0.7415	0.7421	0.7472	0.6830

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. ‡ We added 0.01 to these variables before the logarithmic transformation.

The foci variables of this study are also significant. Labour mobility, for example, is significant at 1%, presenting a parameter of 0.01, whilst the relationship between the scale of the networks and innovation is always positive and strongly significant –no matter whether it is proxied through the average degree centrality or the connectivity measure. Thus, we can conclude that collaborative research networks of inventors boost regional innovation capability and that the mobility of inventors within the local labour market of a region enhances innovative intensity. In addition, network density shows a significant negative impact on innovation intensity, which bestows credibility to Granovetter's (1985) arguments about weak ties and innovation. In other words, it seems that in the European case, strong personal ties hamper innovation once the information flowing becomes redundant. Finally, we must say that the results are robust to the inclusion of a large number of time-variant controls. In this sense, although among the control variables only the share of patents in biotechnology has a significant and negative parameter, we have decided to leave all of them in the regression. However, once they are discarded the main results on the foci variables remain.

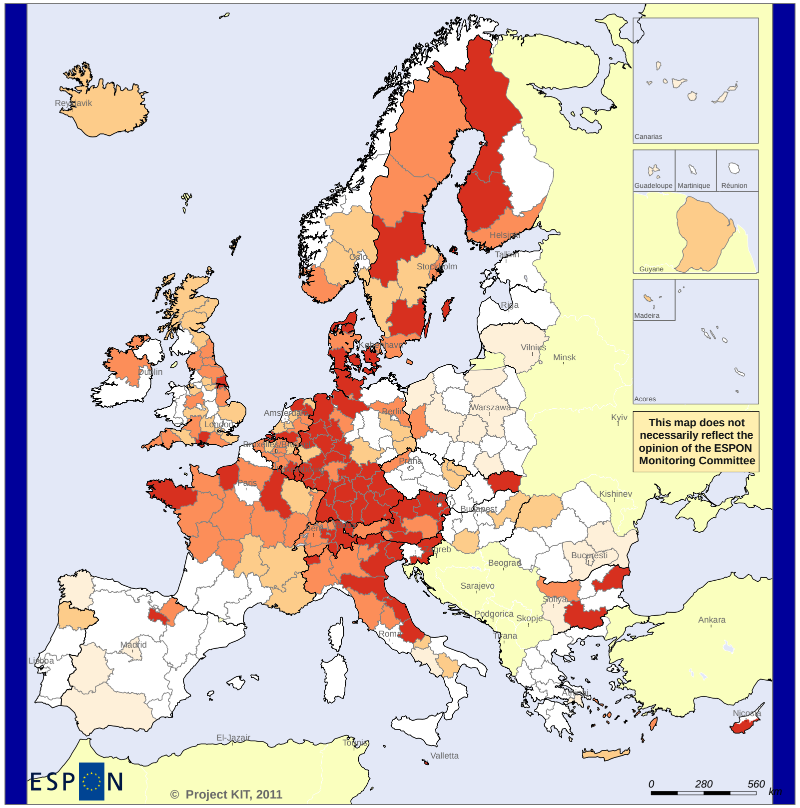
In short, the empirical analyses undertaken here support the hypotheses concerning the importance of labour mobility and networks in the local labour market for the creation of regional innovations. However, several extensions to this initial approach can now be made.

5.5.2. Results on the returns to mobility and networking by typologies of regions

The results for the whole of the European regions mask substantial regional variations in the returns to innovation with respect to mobility and networking. In order to analyse this variability of the elasticity, we have introduced cross-effects of the corresponding focal variable with a dummy for each region. This way we are able to compute a specific elasticity for each regional economy in Europe. Figures 1 to 4 show the extent of these variations.

According to Map 5.1, which plots the elasticity of innovation with respect to labour mobility, it is clear that the highest values are obtained for most of the regions in West Germany, Austria, Denmark and Switzerland, as well as some regions in the Netherlands, North France, North-East Italy, Finland and Sweden, in all the cases with figures higher than 0.09 (first quartile). On the contrary, the non-significant or lowest values of the labour mobility elasticity (values lower than 0.01, fourth quartile) are depicted in almost the whole of the Eastern countries as well as the Mediterranean ones (Spain, Portugal, Greece and the South of Italy). It is worth highlighting some exceptions to this general pattern, since in the group of regions with the highest returns we find Cyprus, two Bulgarian regions, one from the Slovak Republic and another from Spain. On the contrary, some regions hosting capital cities, such as Îlle de France, London or Berlin are among the lowest ranges of the return. A plausible explanation of this a priori contra-intuitive result is the potential existence of non-disclosure agreements between knowledge employers and employees in regions with large levels of internal competition, that prevent the later ones to reveal their secrets to other local competing firms Lissoni, 2001; Marx et al., 2007).

In the case of the elasticity of innovation with respect to the scale of the research networks in the different European regions, the maps look slightly different depending on the measure used. In the case of the average degree centrality (Map 5.3), the distribution resembles very much that of the elasticity of labour mobility just described. However, for the index of connectivity (Map 5.2), although the general pattern of high values in the core countries and lower values in the Eastern and Southern countries is maintained, it must be highlighted that some of the regions in Eastern and Southern countries are not in the range of the lowest elasticities, but in the intermediate ranges (with values between 0.02 and 0.07). Finally, looking at the network density impact on knowledge (Map 5.4), we can conclude that most of the regions where network density hampers innovation more deeply are in the countries of Germany, Austria, Denmark, Switzerland and North of Italy. In such regions, strong ties hamper innovation because the knowledge flowing becomes, at some point, redundant. On the contrary, the regions in the East as well as in the South of Europe (Portugal, West Spain, Greece and South Italy) suffer much more slightly from this redundancy in the information transmitted.



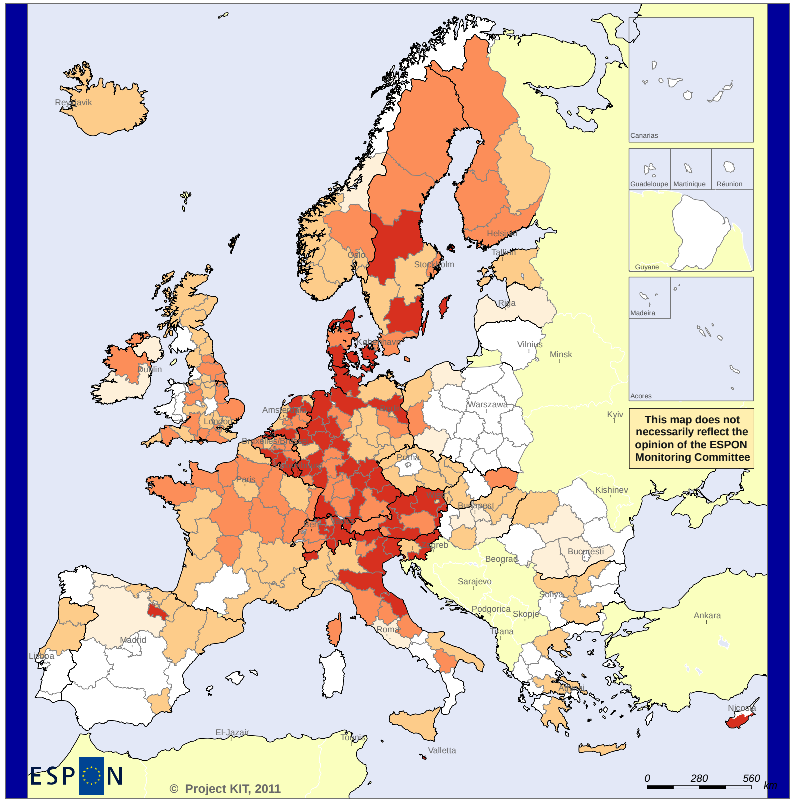
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

Regional level: NUTS 2
Source: AQR elaboration, 2011
Origin of data: EUROSTAT and OECD REGPAT
© EuroGeographics Association for administrative boundaries

Mobility impact on knowledge

- No impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

Map 5.1. Elasticity of mobility on knowledge



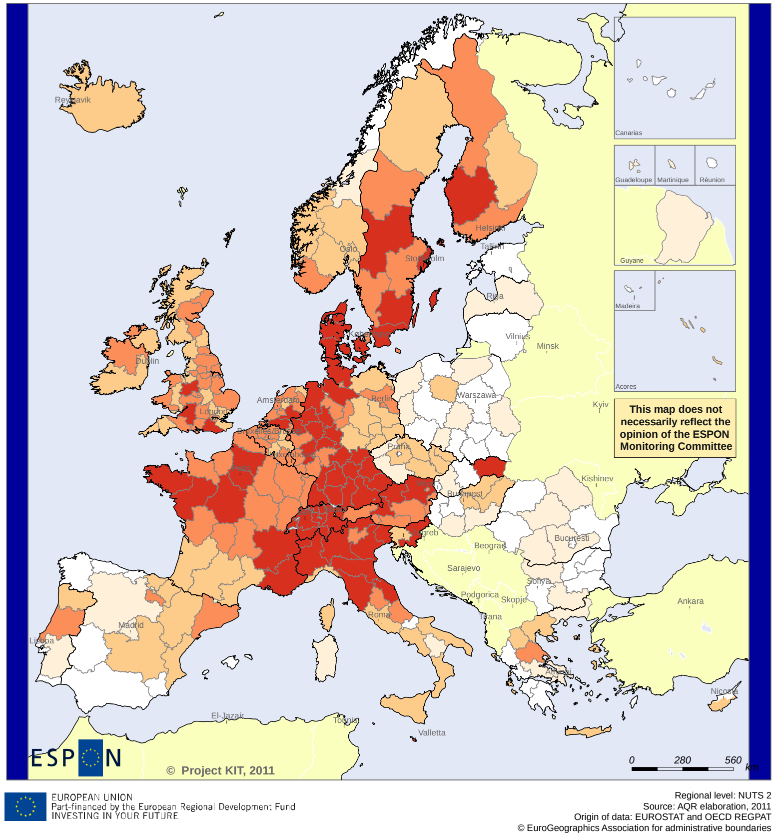
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

Regional level: NUTS 2
Source: AQR elaboration, 2011
Origin of data: EUROSTAT and OECD REGPAT
© EuroGeographics Association for administrative boundaries

Connectivity impact on knowledge

- No impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

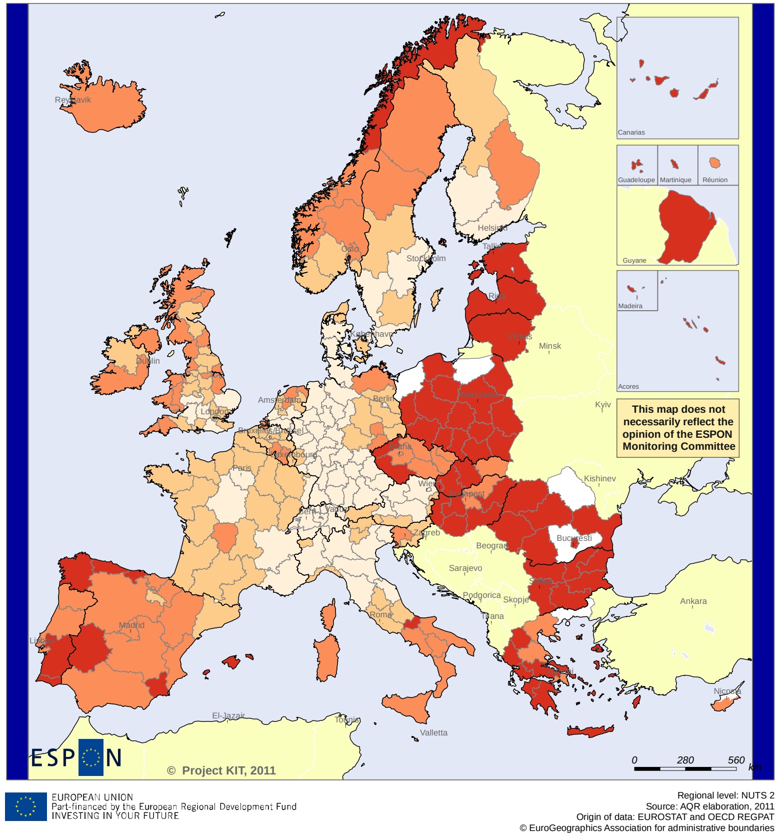
Map 5.2. Elasticity of connectivity on knowledge



Average degree centrality impact on knowledge

- No Impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

Map 5.3. Elasticity of degree centrality on knowledge



Network density impact on knowledge

- No Impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

Map 5.4. Elasticity of network density on knowledge

We turn now to the variation in the return to labour mobility and networking according to different typologies. When taking into account the kind of accession to the European Union (column 1 in Tables 5.2-5.5), it seems clear that the regions belonging to the EU15 countries are the only ones with significant returns to labour mobility and with the highest positive returns to the scope and scale of the research networks. Additionally, they are also the ones that suffer more strongly from the redundancy in the information in dense networks, as shown by the highest negative and significant return of network density.

With respect to the level of development (column 2 in Tables 5.2-5.5), the regions belonging to the competitive group show the highest positive return of knowledge to mobility, followed by the EFTA, the transition and lastly the convergence regions, being all of them significant. The same pattern is observed in the case of the two measures of the scale of the research networks, namely the degree centrality and connectivity indices: the highest in the competitive regions and the lowest in the convergence regions. Further, the same although with negative sign occurs for the return to network density, since competitive regions are hindered more importantly from the existence of dense networks.

Additionally, labour mobility is more efficiently used (i.e. shows a greater elasticity) in those regions that are more knowledge and innovation intensive, such as those in the European science-based area and in the Applied science area (column 3 in Tables 5.6-5.9). On the one hand, the first group is composed of regions that are the most knowledge and innovation intensive, and endowed with those preconditions frequently associated to greater endogenous capacity of knowledge creation (highly educated population and presence of scientific human capital). The second group includes regions that maintain a rather strong knowledge and innovation intensity, but differently from the former ones, they are more technologically diversified. In both cases, the results would suggest that the regions in these two areas are able to translate internal and external knowledge into new specific commercial applications more efficiently than in the rest, and that part of the external knowledge could come from workers coming from other enterprises. On the contrary, regions characterised by low levels of R&D spending as well as a rather narrow innovation profile (Imitative innovation area) do not benefit from the mobility of skilled workers, being their elasticity of knowledge to labour mobility non-significant in this case.

Similarly, the average effect of the research networks hides a great variety of behaviour across regions, both considering the average degree centrality and the connectivity degree indices. In fact, having an important share of inventors participating in research networks is more efficiently used (i.e. shows a greater elasticity) in regions that outperform the other in terms of their propensity to networking, such as those in the European science-based area and in the Applied science area. It must be signalled, though, that the elasticity in the case of the regions of the Smart technological application area, of the Smart and creative diversification area and the Imitative innovation area also show positive and significant elasticities, although of lower magnitude. This can be explained by their rather narrow knowledge and innovation profile. Finally, the same although with negative sign occurs for the return to network density, with regions in the European Science-based area and Applied Science area being hampered more deeply from the existence of dense networks.

Finally, taking into account the three final typologies obtained from the KIT project, both for the elasticity of mobility and that for research network the same conclusion remains: the regions belonging to the Advanced manufacturing group and technologically advanced group, those of the Research intensive area and the Knowledge networking regions obtain higher returns in terms of patents from the recombination of existing ideas embodied in mobile knowledge workers and local research networks.

Table 5.2. Regional within mobility by typologies

Dep. Var.: ln(Patents)$_t$‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
ln(RD)$_{t-1}$	0.59***	0.52***	0.56***
	(0.03)	(0.03)	(0.03)
ln(HK) $_{t-1}$	0.12**	0.04	-0.03
	(0.06)	(0.06)	(0.06)
ln(POP) $_{t-1}$	-0.02	0.15**	0.11**
	(0.06)	(0.06)	(0.06)
EU15*(Mobility) $_{t-1}$	0.03***		
	(0.00)		
New Entrants*(Mobility) $_{t-1}$	-0.00		
	(0.00)		
EFTA*(Mobility) $_{t-1}$	0.01	0.05***	
	(0.01)	(0.01)	
Convergence*(Mobility) $_{t-1}$		0.01**	
		(0.00)	
Transition*(Mobility) $_{t-1}$		0.03***	
		(0.01)	
Competitive*(Mobility) $_{t-1}$		0.07***	
		(0.01)	
Imitative innovation*(Mobility) $_{t-1}$			0.00
			(0.00)
Smart and creative*(Mobility) $_{t-1}$			0.03***
			(0.00)
Smart Techno.*(Mobility) $_{t-1}$			0.05***
			(0.01)
Applied science* (Mobility) $_{t-1}$			0.08***
			(0.01)
Science-Based* (Mobility) $_{t-1}$			0.09***
			(0.01)
ln(Average Degree) $_{t-1}$‡	0.38***	0.34***	0.34***
	(0.03)	(0.02)	(0.02)
(Connectivity Degree) $_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
ln(Network Density) $_{t-1}$‡	-0.51***	-0.46***	-0.51***
	(0.05)	(0.05)	(0.05)
Controls(1)	yes	yes	yes
Constant	0.04	-1.71**	-1.07
	(0.74)	(0.74)	(0.68)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.522	0.913	0.535

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: ln(SpecIn)$_{t-1}$; ln(ConIn)$_{t-1}$ (Share_Chemistry)$_{t-1}$; (Share_Biotechnology)$_{t-1}$; (Share_Pharmaceuticals)$_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 5.3. Average degree centrality by typologies

Dep. Var.: $\ln(\text{Patents})_t$‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
$\ln(\text{RD})_{t-1}$	0.58***	0.48***	0.58***
	(0.03)	(0.03)	(0.03)
$\ln(\text{HK})_{t-1}$	0.10*	0.07	0.03
	(0.06)	(0.06)	(0.06)
$\ln(\text{POP})_{t-1}$	-0.06	0.11*	0.03
	(0.06)	(0.06)	(0.06)
$(\text{Mobility})_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
EU15*ln(Average Degree) $_{t-1}$‡	0.48***		
	(0.03)		
New Entrants* ln(Average Degree) $_{t-1}$‡	0.12***		
	(0.04)		
EFTA* ln(Av.Degree) $_{t-1}$‡	0.18**	0.76***	
	(0.09)	(0.10)	
Convergence* ln(Av.Degree) $_{t-1}$‡		0.30***	
		(0.03)	
Transition* ln(Av.Degree) $_{t-1}$‡		0.41***	
		(0.03)	
Competitive* ln(Av.Degree) $_{t-1}$‡		1.07***	
		(0.05)	
Imitative innovation* ln(Av.Degree) $_{t-1}$‡			0.34***
			(0.03)
Smart and creative* ln(Av.Degree) $_{t-1}$‡			0.32***
			(0.03)
Smart Techno.* ln(Av.Degree) $_{t-1}$‡			0.58***
			(0.05)
Applied science* ln(Av.Degree) $_{t-1}$‡			0.83***
			(0.05)
Science-Based*ln(Av.Degree) $_{t-1}$‡			0.92***
			(0.07)
(Connectivity Degree) $_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
ln(Network Density) $_{t-1}$‡	-0.52***	-0.45***	-0.51***
	(0.05)	(0.05)	(0.05)
Controls(1)	yes	yes	yes
Constant	0.63	-1.10	-0.19
	(0.71)	(0.70)	(0.68)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.875	0.884	0.879

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: $\ln(\text{SpecIn})_{t-1}$; $\ln(\text{ConIn})_{t-1}$ $(\text{Share\_Chemistry})_{t-1}$; $(\text{Share\_Biotechnology})_{t-1}$; $(\text{Share\_Pharmaceuticals})_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 5.4. General within connectivity by typologies

Dep. Var.: $\ln(\text{Patents})_t$‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
$\ln(\text{RD})_{t-1}$	0.62***	0.55***	0.58***
	(0.03)	(0.03)	(0.03)
$\ln(\text{HK})_{t-1}$	0.12*	0.08	0.06
	(0.06)	(0.06)	(0.06)
$\ln(\text{POP})_{t-1}$	-0.09	0.01	-0.00
	(0.06)	(0.06)	(0.06)
$(\text{Mobility})_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
ln(Average Degree) $_{t-1}$‡	0.36***	0.37***	0.36***
	(0.03)	(0.02)	(0.02)
EU15*(Connectivity) $_{t-1}$	0.02***		
	(0.00)		
New Entrants*(Connectivity) $_{t-1}$	0.01***		
	(0.00)		
EFTA*(Connectivity) $_{t-1}$	0.01**	0.02***	
	(0.00)	(0.00)	
Convergence*(Connectivity) $_{t-1}$		0.01***	
		(0.00)	
Transition*(Connectivity) $_{t-1}$		0.01***	
		(0.00)	
Competitive*(Connectivity) $_{t-1}$		0.03***	
		(0.00)	
Imitative innovation* (Connectivity) $_{t-1}$			0.01***
			(0.00)
Smart and creative* ln(Av.Degree) $_{t-1}$‡			0.02***
			(0.00)
Smart Techno.*(Connectivity) $_{t-1}$			0.02***
			(0.00)
Applied science* (Connectivity) $_{t-1}$			0.03***
			(0.00)
Science-Based*(Connectivity) $_{t-1}$			0.04***
			(0.00)
ln(Network Density) $_{t-1}$‡	-0.51***	-0.46***	-0.51***
	(0.05)	(0.05)	(0.05)
Controls(1)	yes	yes	yes
Constant	1.13	0.31	0.34
	(0.72)	(0.71)	(0.68)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.870	0.876	0.875

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: $\ln(\text{SpecIn})_{t-1}$; $\ln(\text{ConIn})_{t-1}$ $(\text{Share\_Chemistry})_{t-1}$; $(\text{Share\_Biotechnology})_{t-1}$; $(\text{Share\_Pharmaceuticals})_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 5.5. Regional network density by typologies

Dep. Var.: ln(Patents)$_t$‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
ln(RD)$_{t-1}$	0.57***	0.50***	0.53***
	(0.03)	(0.03)	(0.03)
ln(HK)$_{t-1}$	0.14**	0.04	-0.04
	(0.06)	(0.06)	(0.06)
ln(POP)$_{t-1}$	-0.02	0.20***	0.14***
	(0.06)	(0.06)	(0.05)
(Mobility)$_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
ln(Average Degree)$_{t-1}$‡	0.38***	0.32***	0.34***
	(0.03)	(0.02)	(0.02)
(Connectivity)$_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
EU15*ln(Net.Density)$_{t-1}$‡	-0.58***		
	(0.05)		
New Entrants* ln(Net.Density)$_{t-1}$‡	-0.47***		
	(0.05)		
EFTA* ln(Net.Density)$_{t-1}$‡	-0.53***	-0.52***	
	(0.06)	(0.05)	
Convergence*ln(Net.Density)$_{t-1}$‡		-0.31***	
		(0.04)	
Transition* ln(Net.Density)$_{t-1}$‡		-0.40***	
		(0.04)	
Competitive* ln(Net.Density)$_{t-1}$‡		-0.59***	
		(0.04)	
Imitative innovation* ln(Net.Density)$_{t-1}$‡			-0.40***
			(0.05)
Smart and creative* ln(Net.Density)$_{t-1}$‡			-0.56***
			(0.05)
Smart Techno.* ln(Net.Density)$_{t-1}$‡			-0.64***
			(0.05)
Applied science* ln(Net.Density)$_{t-1}$‡			-0.71***
			(0.05)
Science-Based* ln(Net.Density)$_{t-1}$‡			-0.76***
			(0.05)
Controls(1)	yes	yes	yes
Constant	0.09	-2.28***	-1.71***
	(0.75)	(0.72)	(0.66)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.871	0.886	0.888

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: ln(SpecIn)$_{t-1}$; ln(ConIn)$_{t-1}$ (Share_Chemistry)$_{t-1}$; (Share_Biotechnology)$_{t-1}$; (Share_Pharmaceuticals)$_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 5.6. Regional within mobility by KIT typologies

Dep. Var.: ln(Patents)$_t$‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
ln(RD)$_{t-1}$	0.66***	0.62***	0.48***
	(0.03)	(0.03)	(0.03)
ln(HK)$_{t-1}$	0.11*	0.19***	-0.00
	(0.06)	(0.07)	(0.06)
ln(POP)$_{t-1}$	-0.16**	-0.21***	0.23***
	(0.06)	(0.07)	(0.06)
Low tech regions*(Mobility)$_{t-1}$	0.01***		
	(0.00)		
Advanced manufacturing*(Mobility)$_{t-1}$	0.05***		
	(0.01)		
Advanced Services*(Mobility)$_{t-1}$	0.02***		
	(0.01)		
Technologically-Advanced*(Mobility)$_{t-1}$	0.04***		
	(0.01)		
Scientific regions*(Mobility)$_{t-1}$		0.03***	
		(0.01)	
Research intensive*(Mobility)$_{t-1}$		0.07***	
		(0.01)	
Other specialis.*(Mobility)$_{t-1}$		0.02***	
		(0.00)	
HK intensive*(Mobility)$_{t-1}$		0.02***	
		(0.01)	
Non-interactive*(Mobility)$_{t-1}$			0.01**
			(0.00)
Clustering*(Mobility)$_{t-1}$			0.05***
			(0.01)
Globalizing*(Mobility)$_{t-1}$			0.07***
			(0.01)
Knowledge networking* (Mobility)$_{t-1}$			0.08***
			(0.01)
ln(Average Degree)$_{t-1}$‡	0.38***	0.39***	0.33***
	(0.03)	(0.03)	(0.02)
(Connectivity Degree)$_{t-1}$	0.01***	0.01***	0.02***
	(0.00)	(0.00)	(0.00)
ln(Network Density)$_{t-1}$‡	-0.52***	-0.52***	-0.47***
	(0.05)	(0.05)	(0.05)
Controls[(1)]	yes	Yes	yes
Constant	1.62**	2.44***	-2.42***
	(0.72)	(0.78)	(0.69)
Observations	1692	1692	1722
Number of Regions	282	282	287
Adjusted R2	0.879	0.882	0.884

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses. (1)**Control variables include**: ln(SpecIn)$_{t-1}$; ln(ConIn)$_{t-1}$ (Share_Chemistry)$_{t-1}$; (Share_Biotechnology)$_{t-1}$; (Share_Pharmaceuticals)$_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 5.7. Average degree centrality by KIT typologies.

Dep. Var.: ln(Patents)$_t$ ‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
ln(RD)$_{t-1}$	0.66***	0.61***	0.44***
	(0.03)	(0.03)	(0.03)
ln(HK) $_{t-1}$	0.10	0.13**	0.01
	(0.06)	(0.06)	(0.06)
ln(POP) $_{t-1}$	-0.14**	-0.14**	0.23***
	(0.06)	(0.06)	(0.05)
(Mobility) $_{t-1}$	0.02***	0.02***	0.01***
	(0.00)	(0.00)	(0.00)
Low tech regions*ln(AverageDegree) $_{t-1}$ ‡	0.34***		
	(0.03)		
Advanced manufacturing*ln(Average Degree) $_{t-1}$ ‡	0.64***		
	(0.04)		
Advanced Services*ln(Average Degree) $_{t-1}$ ‡	0.47***		
	(0.05)		
Technologically-Advanced*ln(Average Degree) $_{t-1}$ ‡	0.66***		
	(0.05)		
Scientific regions*ln(Average Degree) $_{t-1}$ ‡		0.55***	
		(0.06)	
Research intensive*ln(Average Degree) $_{t-1}$ ‡		0.98***	
		(0.06)	
Other specialis.*ln(Average Degree) $_{t-1}$ ‡		0.38***	
		(0.03)	
HK intensive*ln(Average Degree) $_{t-1}$ ‡		0.49***	
		(0.05)	
Non-interactive*ln(Average Degree) $_{t-1}$ ‡			0.30***
			(0.02)
Clustering*ln(Average Degree) $_{t-1}$ ‡			0.91***
			(0.06)
Globalizing*ln(Average Degree) $_{t-1}$ ‡			1.08***
			(0.09)
Knowledge networking*ln(Average Degree) $_{t-1}$ ‡			1.28***
			(0.05)
(Connectivity Degree) $_{t-1}$	0.01***	0.01***	0.02***
	(0.00)	(0.00)	(0.00)
ln(Network Density) $_{t-1}$ ‡	-0.51***	-0.51***	-0.44***
	(0.05)	(0.05)	(0.04)
Controls$^{(1)}$	yes	Yes	yes
Constant	1.58**	1.71**	-2.38***
	(0.69)	(0.72)	(0.65)
Observations	1,692	1,692	1,722
Number of Regions	282	282	287
Adjusted R2	0.879	0.883	0.893

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: ln(SpecIn)$_{t-1}$; ln(ConIn)$_{t-1}$ (Share_Chemistry)$_{t-1}$; (Share_Biotechnology)$_{t-1}$; (Share_Pharmaceuticals)$_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 5.8. General within connectivity by KIT typologies

Dep. Var.: ln(Patents)$_t$‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
ln(RD)$_{t-1}$	0.67***	0.62***	0.46***
	(0.03)	(0.03)	(0.03)
ln(HK) $_{t-1}$	0.15**	0.23***	0.05
	(0.06)	(0.07)	(0.06)
ln(POP) $_{t-1}$	-0.20***	-0.26***	0.12**
	(0.06)	(0.06)	(0.06)
(Mobility) $_{t-1}$	0.02***	0.02***	0.01***
	(0.00)	(0.00)	(0.00)
ln(Average Degree) $_{t-1}$‡	0.38***	0.39***	0.37***
	(0.03)	(0.03)	(0.02)
Low tech regions*(Connectivity) $_{t-1}$	0.01***		
	(0.00)		
Advanced manufac.*(Connectivity) $_{t-1}$	0.02***		
	(0.00)		
Advanced Services*(Connectivity) $_{t-1}$	0.01***		
	(0.00)		
Technologically-Advanced*(Connectivity) $_{t-1}$	0.02***		
	(0.00)		
Scientific regions*(Connectivity) $_{t-1}$		0.01***	
		(0.00)	
Research intensive*(Connectivity) $_{t-1}$		0.03***	
		(0.00)	
Other specialis.* (Connectivity) $_{t-1}$		0.01***	
		(0.00)	
HK intensive*(Connectivity) $_{t-1}$		0.01***	
		(0.00)	
Non-interactive*(Connectivity) $_{t-1}$			0.01***
			(0.00)
Clustering*(Connectivity) $_{t-1}$			0.03***
			(0.00)
Globalizing*(Connectivity) $_{t-1}$			0.04***
			(0.00)
Knowledge networking*(Connectivity) $_{t-1}$			0.05***
			(0.00)
ln(Network Density) $_{t-1}$‡	-0.54***	-0.52***	-0.45***
	(0.05)	(0.05)	(0.05)
Controls(1)	yes	Yes	yes
Constant	1.89***	2.85***	-0.63
	(0.68)	(0.73)	(0.66)
Observations	1,692	1,692	1,722
Number of Regions	282	282	287
Adjusted R2	0.880	0.881	0.884

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: ln(SpecIn)$_{t-1}$; ln(ConIn)$_{t-1}$ (Share_Chemistry)$_{t-1}$; (Share_Biotechnology)$_{t-1}$; (Share_Pharmaceuticals)$_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 5.9. Regional network density by KIT typologies

Dep. Var.: $\ln(\text{Patents})_t$ ‡	(2) Pooled OLS	(4) Pooled OLS	(6) Pooled OLS
$\ln(\text{RD})_{t-1}$	0.66***	0.61***	0.43***
	(0.03)	(0.03)	(0.03)
$\ln(\text{HK})_{t-1}$	0.11*	0.20***	0.02
	(0.06)	(0.07)	(0.06)
$\ln(\text{POP})_{t-1}$	-0.15**	-0.21***	0.27***
	(0.06)	(0.07)	(0.05)
$(\text{Mobility})_{t-1}$	0.02***	0.02***	0.01***
	(0.00)	(0.00)	(0.00)
ln(Average Degree) $_{t-1}$ ‡	0.35***	0.39***	0.30***
	(0.03)	(0.02)	(0.02)
(Connectivity Degree) $_{t-1}$	0.01***	0.01***	0.02***
	(0.00)	(0.00)	(0.00)
Low tech regions*ln(Net.Density) $_{t-1}$ ‡	-0.46***		
	(0.05)		
Advanced manufacturing*ln(Net.Density) $_{t-1}$ ‡	-0.60***		
	(0.05)		
Advanced Services*ln(Net.Density) $_{t-1}$ ‡	-0.52***		
	(0.05)		
Technologically-Advanced*ln(Net.Density) $_{t-1}$ ‡	-0.58***		
	(0.05)		
Scientific regions*ln(Net.Density) $_{t-1}$ ‡		-0.54***	
		(0.05)	
Research intensive*ln(Net.Density) $_{t-1}$ ‡		-0.68***	
		(0.05)	
Other specialis.*ln(Net.Density) $_{t-1}$ ‡		-0.51***	
		(0.05)	
HK intensive*ln(Net.Density) $_{t-1}$ ‡		-0.51***	
		(0.05)	
Non-interactive*ln(Net.Density) $_{t-1}$ ‡			-0.42***
			(0.04)
Clustering*ln(Net.Density) $_{t-1}$ ‡			-0.63***
			(0.04)
Globalizing*ln(Net.Density) $_{t-1}$ ‡			-0.68***
			(0.05)
Knowledge networking*ln(Net.Density) $_{t-1}$ ‡			-0.74***
			(0.04)
Controls(1)	yes	Yes	yes
Constant	1.53**	2.35***	-3.40***
	(0.71)	(0.79)	(0.64)
Observations	1,692	1,692	1,722
Number of Regions	282	282	287
Adjusted R2 & Overall R2(3)	0.881	0.883	0.897

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: $\ln(\text{SpecIn})_{t-1}$; $\ln(\text{ConIn})_{t-1}$ $(\text{Share\_Chemistry})_{t-1}$; $(\text{Share\_Biotechnology})_{t-1}$; $(\text{Share\_Pharmaceuticals})_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

5.5.3. Results on the indirect impact of labour mobility and research networks

As discussed in the research design section, there are theoretical arguments supporting the indirect effects of networking and labour mobility due to knowledge diffusion. As a consequence, the fact of belonging to a research network would imply higher returns to the investments made in R&D and human capital, whereas their returns would also increase with the level of mobile workers.

The results provided in columns (2) to (5) of Table 5.10 gives insights with respect to these hypotheses through the introduction of cross-effects between these two variables (labour mobility and networks) and R&D.

Specifically, we do obtain that regions with higher number of individuals connected within a research network (measured through the average degree centrality measure) may obtain higher returns to R&D investments, probably due to the fact that its inventors are more prone to learn from each other, with faster access to new and complement knowledge. However, when the cross-effect is computed with the index of connectivity degree, no significant parameter is obtained. Additionally, it seems that the density of the network does not imply a reduction of the R&D return, so that we can conclude that even with highly dense networks, researchers belonging to networks may obtain higher returns from the investments made in innovation than in the case of isolated inventors.

However, the parameter for the cross-effect between R&D and labour mobility is not significant. We have, therefore, not obtained evidence that in regions with high levels of mobile workers, the investment made in R&D is more profitable that in those with lower levels of labour mobility.

We now turn to analysing the reinforcing effects of networks and mobility on human capital investments returns on patent production. Results provided in Table 5.10 offer similar conclusions than the ones above. What is more, all the interactions between human capital and our 4 focal variables are positive and significant, indicating the importance of these features to enhance human capital externalities in regions and their impact on local inventiveness levels.

5.5.4. Results on the existence of cross-regional linkages

We turn now to the estimation that includes cross-regional collaborations in patenting as well as inter-regional mobility (Table 5.11) in order to obtain empirical evidence concerning the relevance of cross-regional knowledge for the generation of innovation. The results corroborate the importance of the inflow of skilled-workers for a regional economy, since only the variable considering inward migration rates of such workers present positive and significant parameters. That is, the greater the number of inventors moving into a region, the greater the patenting activity of such region. This geographical mobility of knowledge workers can be considered, thus, a source of knowledge diffusion, allowing for a recombination of previously unconnected pieces of knowledge. However, the other three variables proxying for geographical mobility of knowledge workers (Net migration rate, Outward migration rate and Gross migration rate) offer a non significant parameter. This would point to the fact that once the workers have moved to other regions, the contacts they maintain with their former colleagues do not seem to play a significant role in the patenting activity of a region. Outward migration of skilled individuals cannot be considered, therefore, as an alternative source of knowledge flows and interactions back to the home location of the left skilled employee.

Table 5.10. Baseline estimations. Interaction with HK only

Dep. Var.: ln(Patents)$_t$‡	(1) FE	(2) FE	(3) FE	(4) FE
ln(RD)$_{t-1}$	0.17**	0.14**	0.22***	0.17**
	(0.07)	(0.07)	(0.07)	(0.07)
ln(HK) $_{t-1}$	0.46***	0.45***	0.62***	1.28***
	(0.10)	(0.10)	(0.11)	(0.20)
ln(POP) $_{t-1}$	-0.08	-0.36	-0.19	-0.17
	(0.82)	(0.81)	(0.81)	(0.81)
(Mobility) $_{t-1}$	-0.01	0.00	0.01***	0.00
	(0.01)	(0.00)	(0.00)	(0.00)
ln(Average Degree) $_{t-1}$‡	0.03	-0.33***	0.03	0.05**
	(0.02)	(0.08)	(0.02)	(0.02)
(Connectivity Degree) $_{t-1}$	0.02***	0.01***	0.04***	0.01***
	(0.00)	(0.00)	(0.01)	(0.00)
ln(Network Density) $_{t-1}$‡	-0.19***	-0.19***	-0.18***	-0.94***
	(0.04)	(0.04)	(0.04)	(0.18)
ln(SpecIn) $_{t-1}$‡	0.03	0.00	0.04	-0.03
	(0.11)	(0.11)	(0.11)	(0.11)
ln(ConIn) $_{t-1}$‡	-0.03	-0.01	-0.03	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)
(Chemistry) $_{t-1}$	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
(Biotechnology) $_{t-1}$	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
(Pharmaceuticals) $_{t-1}$	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
ln(HK) $_{t-1}$* (Mobility) $_{t-1}$	0.00*			
	(0.00)			
ln(HK) $_{t-1}$* ln(Average Degree) $_{t-1}$		0.10***		
		(0.02)		
ln(HK) $_{t-1}$*(Connectivity Degree) $_{t-1}$			0.01**	
			(0.00)	
ln(HK) $_{t-1}$* ln(Network Density) $_{t-1}$				0.18***
				(0.04)
Constant	0.11	4.47	0.93	-1.54
	(11.23)	(11.15)	(11.19)	(11.16)
Observations	1,722	1,722	1,722	1,722
Number of Regions	287	287	287	287
R2 within	0.1427	0.1528	0.1440	0.1523
R2 between	0.7353	0.7080	0.7919	0.7168
R2 overall	0.7148	0.6813	0.7691	0.6941

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. ‡ We added 0.01 to these variables before the logarithmic transformation.

In relation with the outside collaborations in the development of patents and their impact on the patenting activity of a region, we obtain a positive and significant impact. However, in column (5) of Table 5.11, when the co-patenting variable is broken down according to the geographical scope of the linkages (with other European regions, with the US, with singular East-Asian countries and with remaining OECD countries), only co-patents with the US and the remaining OECD countries turn out to be significant. The underlying logic of this exercise would state that when the external knowledge is the same to existing competences in the region, it can be absorbed locally, but the new knowledge will not add much to the existing local one (Boschma and Iammarino 2009). This way, one possible interpretation would be that the collaborations maintained between inventors in Europe and other OECD countries or the US provide with less redundant pieces of knowledge, which would allow enhancing creativity.

Again, the average results for the whole of the European regions mask substantial regional variations in the elasticities of innovation with respect to cross-regional mobility and networking. With the inclusion of a cross-effect of the corresponding focal variable with a dummy for each region, we are able to compute a specific elasticity for each regional economy in Europe. Map 5.5 and 5.6 show the extent of these variations.

Table 5.11. External links and innovation: Mobility and cross-regional co-patents

Dep. Var.: ln(Patents)$_t$ ‡	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
ln(RD)$_{t-1}$	0.15**	0.15**	0.14**	0.15**	0.11
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
ln(HK)$_{t-1}$	0.63***	0.69***	0.71***	0.70***	0.65***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
ln(POP)$_{t-1}$	1.12	0.51	0.57	0.49	0.88
	(0.81)	(0.81)	(0.82)	(0.82)	(0.80)
(Net Migration Rate)$_{t-1}$	0.55				
	(0.35)				
(Inward Migration Rate)$_{t-1}$		0.40*			0.39*
		(0.21)			(0.21)
(Outward Migration Rate)$_{t-1}$			0.17		
			(0.11)		
(Gross Migration Rate)$_{t-1}$				0.21	
				(0.22)	
ln(Cross-regional patents)$_{t-1}$	0.05**	0.05**	0.05**	0.05**	
	(0.02)	(0.02)	(0.02)	(0.02)	
ln(Cross-regional pat. Europe)$_{t-1}$					0.03
					(0.02)
ln(Cross-regional patents US)$_{t-1}$					0.04**
					(0.02)
ln(Cross-regional patents Asia)$_{t-1}$					-0.02
					(0.03)
ln(Cross-regional patents remaining OECD countries)$_{t-1}$					0.12***
					(0.02)
ln(SpecIn)$_{t-1}$ ‡	0.02	0.03	0.04	0.04	0.03
	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)
ln(ConIn)$_{t-1}$ ‡	-0.03	-0.02	-0.03	-0.03	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
(Chemistry)$_{t-1}$	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(Biotechnology)$_{t-1}$	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(Pharmaceuticals)$_{t-1}$	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-16.03	-10.52	-10.59	-11.68	-12.20
	(11.13)	(11.25)	(11.35)	(11.41)	(11.20)
Observations	1,722	1,722	1,722	1,722	1,722
Number of Regions	287	287	287	287	287
R2 within	0.0996	0.1008	0.0984	0.0997	0.1193
R2 between	0.4439	0.5091	0.4909	0.5071	0.4299
R2 overall	0.4351	0.4984	0.4807	0.4965	0.4220

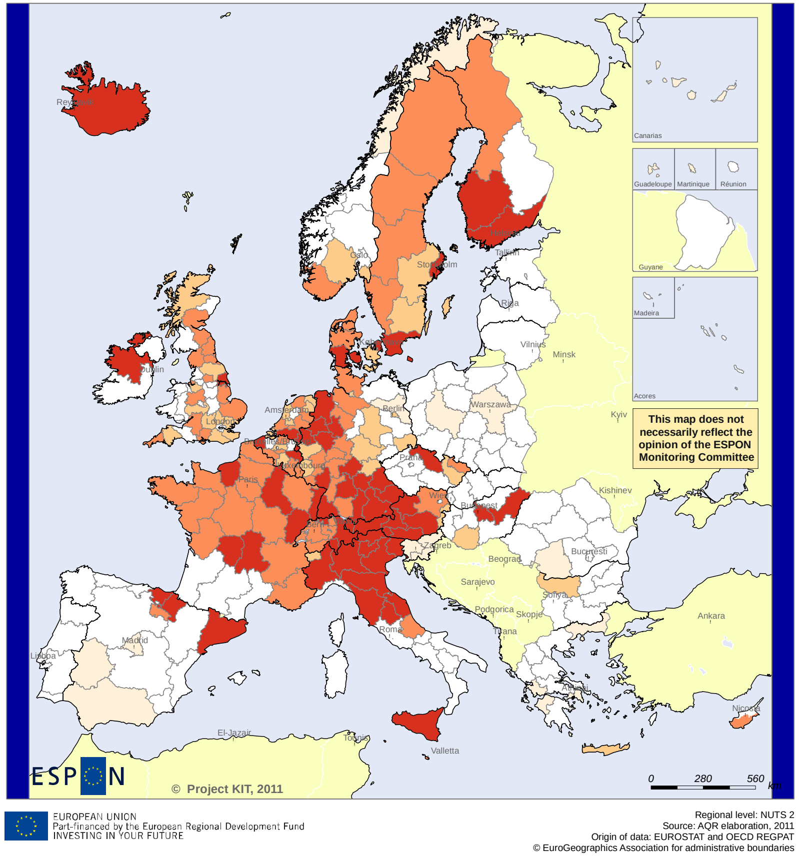
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. ‡ We added 0.01 to these variables before the logarithmic transformation. Since the Net Migration Rate ranges [-1,1], we avoid the logarithmic transformation of all the cross-regional mobility variables. In consequence, their sign and significance can be fairly informative, but any interpretation of their magnitude should be treated with caution.

Map 5.5 plots the elasticity of innovation with respect to geographical mobility. We observe that, as usual in the returns to innovation, the highest values are obtained in some of the regions in Germany, Austria, Denmark, Belgium, the Netherlands and Switzerland, as well as some Finnish and French regions. However, different from other figures, we must highlight the following: firstly, only a little number of regions in those countries get elasticities in the upper quartile; secondly, in any of the cases the regions hosting the capital cities are in this upper range of elasticities; and thirdly, among the regions with the highest elasticities we find many Italian regions (in the north-half part of the country), 3 Spanish regions (Catalonia, the Basque Country and Navarra), 1 Hungarian region (Eszak Alfold), the region of Border Midland in Ireland or Iceland.

A different pattern is detected for the elasticity of innovation with respect to cross-regional co-patenting (Map 5.6). We note that, as usual, many German regions are in the first quartile, together with two Swiss, one Austrian, one Belgian, one Finnish, 2 Dutch, 3 Norwegian, and five British regions, as well as Iceland and Liechtenstein. However, differently from other elasticities of innovation: first, it is only some few regions in those countries that obtain high elasticities; second, some regions in Spain (Galicia and Islas Canarias), in Italy (Abruzzo, and none in the North), in Hungary (Eszak Alfold), in Ireland (Border Midland), in Slovenia (Vzhodna) as well as the whole Iceland, also report very high elasticities of innovation to the co-patenting activity with inventors in other regions.

In sum, from these two maps we can conclude, therefore, that the regions benefiting from knowledge coming from other regions –both in the form of mobile skilled workers and research networks- are not so concentrated in the core of Europe. Put differently, some peripheral regions might get larger advantages –in terms of returns on innovation- in building knowledge linkages with distant knowledge hotspots, compared to the core regions, which most likely source their innovations from their local pools of ideas or the ones from their immediate vicinity.

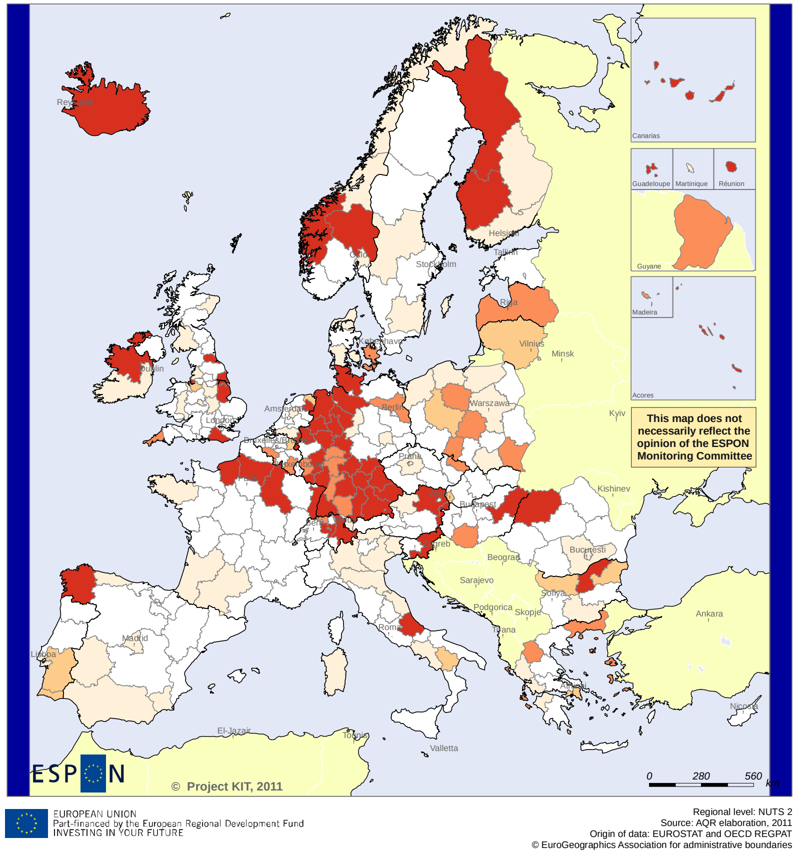
As in the within-the-region case, we turn now to the variation in the return to geographical mobility and networking according to different typologies. According to the level of development (column 2 in Tables 5.12-5.13), the regions belonging to the competitive group show the highest positive return of knowledge to cross-regional mobility and co-patenting, followed by the EFTA and the transition regions, being all of them significant, whereas the convergence regions do not seem to benefit from this geographical diffusion of knowledge. Additionally, the return obtained from this spatial mobility and networks is greater in those regions that are more knowledge and innovation intensive, such as those in the European science-based area and in the Applied science area (column 3 in Tables 5.12-5.13). This is not strange since the regions in these two groups are the most knowledge and innovation intensive, and endowed with those preconditions frequently associated to greater endogenous capacity of knowledge creation (highly educated population and presence of scientific human capital). On the contrary, regions in the Imitative innovation area and Smart and creative diversification area, characterised by knowledge and innovation variables that show smaller values than the EU average, do not benefit from this cross-regional diffusion of knowledge.



Cross-regional mobility impact on knowledge

- No impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

Map 5.5. Elasticity of cross-regional mobility on knowledge



Cross-regional research network impact on knowledge

- No impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

Map 5.6. Elasticity of cross-regional research network on knowledge

Table 5.12. Regional extra-local in-mobility by typologies

Dep. Var.: ln(Patents)$_t$‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
ln(RD)$_{t-1}$	0.85***	0.75***	0.83***
	(0.02)	(0.02)	(0.02)
ln(HK) $_{t-1}$	0.23***	0.17***	0.16**
	(0.06)	(0.06)	(0.06)
ln(POP) $_{t-1}$	-0.25***	0.01	-0.12**
	(0.06)	(0.06)	(0.06)
EU15*(I.M.R.) $_{t-1}$	-0.93***		
	(0.32)		
New Entrants*(I.M.R.) $_{t-1}$	-0.21		
	(0.56)		
EFTA*(I.M.R.) $_{t-1}$	-7.64***	7.42***	
	(2.74)	(2.76)	
Convergence*(I.M.R.) $_{t-1}$		-1.19***	
		(0.27)	
Transition*(I.M.R.) $_{t-1}$		2.23**	
		(0.97)	
Competitive*(I.M.R.) $_{t-1}$		12.09***	
		(0.91)	
Imitative innovation*(I.M.R.) $_{t-1}$			-1.78***
			(0.37)
Smart and creative*(I.M.R.) $_{t-1}$			-0.58
			(0.43)
Smart Techno.*(I.M.R.) $_{t-1}$			2.33***
			(0.82)
Applied science* (I.M.R.) $_{t-1}$			5.82***
			(0.89)
Science-Based* (I.M.R.) $_{t-1}$			7.27***
			(1.63)
ln(Cross-regional patents) $_{t-1}$‡	0.29***	0.26***	0.27***
	(0.02)	(0.02)	(0.02)
Controls(1)	yes	Yes	yes
Constant	5.29***	1.71**	3.57***
	(0.72)	(0.72)	(0.70)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.854	0.870	0.859

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: ln(SpecIn)$_{t-1}$; ln(ConIn)$_{t-1}$ (Share_Chemistry)$_{t-1}$; (Share_Biotechnology)$_{t-1}$; (Share_Pharmaceuticals)$_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation. Since the Net Migration Rate ranges [-1,1], we avoid the logarithmic transformation of all the cross-regional mobility variables. In consequence, their sign and significance can be fairly informative, but any interpretation of their magnitude should be treated with caution.

Table 5.13. Regional extra-local co-patents by typologies

Dep. Var.: ln(Patents)$_t$ ‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
$\ln(RD)_{t-1}$	0.84***	0.76***	0.83***
	(0.03)	(0.03)	(0.02)
$\ln(HK)_{t-1}$	0.27***	0.17**	0.17***
	(0.07)	(0.06)	(0.07)
$\ln(POP)_{t-1}$	-0.17***	0.06	-0.06
	(0.07)	(0.07)	(0.06)
(Inward Migration Rate) $_{t-1}$	-0.29	0.14	-0.32
	(0.30)	(0.29)	(0.29)
EU15*ln(Cross-regional pat.) $_{t-1}$	0.12***		
	(0.03)		
New Entrants*ln(Cross-regional pat.) $_{t-1}$	0.03		
	(0.03)		
EFTA* ln(Cross-regional pat.) $_{t-1}$	0.03	0.34***	
	(0.09)	(0.09)	
Convergence* ln(Cross-regional pat.) $_{t-1}$		-0.03	
		(0.02)	
Transition* ln(Cross-regional pat.) $_{t-1}$		0.16***	
		(0.05)	
Competitive* ln(Cross-regional pat.) $_{t-1}$		0.38***	
		(0.04)	
Imitative innovation*ln(Cross-regional pat.) $_{t-1}$			-0.01
			(0.03)
Smart and creative* ln(Cross-regional pat.) $_{t-1}$			-0.00
			(0.03)
Smart Techno.* ln(Cross-regional pat.) $_{t-1}$			0.14***
			(0.04)
Applied science* ln(Cross-regional pat.) $_{t-1}$			0.31***
			(0.04)
Science-Based* ln(Cross-regional pat.) $_{t-1}$			0.26***
			(0.05)
Controls$^{(1)}$	yes	Yes	yes
Constant	4.59***	1.65**	3.18***
	(0.77)	(0.79)	(0.74)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.841	0.851	0.848

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: $\ln(SpecIn)_{t-1}$; $\ln(ConIn)_{t-1}$ $(Share\_Chemistry)_{t-1}$; $(Share\_Biotechnology)_{t-1}$; $(Share\_Pharmaceuticals)_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation. Since the Net Migration Rate ranges [-1,1], we avoid the logarithmic transformation of all the cross-regional mobility variables. In consequence, their sign and significance can be fairly informative, but any interpretation of their magnitude should be treated with caution.

Finally, if we look at the three typologies obtained from the KIT project, both for the elasticity of spatial mobility and co-patenting, very similar conclusions to those for the internal to the region variables are obtained: the elasticity is higher in the regions belonging to the Research intensive area and the Knowledge networking group (tables 5.14 and 5.15). However, there is a discrepancy in the typology following the specialisation pattern: it seems that the regions specialised in advanced manufacturing are those obtaining higher returns to cross-region co-patenting (the same as for within the region co-patenting) but not in the case of geographical mobility, where the regions specialised in advanced services get higher elasticities.

Table 5.14. Regional extra-local in-mobility by KIT typologies

Dep. Var.: $\ln(\text{Patents})_t^{‡}$	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
$\ln(\text{RD})_{t-1}$	0.86***	0.80***	0.83***
	(0.02)	(0.02)	(0.02)
$\ln(\text{HK})_{t-1}$	0.11*	0.17***	0.18***
	(0.06)	(0.06)	(0.06)
$\ln(\text{POP})_{t-1}$	-0.15**	-0.19***	-0.12**
	(0.06)	(0.06)	(0.06)
Low tech regions *(I.M.R.) $_{t-1}$	-2.80***		
	(0.52)		
Advanced manufacturing *(I.M.R.) $_{t-1}$	2.31***		
	(0.59)		
Advanced Services *(I.M.R.) $_{t-1}$	3.48***		
	(0.87)		
Technologically-Advanced *(I.M.R.) $_{t-1}$	1.64**		
	(0.78)		
Scientific regions *(I.M.R.) $_{t-1}$		3.91***	
		(1.24)	
Research intensive *(I.M.R.) $_{t-1}$		17.84***	
		(1.62)	
Other specialis.*(I.M.R.) $_{t-1}$		-0.45	
		(0.38)	
HK intensive *(I.M.R.) $_{t-1}$		3.05***	
		(0.98)	
Non-interactive *(I.M.R.) $_{t-1}$			-2.27***
			(0.31)
Clustering * (I.M.R.) $_{t-1}$			2.05
			(1.64)
Globalizing * (I.M.R.) $_{t-1}$			2.56*
			(1.42)
Knowledge networking * (I.M.R.) $_{t-1}$			3.60***
			(0.50)
$\ln(\text{Cross-regional patents})_{t-1}^{‡}$	0.27***	0.28***	0.27***
	(0.02)	(0.02)	(0.02)
Controls(1)	yes	yes	yes
Constant	4.26***	4.77***	3.53***
	(0.71)	(0.73)	(0.69)
Observations	1,692	1,692	1,722
Number of Regions	282	282	287
Adjusted R2	0.863	0.868	0.862

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: $\ln(\text{SpecIn})_{t-1}$; $\ln(\text{ConIn})_{t-1}$ $(\text{Share\_Chemistry})_{t-1}$; $(\text{Share\_Biotechnology})_{t-1}$; $(\text{Share\_Pharmaceuticals})_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation. Since the Net Migration Rate ranges [-1,1], we avoid the logarithmic transformation of all the cross-regional mobility variables. In consequence, their sign and significance can be fairly informative, but any interpretation of their magnitude should be treated with caution.

Table 5.15. Regional extra-local co-patents by KIT typologies

Dep. Var.: ln(Patents)$_t$ ‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
ln(RD)$_{t-1}$	0.89***	0.88***	0.83***
	(0.02)	(0.02)	(0.02)
ln(HK)$_{t-1}$	0.19***	0.21***	0.21***
	(0.06)	(0.06)	(0.06)
ln(POP)$_{t-1}$	-0.26***	-0.30***	-0.18***
	(0.06)	(0.06)	(0.06)
(Inward Migration Rate)$_{t-1}$	-0.18	-0.08	-0.87***
	(0.38)	(0.38)	(0.29)
Low tech regions *ln(Cross-regional pat.)$_{t-1}$	0.26***		
	(0.03)		
Advanced manufacturing *ln(Cross-regional pat.)$_{t-1}$	0.49***		
	(0.05)		
Advanced Services * ln(Cross-regional pat.)$_{t-1}$	0.07		
	(0.06)		
Technologically-Advanced * ln(Cross-regional pat.)$_{t-1}$	0.30***		
	(0.08)		
Scientific regions * ln(Cross-regional pat.)$_{t-1}$		-0.18**	
		(0.08)	
Research intensive * ln(Cross-regional pat.)$_{t-1}$		0.94***	
		(0.13)	
Other specialis.*ln(Cross-regional pat.)$_{t-1}$		0.30***	
		(0.02)	
HK intensive * ln(Cross-regional pat.)$_{t-1}$		0.26***	
		(0.06)	
Non-interactive * ln(Cross-regional pat.)$_{t-1}$			0.27***
			(0.02)
Clustering * ln(Cross-regional pat.)$_{t-1}$			-0.22
			(0.15)
Globalizing * ln(Cross-regional pat.)$_{t-1}$			0.22
			(0.20)
Knowledge networking * ln(Cross-regional pat.)$_{t-1}$			0.58***
			(0.06)
Controls(1)	yes	yes	yes
Constant	5.51***	5.92***	4.44***
	(0.69)	(0.69)	(0.70)
Observations	1,692	1,692	1,722
Number of Regions	282	282	287
Adjusted R2	0.863	0.868	0.862

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: ln(SpecIn)$_{t-1}$; ln(ConIn)$_{t-1}$ (Share_Chemistry)$_{t-1}$; (Share_Biotechnology)$_{t-1}$; (Share_Pharmaceuticals)$_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation. Since the Net Migration Rate ranges [-1,1], we avoid the logarithmic transformation of all the cross-regional mobility variables. In consequence, their sign and significance can be fairly informative, but any interpretation of their magnitude should be treated with caution.

5.6. Conclusions, implications and limitations

The research conducted here sought to assess the importance of specific knowledge flow and knowledge creation mechanisms, namely networks of co-invention and labour mobility, on regional innovation, as opposed to the impact from R&D efforts or other mechanisms of knowledge creation and diffusion. Within a KPF framework, several hypotheses have been suggested and, although we are unable to confirm them all, a number of interesting conclusions can be identified.

Strong support for the positive relationship between regional labour market mobility and regional innovation intensity is found. The influence of networks is also fairly important, but the strength of these ties (measured as the network density) was found to have a negative influence on innovation. In line with studies elsewhere, we rely on the explanations proffered by Grannovetter (1985) concerning the importance of weak ties for innovation.

As labour mobility and research networks have been obtained to be a fundamental factor in the creation of knowledge, the unequal distribution of such features in the territory could explain regional differences in innovation performance and economic development. In this sense, policies aimed at encouraging the mobility of high skilled workers or enhancing the participation in research networks (as promoted by the European Commission through Marie Curie programs or the Framework Program Projects), specially in less innovative regions, may play a critical role in the creation of knowledge, and subsequent economic growth. Clearly, though, the effectiveness of such policies, as shown by the results of this section, crucially depends on each region's capacity to give returns to such labour mobility and the participation in research networks. To this respect, we have provided evidence that those regions that are more knowledge and innovation intensive obtain higher returns since they are able to translate internal and external knowledge into new specific commercial applications more efficiently than the less innovative regions. Recall, however, that certain threshold effects seem to arise as evidenced by the negative influence of the networks' strength and the null impact of mobility in certain high performance regions.

Finally, from a policy perspective, the present chapter fleshes out empirically pivotal pillars of the Smart Specialisation strategy put recently to the fore by the European Commission. Thus, the concepts of local *embeddedness* of the local networks and labour market, as well as the degree of *connectedness* to external sources of knowledge, constitute core ideas of the Strategy. To some extent, both concepts are crucially related to the regional and cross-regional meaningful features which have been scrutinized in this section.

5.7. References

Acs ZJ, Audretsch DB, Feldman MP (1994) R&D spillovers and recipient firm size. Review of Economics and Statistics 76: 363-367

Agrawal A, Cockburn I, McHale J (2006) Gone but not forgotten: labour flows, knowledge spillovers, and enduring social capital. Journal of Economic Geography 6: 571-591

Agrawal A, Kapur D, McHale J (2008) How do spatial and social proximity influence knowledge flows? Evidence from patent data. Journal of Urban Economics 64: 258-269

Agrawal A, Kapur D. McHale J, Oettl A (2011) Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. Journal of Urban Economics 69: 43-55

Almeida P, Kogut B (1997) The exploration of technological diversity and the geographic localization of innovation. Small Business Economics 9: 21–31

Almeida P, Kogut B (1999) Localisation of knowledge and the mobility of engineers in regional networks. Management Science 45: 905-917

Anselin L., Varga A. and Acs Z. (1997) Local Geographic Spillovers between University Research and High Technology Innovations, Journal of Urban Economics 42, 422-48;

Audretsch DB, Feldman MP (1996) R&D Spillovers and the geography of innovation and production. The American Economic Review 86: 630-640

Audretsch DB, Feldman M (2004) Knowledge Spillovers and the Geography of Innovation. In: Henderson V, Thisse J (eds) Handbook of Urban and regional Economics, Volume 4

Autant-Bernard C., Mairesse J. and Massard N. (2009) Spatial knowledge diffusion through collaborative networks. Introduction, *Papers in Regional Science* 86, 3, 341-50;

Balconi M., Breschi S. and Lissoni F. (2004) Networks of inventors and the role of academia: an exploration of Italian patent data, Research Policy 33, 127–45;

Bathelt H, Malberg A, Maskell P (2004) Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. Progress in Human Geography 28: 31-56

Bergman E. M. (2009) Embedding network analysis in spatial studies of innovation, *The Annals of Regional Science* 43, 3, 559-65;

Bettencourt L., Lobo J., Helbing D., Kühnert C., and West G. (2007a) Growth, innovation, scaling, and the pace of life in cities, Proceeding of the National Academy of Sciences 104, 7301-06;

Bettencourt L., Lobo J., and Strumsky D. (2007b) Invention in the city: Increasing returns topatenting as a scaling function of metropolitan, Research Policy 36, 107-20;

Boschma R (2005) Proximity and Innovation: A Critical Assessment. Regional Studies 39: 61-74

Boschma R, Eriksson R, Lindgren U (2009) How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity. Journal of Economic Geography 9: 169-190

Boschma R, Frenken K (2010) The spatial evolution of innovation networks. A proximity perspective. In: Boschma R, Martin R (eds) The Handbook of Evolutionary Economic Geography, Cheltenham: Edward Elgar, pp 120-135

Boschma RA, Iammarino S (2009) Related Variety, Trade Linkages and Regional Growth. Economic Geography 85: 289-311

Bottazzi L. and Peri G. (2003) Innovation and spillovers in regions: Evidence from European patent data, European Economic Review 47, 687 – 710;

Breschi S. and Catalini C. (2009) Tracing the linkages between science and technology: An exploratory analysis of the research networks among scientists and inventors, Research Policy 39, 14-26;

Breschi S, Lenzi C (2011) Net and the city. Co-invention networks and the inventive productivity of US cities, mimeo

Breschi S, Lissoni F (2001) Localised knowledge spillovers vs. innovative millieux: Knowledge "tacitness" reconsidered. Papers in Regional Science 80: 255-273

Breschi S. and Lissoni F. (2004) Knowledge networks from patent data: methodological issues and research targets, in Moed H., Glänzel W. and Schmoch U. (Eds) Handbook of Quantitative Science and Technology Research: The Use of Publication and Patent Statistics in Studies of S&T Systems, pp. 613–643. Springer Verlag, Berlin.

Breschi S. and Lissoni F. (2006) Cross-firm inventors and social networks: localised knowledge spillovers revisted, Annales d'Economie et de Statistique, 79-80;

Breschi S. and Lissoni F. (2009) Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows, Journal of Economic Geography 9, 4, 439-68;

Breschi S, Lenzi C, Lissoni F, Vezzulli A (2010) The geography of knowledge spillovers: the role of inventors' mobility across firms and in space. In: Boschma R, Martin R (eds) The Handbook of Evolutionary Economic Geography, Cheltenham: Edward Elgar, pp. 353-369

Camagni R (1991) Innovation networks: spatial perspectives. Belhaven-Pinter: London

Coe NM, Bunnell T (2003) 'Spatializing' knowledge communities: towards a conceptualisation of transnational innovation networks. Global Networks 3: 437-456

Corredoira R. A. and Rosenkopf L. (2006) Learning from those who left: the reverse transfer of knowledge through mobility ties, Management Department Working Paper

Cowan R. and Jonard N. (2004) Network structure and the diffusion of knowledge, Journal of Economic Dynamics and Control 28, 1557-75;

Crespi G., Geuna A. and Nesta L. (2007) The mobility of university inventors in Europe, Journal of Technology Transfer 32, 3, 195-215;

Feldman MP, Audretsch D (1999) Innovation in cities: Science-based diversity, specialization and localized competition. European Economic Review 43: 409-429

Foray D, David PA, Hall B (2009) Smartt Specialisation – The Concept. Knowledge Economists Policy Brief No. 9

Fleming L., King C., and Juda A. (2007) Small worlds and innovation, Organization Science 14, 5, 375-93;

Fratesi U, Senn L (2009) Regional Growth, Connections and Economic Modelling: An Introduction. In Fratesi U, Senn L (eds) Growth and Innovation of Competitive Regions: The Role of Internal and External Connections, pp. 3-28. Springer-Verlag, Berlin.

Gertler MS, Levite YM (2005) Local nodes in global networks: the geography of knowledge flows in biotechnology innovation. Industry and Innovation 12: 487-507

Gittelman M (2007) Does geography matter for science-based firms? Epistemic communities and the geography of research and patenting in biotechnology. Organization Science 18: 724-741

Glaeser E, Glaeser, E., H. Kallal, J. Scheinkman, and A. Shleifer (1992) Growth in Cities. Journal of PoliticalEconomy, 100.6, 1126-52.

Gomes-Casseres B., Hagedoorn J., and Jaffe A. B. (2006) Do alliances promote knowledge flows?, Journal of Financial Economics 80, 5-33;

Grabher G. (1993) The weakness of strong ties: the lock-in of regional development in the Ruhr area. In: Grabher G (ed) The Embedded Firm, London: Routledge, pp. 255–277

Granovetter M. S. (1985) The strength of weak ties, American Journal of Sociology 78, 1360-80;

Griliches Z. (1979) Issues in assessing the contribution of research and development to productivity growth, The Bell Journal of Economics 10, 1, 92-116;

Griliches Z. (1991) Patent Statistics as Economic Indicators: A Survey, NBER Working Papers No. 3301, National Bureau of Economic Research;

Hausman JA (1978) Specification test in econometrics. Econometrica 46: 1251-1271

Hausman J.A., Hall B.H. and Griliches Z. (1984) Econometric models for count data with an application to the patent-R&D relationship, Econometrica 51, 4, 909-38;

Hoekman J., Frenken K. and van Oort F. (2009) The geography of collaborative knowledge production in Europe, The Annals of Regional Science 43, 3, 721-38;

Hoisl K. (2007) Does mobility increase the productivity of inventors?, Journal of Technology Transfer 34, 212-25;

Hoisl K. (2009) Tracing mobile inventors: The causality between inventor mobility and inventor productivity, Research Policy 36, 5, 615-36;

Jaffe A. B. (1986) Technological opportunity and spillovers of R&D: evidence from firms patents, profits and market value, American Economic Review 76, 5, 984-1001;

Jaffe A. B. (1989) Real effects of academic research, American Economic Review 79, 5, 957-70;

Jaffe AB, Trajtenberg M, Henderson R (1993) Geographic localisation of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics 108: 577-598

Kerr WR (2008) Ethnic Scientific Communities and International Technology Diffusion. The Review of Economics and Statistics 90: 518-537

Kim J., Lee S. J. and Marschke G. (2006) International Knowledge Flows: Evidence from an Inventor-Firm Matched Data Set, NBER Working Paper No. 12692

Kroll H. (2009) Spillovers and proximity in perspective: A network approach to improving the operationalisation of proximity, Working Papers Firms and Regions No. R2/2009, Fraunhofer ISI;

Lambooy JG, Boschma RA (2001) Evolutionary economics and regional policy. Annals of Regional Science 35: 113-133

Laudel G (2003) Studying the Brain Drain: Can Bibliometric Methods Help? Scientometrics 57: 215-237

Lenzi C. (2009) Patterns and determinants of skilled workers' mobility: evidence from a survey of Italian inventors, Economics of Innovation and New Technology 18, 2, 161-79;

Lissoni F (2001) Knowledge codification and the geography of innovation: the case of Brescia mechanical cluster. Research Policy 30: 1479-1500

Lobo J. and Strumsky D. (2008) Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects, Journal of Urban Economics 63, 871-84;

Maggioni MA, Nosvelli M, Uberti TE (2007) Space versus networks in the geography of innovation: A European analysis. Papers in Regional Science 86: 471-493

Maggioni MA, Uberti TE (2008) Knowledge networks across Europe: which distance matters? The Annals of Regional Science 43: 691-720

Maskell P, Bathelt H, Malmberg A (2006) Building global knowledge pipelines: The role of temporary clusters. European Planning Studies 14: 997-1013

Martin, P. and Ottaviano, G. (1999) Growing locations: Industry location in a model of endogenous growth. European Economic Review 43(2): 281-302.

Marx M, Strumsky S, Fleming L (2007) Noncompetes and Inventor Mobility: Specialists, Stars, and the Michigan Experiment, Harvard Business School WP 07-042

McCann P, 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

Miguélez E, Gómez-Miguélez IG (2011) Singling out individual inventors from patent data. IREA Working Paper 2011/05

Moreno R., Paci R. and Usai S. (2005a) Spatial spillovers and innovation activity in European regions, Environment and Planning A 37, 10, 1793-812;

Oettl A, Agrawal A (2008) International labor mobility and knowledge flow externalities. Journal of International Business Studies 39(8): 1242-1260

Owen-Smith J, Powell WW (2004) Knowledge networks as channels and conduits: the effects of spillovers in the Boston biotechnology community. Organization Science 15(1): 5- 21

Ponds R., van Oort F. and Frenken K. (2007) The geographical and institutional proximity of research collaboration, Papers in Regional Science 86, 3, 423-43;

Ponds R, Van Oort FG, Frenken K (2010) Innovation, spillovers and university-industry collaboration: An extended knowledge production function approach. Journal of Economic Geography 10 (2): 231-255

Rodríguez-Pose A (1999) Innovation prone and innovation averse societies: Economic performance in Europe. Growth and Change 30: 75-105

Rodríguez-Pose A, Crescenzi R (2008) Reseacrh and Development, Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe. Regional Studies 42: 51-67

Romer P. M. (1986) Increasing Returns and Long-run Growth, Journal of Political Economy 94, 5, 1002-37;

Romer P. M. (1990) Endogenous Technological Change; Journal of Political Economy 98, 5, 71-102;

Rosenkopf L. and Almeida P. (2003) Overcoming Local Search Through Allainces and Mobility, Management Science 49, 6, 751-66;

Saxenian A. (1994) Regional Advantage. Culture and Competition in Silicon Valley and Route 128. Harvard University Press, Cambridge, MA.

Saxenian A (2006) The New Argonauts: Regional Advantage in a Global Economy, Harvard University Press.

Schilling MA, Phelps CC (2007) Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation. Management Sci. 53(7): 1113-1126

Simonen J, McCann P (2008) Firm innovation: The influence of R&D cooperation and the geography of human capital inputs. Journal of Urban Economics 64(1): 146-154

Singh J. (2005) Collaborative Networks as Determinants of Knowledge Diffusion Patterns, Management Science 51, 5, 756-70;

Singh J, Agrawal AK (2011) Recruiting for Ideas: How Firms Exploit the Prior Inventions of New Hires. Management Science 57(1): 129–150

Shalem R. and Trajtenberg M. (2008) Software patents, inventors and mobility, Working Paper

Song J., Almeida P. and Wu G. (2003) Learning-by-hiring: When is mobility more to facilitate interfirm knowledge transfer?, Management Science 49, 4, 351-65;

Ter Wal A. L. J. and Boschma R. (2009) Applying social network analysis in economic geography: framing some key analytic issues, The Annals of Regional Science 43, 739-56;

Trippl M. and Maier G. (2007) Knowledge spillover agents and regional development, SRE-Discussion 2007/01

Watts DJ, Strogatz SH (1998) Collective dynamics of 'small-world' networks. Nature 393: 440-442

Wasserman S. and Faust K. (1994) Social Network Analysis: Methods and Applications. Cambridge University Press, Cambridge.

Zucker LG, Darby MR, Armstrong J (1998) Geographically Localized Knowledge: Spillovers or Markets? Economic Inquiry 36(1): 65-86

Annex A.5.1. Variables, data construction, and data source

Variable	Proxy	Source
Patents	Patents, fractional count, 3-year moving average	REGPAT January 2010 edition
R&D	R&D expenditures (in euros), 3-year moving average	Eurostat
Human capital	Total population with tertiary education	Eurostat
Mobility	Share of multi-patent inventors with more than one applicant	REGPAT January 2010 edition
Average degree centrality	Average number of personal links in the form of co-patents per inventor	REGPAT January 2010 edition
Connectivity	Share of multi-patent inventors with at least 1 co-inventor	REGPAT January 2010 edition
Network density	$\mathrm{DENS}_{it} = \frac{\mathrm{T}_{it}}{\mathrm{Q}_{it}(\mathrm{Q}_{it}-1)/2}$	REGPAT January 2010 edition
Net Migration Rate	Inflows minus outflows of inventors to the local no. of inventors	REGPAT January 2010 edition
Inward Migration Rate	Inflows of inventors to the local no. of inventors	REGPAT January 2010 edition
Gross Migration Rate	Inflows plus outflows of inventors to the local no. of inventors	REGPAT January 2010 edition
Outward Migration Rate	Outflows of inventors to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks	No. of patents, fractional count, co-authored with outside inventors, to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks – Europe (ESPON countries)	No. of patents, fractional count, co-authored with inventors from the remaining ESPON regions, to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks – US	No. of patents, fractional count, co-authored with inventors from the US, to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks – China, Japan and India	No. of patents, fractional count, co-authored with inventors from China, Japan and India, to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks – remaining OECD countries	No. of patents, fractional count, co-authored with inventors from remaining OECD countries, to the local no. of inventors	REGPAT January 2010 edition
Specialisation Index	$\mathrm{SpIn}_{it} = \frac{1}{2}\sum_{j}\left\lvert\frac{\mathrm{PAT}_{ijt}}{\mathrm{PAT}_{it}} - \frac{\mathrm{PAT}_{Cjt}}{\mathrm{PAT}_{Ct}}\right\rvert$	REGPAT January 2010 edition
Concentration index	$\mathrm{ConIn}_{it} = \sum_{jt}\left(\mathrm{PAT}_{ijt}/\mathrm{PAT}_{jt}\right)^2$	REGPAT January 2010 edition
% Organic chemistry	Share of patents in IPC chemistry	REGPAT January 2010 edition
% Pharmaceuticals	Share of patents in IPC pharmaceuticals	REGPAT January 2010 edition
% Biotechnology	Share of patents in IPC biotechnology	REGPAT January 2010 edition

Annex A.5.2. List of abbreviations

EFTA - European Free Trade Association
EPO – European Patent Office
EU – European Union
GMR – Gross Migration Rate
KIT – Knowledge, Innovation and Territory
KPF – Knowledge Production Function
IMR – Inward Migration Rate
IPC – International Patent Classification
MSA – Metropolitan Statistical Areas
NMR – Net Migration Rate
NUTS – "Nomenclature d'unites territoriales statistiques"
OECD – Organisation for Economic Cooperation and Development
OMR – Outward Migration Rate
OST - Observatoire des Sciences et des Techniques
R&D – Research and Development
SNA – Social Network Analysis
US – United States

Chapter 6. Innovation and regional performance[31]

6.1. Summary and descriptive statistics of data

Table 6.1 and 6.2 provide the description and summary statistics of the variables used in the impact analyses described in Sections 6.2, 6.3, 6.4 and 6.5.

Table 6.1. Variables description

Indicators	Measures	Computation	Year	Source
Dependent variables				
Section 6.2				
Product and/or process innovation	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
Section 6.3				
Employment growth	Employment dynamics	Annual rate of growth	2005-2007	EUROSTAT
Section 6.4				
Total Factor Productivity (TFP)	Economic efficiency	TFP level (min-max normalized)	Average value 2005-2007	Own estimation
Section 6.5				
GDP growth	Economic growth	Annual rate of growth	2005-2007	EUROSTAT
Independent variables				
Section 6.2				
R&D	R&D expenditures	Share of R&D expenditures on GDP	Average value 2000-2000	CRENoS database
Highly educated human capital	Share of highly educated population	Share of people aged 15 and over with tertiary education on total population	Average value 1999-2001	EUROSTAT
Section 6.3				
Value added	Demand	Annual rate of growth	2002-2004	EUROSTAT
Labour cost	Labour cost per employee	Annual rate of growth	2002-2004	Cambridge Econometrics
Labour market policies	National labour market regulation	National expenditures in labour market policies as percentage of GDP	Average value 2002-2004	EUROSTAT
Product innovation	Firms introducing a new product in the market	Share of firms introducing a product innovation	One value for the period 2002-2004	Authors' estimation on CIS (EUROSTAT) data
Process innovation	Firms introducing a new process in the market	Share of firms introducing a process innovation	One value for the period 2002-2004	Authors' estimation on CIS (EUROSTAT) data
FDI	Foreign direct investments	Number of FDI in manufacturing on total population	Average value 2005-2007	FDI-Regio, Bocconi-ISLA
Functional specialisation	% of 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
Northern Europe	Denmark, Finland, Ireland, Sweden, United Kingdom	Dummy variable taking value 1 in the following countries: Denmark, Finland, Ireland, Sweden, United Kingdom	2004	EUROSTAT
Western Europe	France, Germany, Austria, Belgium, The Netherlands and Luxemburg	Dummy variable taking value 1 in the following countries: France, Germany, Austria, Belgium, The Netherlands and Luxemburg	2004	EUROSTAT

[31] This chapter has been written by Roberta Capello and Camilla Lenzi, BEST – Politecnico di Milano.

Southern Europe	Greece, Italy, Portugal, Spain	Dummy variable taking value 1 in the following countries: Greece, Italy, Portugal, Spain	2004	EUROSTAT
New member states (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
Mega (Metropolitan European Growth Areas)	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
Section 6.4				
Specialisation in manufacturing activities	LQ in manufacturing	Location quotient computed on the basis of employment in manufacturing (Sectors D and E, NACE 1 Rev.1 classification)	2002	EUROSTAT
Social capital	Trust	Share of people trusting each other	2000	European Value Survey
Mega	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
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
Knowledge	Share of patents	Regional share of EU total patents	Total patents in the period 1998-2001	Authors' elaboration on CRENoS database
Capabilities (knowledge embedded in human capital)	Share of SMEs managers and technicians	Factor analysis on the share of managers of SMEs and technicians	Average value 1997-2001	European Labour Force Survey
Product and/or process innovation	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
Section 6.5				
Employment growth rate in manufacturing	Employment dynamics	Annual rate of growth	2002-2004	EUROSTAT
Infrastructure endowment	Rail and road network length by usable land	Km of rail and road network on usable land	2000	ESPON
Structural funds expenditures	Millions (Euro) of expenditures on population	Natural logarithm	1994-1999	ESPON
Social capital	Trust	Share of people trusting each other	2000	European Value Survey
FDI	Foreign direct investments	Number of FDI in manufacturing on total population	Average value 2005-2007	FDI-Regio, Bocconi-ISLA

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
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
Mega	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	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
Product and/or process innovation	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 6.2. Summary statistics

Indicators	N. observations	Mean	St.dev.	Min.	Max.
Dependent variables					
Section 6.2					
Product and/or process innovation	262	35,54	13,27	7,97	87,10
Section 6.3					
Employment growth	262	3,78	3,16	-6,65	15,77
Section 6.4					
TFP	258	0,28	0,18	0	1
Section 6.5					
GDP growth	262	3,64	2,05	-1,332	12,41
Independent variables					
Section 6.2					
R&D	262	1,37	1,21	0,1	6,6
Highly educated human capital	262	9,1636	4	1,98	22,14
Section 6.3					
Value added	262	7,99	6,79	-7,45	3,41
Labour cost	262	-1,06	3,85	-15,43	19,60
Labour market policies	262	1,88	1,17	0,25	4,29
Product innovation	262	10,40	7,75	0,89	38,21
Process innovation	262	11,05	3,47	0,65	25,92
FDI	262	0,19	0,40	0	4,29
% of blue collars professions	262	24,11	6,65	7,89	46,78
Northern Europe	262	0*	-	0	1
Western Europe	262	0*	-	0	1
Southern Europe	262	0*	-	0	1
EU12	262	0*	-	0	1
Mega	262	0*	-	0	1
Section 6.4					
LQ in manufacturing	258	0,99	0,33	0,24	1,934
Trust	258	31,03	15,76	3	82
Mega	258	0*	-	0	1
EU12	258	0*	-	0	1
Knowledge	258	0,36	0,72	0	5,65
Capabilities	258	-0,05	0,94	-2,49	3,55
Product and/or process innovation	258	35,47	13,31	7,97	87,10
Section 6.5					
Employment growth rate in manufacturing	262	2,01	3,41	-21,32	13,41
Infrastructure endowment	262	22,04	15,59	0	86,46
Structural funds expenditures	262	334540	561408,8	0	4348666
Trust	262	30,97	15,77	0	82
FDI	262	0,19	0,40	0	4,29
% blue collars professions	262	24,11	6,65	7,89	46,78
EU12	262	0*	-	0	1
Mega	262	0*	-	0	1
Capabilities	262	-0,05	0,94	-2,49	3,55
R&D	262	1,37	1,21	0,1	6,6
Product and/or process innovation	262	35,54	13,27	7,97	87,10

*Modus value

Table 6.3. Regional typologies

Regional typologies	N. of observations	Computation	Year	Source
Mega	77	Dummy variable equal to 1 if the region is classified as mega	2000	ESPON
EU12	56	Dummy variable equal to 1 if the region is located in a EU12 country	2004	EUROSTAT
EU15	215	Dummy variable equal to 1 if the region is located in a EU15 country	2004	EUROSTAT
EFTA4	16	Dummy variable equal to 1 if the region is located in a EFTA4 country	2004	EUROSTAT
Convergence	84	Dummy variable equal to 1 if the region is classified as convergence	2007	EUROSTAT
Transition	29	Dummy variable equal to 1 if the region is classified as transition	2007	EUROSTAT
Competitive	159	Dummy variable equal to 1 if the region is classified as competitive	2007	EUROSTAT
European science-based area	22	Dummy variable equal to 1 if the region is located in the European science-based area*	2002-2004	Authors' elaboration
Applied science area	54	Dummy variable equal to 1 if the region is located in the Applied science area*	2002-2004	Authors' elaboration
Smart technological application area	68	Dummy variable equal to 1 if the region is located in the Smart technological application area*	2002-2004	Authors' elaboration
Smart and creative diversification area	92	Dummy variable equal to 1 if the region is located in the Smart and creative diversification area*	2002-2004	Authors' elaboration
Imitative innovation area	51	Dummy variable equal to 1 if the region is located in the Imitative innovation area*	2002-2004	Authors' elaboration

*See Chapter 2 of the Scientific report for fuller details on the elaboration of this typology.

6.2. Knowledge, human capital and innovation

To analyse the relationship between innovation, human capital and knowledge we regressed the innovation variable (i.e. the share of firms introducing product and/or process innovation) on the share of R&D expenditures and the share of population with tertiary education. Details on indicators, sources and descriptive statistics are available in Tables 6.1 and 6.2. In the analysis we also controlled for country specific effects (by introducing country dummies) to account for the differences in national education and innovation systems across EU member states. To better emphasise territorial heterogeneity in knowledge and innovation behaviours we re-run the analysis for specific groups of regions, namely, EU15, EU12 and EFTA4 countries, Convergence, Transition and Competitive regions, Metropolitan and non-metropolitan regions, and, lastly, the five territorial patters of innovation identified in chapter 2. Details on the regional typologies used are available in Table 6.3.

The model implemented is the following:

$Innovation_r = F(R\&D_r, \text{Human capital}_r, \text{country dummies}) + \varepsilon_r$

Estimates are reported in tables 6.5 and 6.6 whereas elasticity of innovation to R&D and to human capital, both at the EU level and by regional typologies, in table 6.4. Elasticity is the measurement of how changing one independent variable affects the dependent variable; in detail, it is the ratio of the percentage change in one independent variable to the percentage change in the dependent variable, being thus independent of units. The regional elasticity of innovation to R&D ($E_{Innovation,\ R\&D}$) is obtained by multiplying the R&D estimated coefficient times ($\beta_{R\&D}$) times the ratio between the regional R&D level and the regional innovation level, as the formula below summarizes:

$E_{Innovation,\ R\&D} = (\%\Delta R\&D_r)/(\%\Delta Innovation_r) = \beta_{R\&D} * (R\&D_r/Innovation_r)$

Whereas formal knowledge, either measured as R&D investments or patent applications, is, on average, a crucial enabler of superior innovative performances, this relationships becomes more and more complex when the greater variety of knowledge and innovation behaviours across regions is considered. Table 6.4 displays the elasticity of innovation (here measured as the share of firms introducing product and/or process innovation) to R&D (i.e. R&D expenditures as percentage of GDP). Whereas, on average, 1 percentage point increase in R&D yields 0.09% increase in innovation, this is not the case across all types of regions. In fact, R&D is more efficiently used (i.e. shows a greater elasticity) in those regions that considerably invest in R&D, such as those in the European science-based area, and, to a lower extent, in the Smart technological application area and in the Applied science area. On the other hand, regions characterised by low levels of R&D spending, little benefit from further investments in R&D to improve their innovation performance being their elasticity of innovation to R&D nil, if not negative. These results, thus, point to two key messages. First, **returns to R&D (in terms of innovation performance) are likely to accrue in those regions where a critical mass of R&D efforts and investments is already concentrated**. Second, regions differ considerably in their sources of knowledge for their innovative activities. **Some regions strongly link their innovative performance to their large science and formal knowledge base, others are more likely to rely upon diverse sources of knowledge, possibly embedded in technical and managerial capabilities** (e.g. Smart and creative diversification area).

The effect of knowledge embodied in human capital (measured as the share of population holding a tertiary degree) is comparable to that of R&D. On average, the elasticity of innovation to human capital is positive; in particular, 1 percentage point increase in R&D leads to 0.18% increase in innovation. Again, this average effect hides a greater variety of behaviours across regions. In fact, knowledge embodied in human capital is more efficiently used (i.e. shows a greater elasticity) in regions endowed with a larger share of graduates, such as those in the European science-based area, in the Smart technological application area and in the Applied science area.

On the other hand, regions characterised by a lower share of tertiary educated population benefit less (in terms of increased innovative performance) from an increase in the share of tertiary educated population being their elasticity of innovation to human capital nil, if not negative (such as in the Smart and creative diversification area and in the Imitative innovation area, respectively).

Moreover, the innovation benefits stemming from additional investments in R&D and education are unevenly distributed among EU member states and specifically accrue to EU15 countries, being negligible in EU12 countries. Similarly, competitive regions look more efficient in translating R&D and human capital into innovations than transition and convergence regions, where additional R&D and human capital do not yield increases in innovation level (if not a decrease). Lastly, especially metropolitan areas seem to benefit from additional R&D and human capital to improve their innovative performance (Tables 6.5 and 6.6).

The two sets of results are largely consistent within each other. R&D expenditures and the share of tertiary educated population, in fact, show a relatively large correlation index (0,5).

All in all, they confirm that **the relationship between formal knowledge and innovation is actual but, importantly, they allow to better qualify their interplay**. In fact, on the one hand, investments in knowledge creation appear to be characterised by scale advantages and their returns are better exploited in areas characterised by a critical mass of knowledge resources. On the other, different knowledge sources from formal knowledge can be made available and exploited to engage in and to sustain innovation creation processes.

Table 6.4. Elasticity of innovation to R&D and human capital by regional typologies

Regional typologies	Elasticity of innovation to R&D	Elasticity of innovation to human capital
EU average	0,088	0,180
Competitive regions	0,099	0,196
Convergence regions	-0,065	no impact
Transition regions	-0,061	no impact
EU15	0,098	0,210
EU12	no impact	no impact
EFTA4	0,088	0,180
European science-based area	0,255	0,345
Applied science area	0,069	0,194
Smart technological application area	0,085	0,202
Smart and creative diversification area	-0,065	no impact
Imitative innovation area	-0,289	-0,339
Megas	0,143	0,186
Non megas	0,064	0,110

Note: Elasticity based on SAR models of Table 6.5 and 6.6 unless stated differently and statistically significant at conventional levels.

Table 6.5. Relationship between innovation and R&D by regional typologies

Dependent variable: Innovation	(1) OLS	(2) SAR	(3) OLS	(4) OLS	(5) SAR	(6) OLS	(7) OLS	(8) SAR
Human capital	0,685***	0,698***	0,775***	0,747***	0,760***	0,609***	0,523**	0,531***
	(0,231)	(0,191)	(0,231)	(0,233)	(0,192)	(0,179)	(0,225)	(0,197)
R&D	2,279***	2,277***					1,798***	1,778***
	(0,653)	(0,440)					(0,603)	(0,469)
R&D*competitive			2,208***					
			(0,652)					
R&D*convergence			-2,700**					
			(1,281)					
R&D*transition			-2,441*					
			(1,351)					
R&D*EU15				2,379***	2,376***			
				(0,668)	(0,440)			
R&DEU12				-1,523	-1,485			
				(1,181)	(2,061)			
R&D*European science-based area						6,286***		
						(0,852)		
R&D*Applied science area						1,756***		
						(0,628)		
R&D*Smart technological application area						1,900***		
						(0,461)		
R&D*Smart and creative diversification area						-1,854**		
						(0,755)		
R&D* Imitative innovation area						-12,688***		
						(2,648)		
R&D*Megas							1,317*	1,364***
							(0,682)	(0,491)
Constant	0,230***	0,123**	0,226***	0,220***	0,114**	0,250***	0,254***	0,143***
	(0,025)	(0,051)	(0,025)	(0,025)	(0,051)	(0,021)	(0,024)	(0,051)
Lagrange multiplier (spatial error)	0,894		0,101	0,901		0,547	1,321	
Lagrange multiplier (spatial lag)	5,616**		2,306	5,618**		1,571	6,342**	
Rho		0,291**			0,290**			0,305**
		(0,123)			(0,123)			(0,122)
R2 (OLS) – Squared correlation (SAR)	0,76	0,77	0,79	0,76	0,77	0,84	0,77	0,77
Observations	262	262	262	262	262	262	262	262

* *p* < 0,10, ** *p* < 0,05, *** *p* < 0,01. Country dummies included; OLS with robust standard errors
The SAR estimates are based on a row-standardised continuous distance matrix.

Table 6.6. Relationship between innovation and human capital by regional typologies

Dependent variable: Innovation	(1) OLS	(2) SAR	(3) OLS	(4) SAR	(5) OLS	(6) SAR	(7) OLS	(8) SAR
R&D	1,906***	1,922***	2,241***	2,231***	1,132***	1,126***	2,178***	2,174***
	(0,617)	(0,423)	(0,653)	(0,440)	(0,425)	(0,352)	(0,634)	(0,438)
Human capital*convergence	-0,071	-0,042						
	(0,296)	(0,221)						
Human capital*competitive	0,758***	0,761***						
	(0,222)	(0,179)						
Human capital*transition	0,192	0,215						
	(0,240)	(0,211)						
Human capital*EU15			0,787***	0,822***				
			(0,271)	(0,210)				
Human capital*EU12			0,275	0,202				
			(0,291)	(0,407)				
Human capital*European science-based area					1,914***	1,936***		
					(0,386)	(0,192)		
Human capital*Applied science area					0,795***	0,814***		
					(0,189)	(0,154)		
Human capital*Smart technological application area					0,724***	0,721***		
					(0,177)	(0,168)		
Human capital*Smart and creative diversification area					-0,070	-0,067		
					(0,192)	(0,173)		
Human capital* Imitative innovation area					-1,301***	-1,143***		
					(0,309)	(0,329)		
Human capital							0,431*	0,441**
							(0,239)	(0,220)
Human capital*megas							0,218**	0,222**
							(0,102)	(0,098)
Constant	0,237***	0,157***	0,218***	0,103**	0,261***	0,181***	0,256***	0,148***
	(0,024)	(0,049)	(0,029)	(0,053)	(0,020)	(0,042)	(0,024)	(0,052)
Lagrange multiplier (spatial error)	0,263		1,036		0,133		1,255	
Lagrange multiplier (spatial lag)	3,409*		6,262**		4,838**		5,926**	
Rho		0,219*		0,308**		0,224**		0,296**
		(0,120)		(0,123)		(0,103)		(0,122)
R2 (OLS) – Squared correlation (SAR)	0,79	0,79	0,76	0,77	0,86	0,86	0,76	0,77
Observations	262	262	262	262	262	262	262	262

* *p* < 0,10, ** *p* < 0,057, *** *p* < 0,01. Country dummies included; OLS with robust standard errors
The SAR estimates are based on a row-standardised continuous distance matrix.

6.3. Innovation and employment growth

Eq. (1) models the determinants of employment change (regempgr) that are traditionally highlighted in the literature: change in the local demand (value added) (VAgr), change in labour costs per employee (clupgr), expenditures on labour market policies at the national level (lmp), the share of FDI on population at regional level (FDI) and the relevance and nature of innovative efforts (in).

$$regempgr_r = \alpha_0 + \beta_1 VAgr_r + \beta_2 clupgr_r + \beta_3 lmp_n + \beta_4 FDI + \beta_5 in_r + \varepsilon_r \qquad (1)$$

We are conscious that with this specification many aspects, like regulatory laws in the labour market and cyclical macroeconomic effects, that act at national level, are not taken into account and are only partially controlled for by the expenditures on labour market policies at the national level. However, our aim is to capture the (rather small) part of employment dynamics that is mostly related to long term regional structures.

Variables aimed at capturing the structural characteristics of the regions, namely the share of blue collars professions (BC) and a dummy variable for the settlement structure of the regions (D) are added to eq. (1) to control for the regional structural specificities, and the national variable of the expenditures on labour market policies:

$$regempgr_r = \alpha_0 + \beta_1 VAgr_r + \beta_2 clupgr_r + \beta_3 lmp_n + \beta_4 FDI_r + \beta_5 in_r + \beta_6 BC_r + \beta_7 D_r + \varepsilon_r \qquad (2)$$

In order to understand the role played by the different regional structural elements on regional growth, we interact the innovative efforts with the share of blue collars professions and the dummy on the regional settlement structure in order to test whether the estimated coefficients varied across types of regions. This strategy makes it possible to assess whether innovative activities have different impacts on employment growth according to the different structural economies. The estimated model therefore becomes:

$$regempgr_r = \alpha_0 + \beta_1 VAgr_r + \beta_2 clupgr_r + \beta_3 lmp_n + \beta_4 FDI_r + \beta_5 in_r + \beta_6 BC_r + \beta_6 D_r + ,$$
(3)

The signs and significance of the coefficients show whether our assumptions are empirically confirmed.

Estimates are reported in tables 6.7 to 6.9. Table 6.10 shows the elasticity of employment growth to product innovation and to process innovation at the EU level and by regional typologies. Elasticity is the measurement of how changing one independent variable affects the dependent variable; in detail, it is the ratio of the percentage change in one independent variable to the percentage change in the dependent variable, being thus independent of units. The elasticity of regional employment growth rate to process innovation ($E_{\text{Employment growth rate, Process innovation}}$) is obtained by multiplying the process innovation estimated coefficient ($\beta_{\text{process innovation}}$) times the ratio between the regional process innovation level and the regional employment growth rate, as the formulas below summarize:

$E_{\text{Employment growth rate, Process innovation}}$ = (%Δ process innovation$_r$)/(%Δ employment growth rate$_r$)

$E_{\text{Employment growth rate, Process innovation}}$ = $\beta_{\text{process innovation}}$* (process innovation$_r$/ employment growth rate$_r$)

Similarly, the elasticity of regional employment growth rate to product innovation ($E_{\text{Empl\_gr\_rate, Prod\_inno*BC}}$) at different level of blue collar functions is computed as follows:

$E_{\text{Emp\_gr\_rate, Prod\_inno*BC}}$ = ($\beta_{\text{prod\_inno}}$+ $\beta_{\text{prod\_inno*BC}}$*BC$_r$)*(product innovation$_r$/ employment growth rate$_r$)

Lastly, the elasticity of regional employment growth rate to process innovation ($E_{\text{Empl\_gr\_rate, Proc\_inno*D}}$) in urban settlement structure is computed as follows:
$E_{\text{Emp\_gr\_rate, Proc\_inno*D}}$ = ($\beta_{\text{proc\_inno}}$+ $\beta_{\text{proc\_inno*D}}$*D$_r$)*(process innovation$_r$/ employment growth rate$_r$)

Table 6.7 reports the estimates of the baseline specification, both by using OLS estimates with robust standard errors (column 1) and of the SEM and SAR specifications (column 2 and 3 respectively). Our dependent variable is characterized by a significant level of spatial dependency (Moran's I=0,132; p-value<0,01). Spatial econometrics techniques are therefore requested to produce consistent estimates.[32] The spatial dependency coefficients are, in fact, highly significant across all the specifications we test. The reason for these results may be due to the fact that, although we capture some national effects through the national labour market policies, and through social and cultural similarities in the labour market, some specific national aspects still remain unexplained.

To preserve degrees of freedom in estimation and to keep interpretability of the coefficient of the simple effect of the innovation variables, each interaction effect is estimated independently.

A general consideration that holds for all models analyzed is the low level of the R-square. This result is consistent with all efforts of this kind present in the literature, where the R-squares of the estimated models are between 0.06 and 0.20, and can easily be explained by the fact that what explains most of the employment dynamics through regulatory laws in the labour market, cyclical macroeconomic effects and growth patterns are controlled for through spatial autocorrelation. What remains to be explained is a limited part of employment growth rate, as the low R-square values show.

Differently from previous findings in the literature at national level (see among the many others Bogliacino and Pianta, 2010), demand growth (i.e. VA growth) does not influence employment rate. This result finds an explanation in the fact that this is an average result for Europe as a whole, averaging between rather different national growth patterns; Eastern countries link their demand growth rates to employment growth, while most Western countries respond to a demand growth through productivity increases. This result is stable across all the specifications tested, as Tables 6.7 to 6.9 below show.

Table 6.7. Determinants of the employment rate of growth (2005-2007)

Employment growth (rate of growth 2005-2007)	OLS	SAR	SEM
Value added (rate of growth 2002-2004)	-0,014	-0,021	-0,016
	(0,046)	(0,033)	(0,031)
Labour cost (rate of growth 2002-2004)	-0,127*	-0,146***	-0,121**
	(0,075)	(0,055)	(0,053)
Labour market policies expenditures	0,008***	0,006*	0,006**
	(0,003)	(0,003)	(0,00310)
FDI	0,006**	0,007	0,006
	(0,003)	(0,005)	(0,005)
EU12	0,0292***	0,023***	0,022**
	(0,009)	(0,010)	(0,009)
Western Europe	-0,000	0,008	0,001
	(0,007)	(0,009)	(0,007)
Southern Europe	0,019**	0,018*	0,014*
	(0,008)	(0,010)	(0,008)
Product innovation	-0,011	-0,004	-0,011
	(0,031)	(0,034)	(0,033)
Process innovation	-0,054	-0,019	-0,029
	(0,094)	(0,079)	(0,073)
Constant	0,017	0,016	0,010
	(0,013)	(0,014)	(0,0122)
Lagrange multiplier (spatial error)	4,032**		
Lagrange multiplier (spatial lag)	3,497*		
Lambda		0,556***	
		(0,198)	
Rho			0,337*
			(0,185)
R2 (OLS) – Sq, Corr, (SAR, SEM)	0,16	0,17	0,14
Observations	262	262	262

* $p < 0.10$, ** $p < 0.057$, *** $p < 0.01$

[32] This result is robust to the use of different weight matrices (i.e. first order contiguity matrix as well as continuous distance matrix). The estimates reported in the paper are based on a continuous distance matrix.

As to the innovation variables, both product innovation and process innovation show a non significant effect. Whereas the result on process innovation is consistent with several contribution in the literature (Pianta, 2005) and points to the existence of compensation mechanisms at the regional and interregional levels mitigating the labour-saving effects of process innovation, the result on product innovation deserves some additional explanations (albeit not significant at conventional levels). It is possible that compensation mechanisms taking place at the firm or the sectoral level are offset at the regional level. In particular, the business stealing effect (Spezia and Vivarelli, 2002) can prevail, making the overall effect of product innovation negative.

6.3.1. The role of functional specialisation

The functional specialization, in the form of a larger presence of blue collars professions, seems to mitigate (and to turn the effect from negative to a positive one) the role of product innovation on employment dynamics (Table 6.8). This supports the idea that product innovation is strongly complementary with (low) skills and lower level functions, and that, as expected, the positive effects of producing new goods are displayed where production activities are located.

Table 6.8. Employment rate of growth (2005-2007) and functional specialization

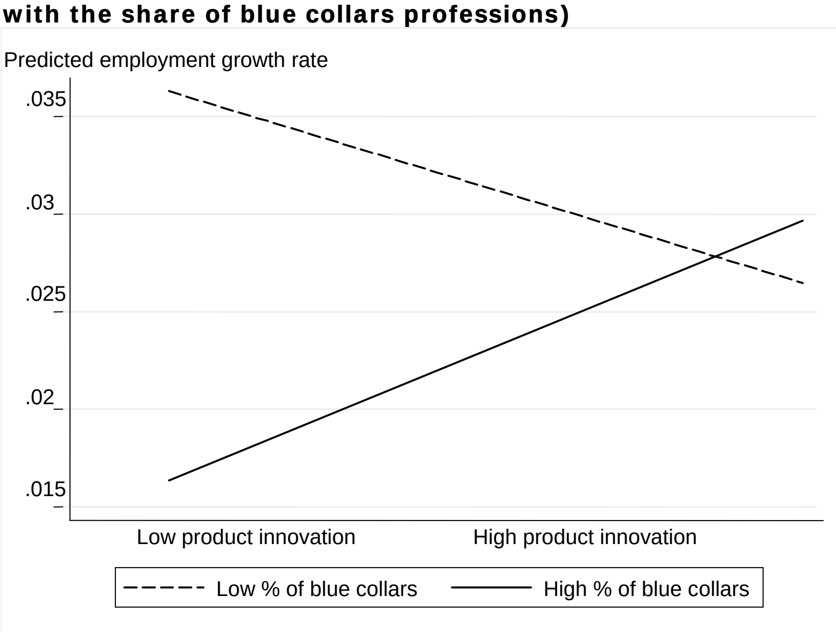
Employment growth (rate of growth 2005-2007)	Product innovation		Process innovation	
	OLS	SAR	OLS	SAR
Value added (rate of growth 2002-2004)	0.013	0.008	0.019	0.013
	(0.046)	(0.031)	(0.050)	(0.034)
Labour cost (rate of growth 2002-2004)	-0.130*	-0.128**	-0.118	-0.113**
	(0.075)	(0.051)	(0.075)	(0.052)
Labour market policies expenditures	0.008***	0.005*	0.009***	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
FDI	0.008***	0.008*	0.007**	0.006
	(0.003)	(0.005)	(0.003)	(0.005)
EU12	0.038***	0.030***	0.040***	0.033***
	(0.010)	(0.009)	(0.011)	(0.009)
Western Europe	-0.000	0.001	0.001	0.003
	(0.007)	(0.007)	(0.007)	(0.006)
Southern Europe	0.021***	0.017**	0.022***	0.018**
	(0.008)	(0.008)	(0.007)	(0.007)
% Blue collars	-0.151***	-0.143**	-0.193*	-0.161
	(0.056)	(0.056)	(0.107)	(0.109)
Product innovation	-0.199**	-0.178*		
	(0.090)	(0.107)		
Product innovation * % Blue collars	0.847**	0.761*		
	(0.396)	(0.477)		
Process innovation			-0.321	-0.218
			(0.250)	(0.255)
Process innovation * % Blue collars			1.168	0.843
			(0.957)	(0.990)
Constant	0.044***	0.037**	0.055**	0.040
	(0.016)	(0.016)	(0.027)	(0.029)
Lagrange multiplier (spatial error)	2,348		2,260	
Lagrange multiplier (spatial lag)	3,397*		2,949*	
Rho		0.324*		0.320*
		(0.183)		(0.189)
R2 (OLS) – Sq, Corr, (SAR, SEM)	0,18	0,19	0,17	0,18
Observations	262	262	262	262

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Differently, the effect of process innovation is not significant. This is, however, consistent with our expectations. In fact, process innovations look more pervasive and are likely to affect employment dynamics regardless the functional specialization of a region.

To better clarify the magnitude of the interaction effects, Figure 6.1 plots the effect of the interaction between product innovation and the share of blue collars employment on the predicted employment growth rate in the SAR model (Table 6.8, column 2). The '*low blue collars*' line shows the slope of the effect of product innovation on employment growth when blue collars is set at the 10th percentile value; the '*high blue collars*' line illustrates the same effect when blue collars is set at 90th percentile value. The end points of each line are calculated by setting product innovation, respectively, at the 10th percentile value and at 90th percentile value. Consistent with our results, the plot shows that the impact of product innovation on employment growth increases in those areas specialized in blue collars (production) functions. On the contrary, when regions have a low level of production functions, the positive effects of product innovation on employment growth is highly reduced. In particular, by comparing the end points of the two lines, i.e., when product innovation is set at 90th percentile value, we note that a high share of blue collars yields an increase in employment growth rate, from 0.026 to 0.030, with respect to a low share of blue collars, about 15%.

Figure 6.1. Marginal effect of product innovation on employment growth (interaction effect with the share of blue collars professions)



6.3.2. The role of the regional settlement structure

The control for the regional settlement structure highlights some interesting differences from the previous results. In fact, the effect of the settlement structure is significant and positive, suggesting that metropolitan areas are an important engine of employment growth; however, this is the case of process innovation only. Importantly, the labour-saving effects of process innovation look amplified in metropolitan settings than elsewhere, even after controlling for interregional interdependencies (Table 6.9, column 4 to 6). This is indeed consistent with our expectations. On the one hand, cities are key engines of economic dynamics (and, consequently, of employment growth); on the other, cities show higher density of service activities which have a higher propensity to introduce process innovations, leading to magnified labour-displacing effects of process innovation.

Similarly to Figures 6.1, Figure 6.2 shows the effect of process innovation on the predicted employment growth rate of the SAR model (Table 6.9, column 6) in case a region is characterized by megas or not. The 'Mega = 0' line shows the slope of the effect of process innovation on employment growth when the dummy variable 'Mega' is equal to 0; the 'Mega = 1' line illustrates the same effect when the dummy variable 'Mega' is equal to 1. The end points of each line are calculated by setting process innovation, respectively, at the 10th percentile value and at the 90th percentile value. The plot shows that the negative impact of process innovation on employment growth increases in metropolitan areas (Mega equal to 1). In particular, by comparing the end points of the two lines, i.e., when process innovation is set at the 90th percentile value, we note that being the region a metropolitan area (i.e. Mega equal to 1) yields a decrease in employment rate of growth, from 0.023 to 0.021, about 8,7%.

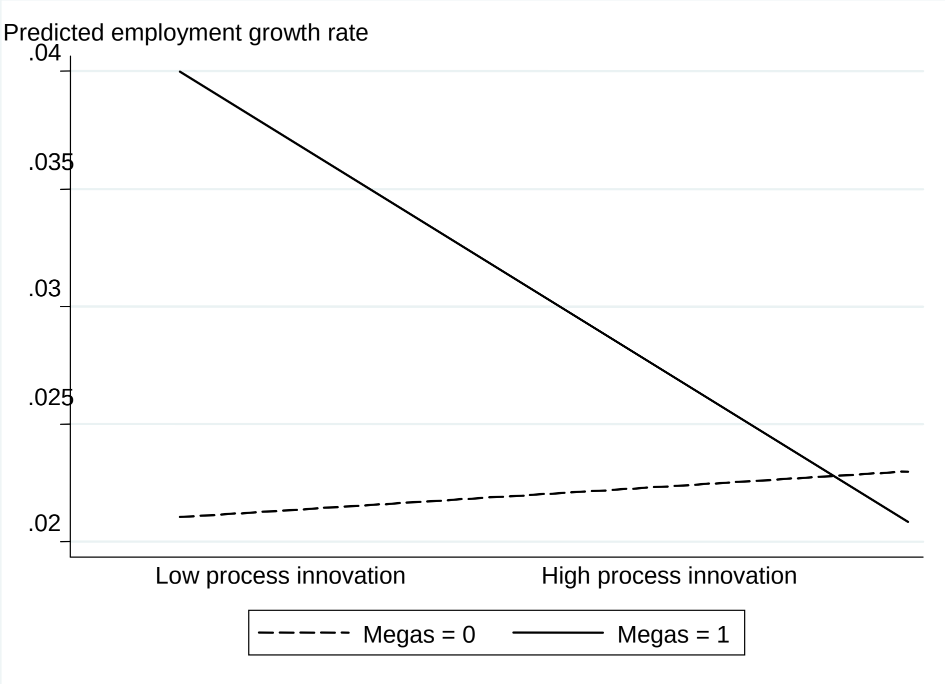
Table 6.9. Employment rate of growth (2005-2007) and settlement structure

Employment growth (rate of growth 2005-2007)	Product innovation OLS	Product innovation SEM	Product innovation SAR	Process innovation OLS	Process innovation SEM	Process innovation SAR
Value added (rate of growth 2002-2004)	-0,006	-0,018	-0,010	-0,006	-0,019	-0,008
	(0,045)	(0,033)	(0,030)	(0,046)	(0,033)	(0,030)
Labour cost (rate of growth 2002-2004)	-0,112	-0,139**	-0,110**	-0,128*	-0,147***	-0,122**
	(0,072)	(0,054)	(0,051)	(0,073)	(0,054)	(0,052)
Labour market policies expenditures	0,008***	0,006*	0,005*	0,008***	0,006*	0,005*
	(0,003)	(0,003)	(0,003)	(0,003)	(0,003)	(0,003)
FDI	0,005	0,006	0,005	0,003	0,004	0,003
	(0,003)	(0,005)	(0,005)	(0,004)	(0,005)	(0,005)
EU12	0,029***	0,026***	0,020**	0,027***	0,024**	0,019**
	(0,009)	(0,010)	(0,009)	(0,009)	(0,010)	(0,008)
Western Europe	0,000	0,008	0,001	0,001	0,008	0,002
	(0,007)	(0,009)	(0,006)	(0,007)	(0,008)	(0,006)
Southern Europe	0,016**	0,016	0,012	0,021***	0,018**	0,015**
	(0,007)	(0,010)	(0,007)	(0,007)	(0,009)	(0,007)
Megas	0,008	0,009	0,008	0,036**	0,038***	0,039***
	(0,008)	(0,007)	(0,007)	(0,016)	(0,014)	(0,014)
Product innovation	-0,018	-0,005	-0,014			
	(0,031)	(0,037)	(0,036)			
Product innovation * Megas	-0,012	-0,026	-0,018			
	(0,045)	(0,051)	(0,052)			
Process innovation				-0,007	0,049	0,026
				(0,097)	(0,084)	(0,077)
Process innovation * Megas				-0,261**	-0,282**	-0,282**
				(0,125)	(0,114)	(0,115)
Constant	0,012	0,014	0,006	0,010	0,008	0,000
	(0,009)	(0,011)	(0,009)	(0,013)	(0,013)	(0,012)
Lagrange multiplier (spatial error)	4,114**			4,137		
Lagrange multiplier (spatial lag)	4,128**			4,461		
Lambda		0,564***			0,586***	
		(0,194)			(0,191)	
Rho			0,354**			0,375**
			(0,181)			(0,181)
R2 (OLS) – Sq, Corr, (SAR, SEM)	0,16	0,15	0,18	0,18	0,16	0,20
Observations	262		262		262	262

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The most striking findings concern the role that the regional structural characteristics have in emphasizing the effects of innovation on regional employment growth. The direct effects of both product and process innovation suffer from conflicting empirical results (namely, insignificant signs of the parameters), which find a conceptual explanation in the compensating mechanisms that are at work and that we may have been unable to capture. But what is clear is that the impact of innovation on regional employment growth strongly depends on the specificities of local economies, that reinforce the positive or negative impact of the direct effects.

Figure 6.2. Marginal effect of process innovation on employment growth (interaction effect with settlement structure)



As previously mentioned, the average direct effect of process innovation is nil, and so also in the more science oriented patterns of innovation (namely in the European science-based area and in the Applied science area). However, when the analysis is developed at territorial pattern level, the results differ. In particular, **the compensation effects on the negative employment levels do not take place in the three patterns less endowed of technological and formal knowledge**; possibly, the absence (or limited presence) of new machine production effect does not absorb that part of the job displacement generated by process innovation.

Lastly, **the labour-saving effects of process innovation look amplified in metropolitan settings** (Megas)[33], even after controlling for interregional interdependencies (Figure 6.2 and Table 6.9). In fact, the negative impact of process innovation on the predicted employment growth rate is more detrimental in metropolitan areas (as captured by the steeper negative slope of the dark line) than in other types of regions (as captured by the relatively positive slope of the dashed line). Despite cities being key engines of economic dynamics (and, consequently, of employment growth), they show higher density of service activities which have a higher propensity to introduce process innovations, leading to magnified labour-displacing effects of process innovation.

In conclusion, these results highlight that the relationship between technological change and employment is not spatially invariant and emphasize the mediating effects of territorial characteristics in determining the final outcome of the interplay between innovation and employment growth.

[33] Metropolitan areas are here captured by a dummy variable taking value 1 if a region includes at least one of the 76 'MEGAs' - FUAs with the highest scores on a combined indicator of transport, population, manufacturing, knowledge, decision-making in the private sectors.

Table 6.10. Elasticity of employment growth to product and process innovation by regional typologies

Regional typologies	Elasticity of employment growth to product innovation	Elasticity of employment growth to process innovation
EU average	no impact	no impact
Competitive regions	no impact*	no impact*
Convergence regions	no impact*	no impact*
Transition regions	no impact*	no impact*
EU15	no impact*	no impact*
EU12	no impact*	no impact*
EFTA4	no impact*	no impact*
European science-based area	no impact*	no impact
Applied science area	no impact*	no impact
Smart technological application area	no impact*	-3,497
Smart and creative diversification area	no impact*	-2,022
Imitative innovation area	no impact*	-2,308
Megas	no impact*	-0,791
Non megas	no impact*	no impact

Note: Elasticity based on SAR models of tables 6.7-6.9 unless stated differently and statistically significant at conventional levels. * Estimates not reported as this dichotomy does not lead to statistically significant results.

6.4. Innovation and TFP

The second performance indicator used is Total Factor Productivity (TFP), which is a comprehensive measure of productivity and technology efficiency (i.e. efficiency in the use of factor endowments).
TFP has been estimated from the log-linearized version of the traditional Cobb-Douglas production function model, taking the following form:

$$GDP_r = \alpha + \beta \times K_r + \gamma \times L_r + d + \varepsilon_r$$

where GDP_r is the regional gross domestic product, K_r is the capital stock constructed by applying the perpetual inventory method on investment series, L_r is the regional employment level, d represent a set of country dummies and ε_r represents the regional idiosyncratic error. GDP, capital stock and labour are averaged over the years 2005-2007 to smooth possible effects related to specific years of estimation. Estimates are obtained by 2SLS due to possible endogeneity problems[34], where instruments are represented by one period lagged capital and labour regressors (Marrocu et al., 2010). Table 6.11 reports the factor endowments coefficient estimates that are close to the elasticity values generally used within the growth accounting approach under the assumption of constant returns to scale (0,3 for capital stock and 0,7 for labour).

Table 6.11. TFP computation

Dependent variable: Real GDP (Average value 2005-2007)	TSLS
Capital (Average value 2005-2007)	0.268**
	(0.118)
Labour (Average value 2005-2007)	0.716***
	(0.147)
Constant	3.658***
	(0.192)
R2	0.93
Observations	262

* *p* < 0.10, ** *p* < 0.05, *** *p* < 0.01
TSLS robust standard errors. Instruments are one year-lagged explanatory variables. Country dummies included.

[34] The Durbin-Wu-Hausman tests support this result.

To measure the impact of different types of knowledge and innovation on TFP, we estimated the following models:

TFP_r = F (Specialisation in manufacturing$_r$, Trust$_r$, EU12, Mega, Knowledge$_{r,}$) + ε_r
(1)

TFP_r = F (Specialisation in manufacturing$_r$, Trust$_r$, EU12, Mega, Capabilities$_r$) + ε_r
(2)

TFP_r = F (Specialisation in manufacturing$_r$, Trust$_r$, EU12, Mega, Innovation$_r$) + ε_r
(3)

In the estimates, we introduce controls for specific regional characteristics, such as the specialization in manufacturing activities, an indicator of social capital (i.e. trust), the settlement structure and the distinction between EU12 and EU15, as TFP level and dynamics have been shown to differ quite sharply in New and Old member states. All these elements proved to be relevant determinants of TFP level and growth in the recent years (Dettori et al., 2009; Marrocu et al., 2010; Marrocu and Paci, 2011).

Details on indicators, sources and descriptive statistics are available in Tables 6.1 and 6.2. To better emphasise territorial differences in knowledge and innovation behaviour we re-run the analysis for specific groups of regions, namely, EU15, EU12 and EFTA4 countries, Convergence, Transition and Competitive regions, Metropolitan and non-metropolitan regions, the five territorial patters of innovation identified in Chapter 2.

Table 6.12 reports TFP elasticity to knowledge, capabilities and innovation at the EU level and by regional typologies. Table 6.13 reports the TFP level in the different territorial patterns of innovation. Estimates are reported in tables 6.14 to 6.17. Elasticity is the measurement of how changing one independent variable affects the dependent variable; in detail, it is the ratio of the percentage change in one independent variable to the percentage change in the dependent variable, being thus independent of units. The regional elasticity of TFP to innovation ($E_{TFP, Innovation}$) is obtained by multiplying the innovation estimated coefficient ($\beta_{Innovation}$) times the ratio between the regional innovation level and the EU average TFP level, as the formula below summarizes:

$E_{TFP, Innovation} = (\%\Delta Innovation_r)/(\%\Delta TFP_r) = \beta_{Innovation}*(Innovation_r/TFP_r)$

Details on the regional typologies used are available in Table 6.3.

Interestingly, the efficiency level of European regions (here measured in terms of TFP level) is not only linked to the strength of the local formal knowledge base.
As expected, the European science-based area reports the highest efficiency level; however, **the efficiency ranking does not strictly reflect the knowledge ranking, either in the form of R&D expenditures or in the form of number of patent applications**. In fact, despite relatively limited R&D efforts and patent intensity, the Smart and creative diversification area comes second in the efficiency ranking of European regions, followed next by the Smart technological application area, the Applied science area and the Imitative innovation area, which show comparable efficiency levels. In particular, regions in the European science-based area show almost 30% higher efficiency level than regions in the bottom three groups.
This result suggests that formal knowledge is not the only and chief driver leading to higher efficiency performances. Rather, a tight relationship between knowledge and efficiency level seems to be at place only in those groups of regions in which the local knowledge base is already quite developed and rich. Table 6.15 supports this interpretation. In fact, the elasticity of TFP level to knowledge (as measured by patents), on average positive but quiet limited in size (0.047%), maintains its positive and significant effect in those groups of regions strongly endowed with formal knowledge, namely the European science-based area

and the Applied science area, where it strongly increases TFP level. In particular, 1 percentage point increase in R&D expenditures leads to 0.154% and 0.078% increase in TFP level in the European science-based area and the Applied science area, respectively. Differently, in the other groups, TFP level does seem to react to increases in formal knowledge. Interestingly, TFP seems to benefit more from increase in knowledge in EU12 rather than in EU15; however, especially competitive regions look better able to turn additional knowledge into efficiency gains. Lastly, both metropolitan and, especially, non metropolitan areas benefit from an expansion of the knowledge base.

On parallel, the efficiency level in the Smart and creative diversification area is linked to informal and tacit knowledge embedded in managerial and technical capabilities rather than to formal knowledge. In fact, 1 percentage point increase in capabilities leads to 0.05% increase in TFP level (Table 6.16). However, this mechanism is not at place in all regions. In fact, the average impact of capabilities on TFP is negligible, and only the European science-based area seems to experience efficiency gains from increases in the local capabilities level. The impact of capabilities is not much different in EU12 (nil) and EU15 (close to zero but negative); however, it is especially positive and large in transition regions, and moderately, in convergence regions. This supports the idea that efficiency gains can be achieved not only from further investments in formal knowledge, but also from further investments in tacit and embodied knowledge into human capital and professions. Lastly, increase in capabilities look better translated into efficiency gains in metropolitan settings.

Lastly, **innovation** (here measured as the share of firms introducing product and/or process innovation) **looks, on average, crucial to achieve higher efficiency levels**; on average, 1 percentage point increase in innovation leads to 0.21% increase in TFP level (Table 6.17). **However, these benefits are likely to be unevenly reaped by the different groups of regions**. In particular, only regions in the European science-based area seem able to benefit from innovation increases, whereas in the other regions innovation does not seem to bear a considerable impact on efficiency increases. Interestingly, TFP seems to benefit more from increase in innovation in EU12 rather than in EU15; however, especially competitive regions look better able to turn additional innovation into efficiency gains.

Table 6.12. Elasticity of TFP level to knowledge, capabilities and innovation by regional typologies

Regional typologies	Elasticity of TFL level to knowledge	Elasticity of TFL level to capabilities	Elasticity of TFL level to innovation
EU average	0,047	no impact	0,210
Competitive regions	0,066	no impact	0,214
Convergence regions	-0,067	0,029	no impact
Transition regions	no impact	0,137	no impact
EU15	0,062	-0,002	no impact
EU12	0,102	no impact	0,361
EFTA	0,047	no impact	0,210
European science-based area	0,154	0,287	0,372
Applied science area	0,078	no impact	no impact
Smart technological application area	no impact	no impact	no impact
Smart and creative diversification area	no impact	0,046	no impact
Imitative innovation area	no impact	no impact	no impact
Megas	0,045	0,011	no impact*
Non megas	0,080	0,002	no impact*

Note: Elasticity based on SEM models of tables 6.14-6.17 unless stated differently and statistically significant at conventional levels.
* Estimates not reported as this dichotomy does not lead to statistically significant results.

Table 6.13. TFP level in different territorial patterns of innovation (elasticities)

Territorial patterns of innovation	TFP level
European science-based area	0,478
Applied science area	0,394
Smart technological application area	0,393
Smart and creative diversification area	0,405
Imitative innovation area	0,325

Note: Coefficients based on SEM models of table 6.14 and statistically significant at conventional levels.

Table 6.14. TFP level in different territorial patterns of innovation (estimates)

Average TFP level 2005-2007	OLS	SEM
LQ in manufacturing sector	-0,218***	-0,224***
	(0,042)	(0,034)
Trust	0,091	0,134*
	(0,062)	(0,075)
EU12	0,128***	0,133***
	(0,038)	(0,038)
Megas	0,132***	0,133***
	(0,022)	(0,022)
European science-based area	0,148***	0,153***
	(0,052)	(0,053)
Applied science area	0,060	0,069*
	(0,044)	(0,041)
Smart technological application area	0,057	0,068*
	(0,038)	(0,040)
Smart and creative diversification area	0,076**	0,080**
	(0,035)	(0,035)
Imitative innovation area (Constant)	0,342***	0,325***
	(0,049)	(0,051)
Lagrange multiplier (spatial error)	3,622*	
Lagrange multiplier (spatial lag)	0,300	
Lambda		
R2 (OLS) – Squared Correlation (SEM)	0,33	0,33
Observations	258	258

* *p* < 0,10, ** *p* < 0,05, *** *p* < 0,01. OLS with robust standard errors. Four outliers dropped from the analysis. The SEM estimates are based on a row-standardised continuous distance matrix.

Table 6.15. Relationship between TFP level and knowledge by regional typologies

Average TFP level 2005-2007	(1) OLS	(2) SEM	(3) OLS	(4) SEM	(5) OLS	(6) SEM	(7) OLS	(8) SEM	(9) OLS	(10) SEM
LQ in manufacturing sector	-0,218***	-0,223***	-0,212***	-0,216***	-0,216***	-0,218***	-0,220***	-0,228***	-0,226***	-0,232***
	(0,039)	(0,033)	(0,041)	(0,033)	(0,038)	(0,032)	(0,039)	(0,033)	(0,040)	(0,033)
Trust	0,077	0,116	0,078	0,115	0,068	0,101	0,080	0,120*	0,074	0,120*
	(0,063)	(0,072)	(0,064)	(0,072)	(0,063)	(0,070)	(0,061)	(0,071)	(0,063)	(0,073)
EU12	0,103***	0,104***	0,097***	0,099***	0,072**	0,072**	0,102***	0,098***	0,110***	0,112***
	(0,030)	(0,033)	(0,030)	(0,034)	(0,028)	(0,034)	(0,030)	(0,034)	(0,032)	(0,034)
Megas	0,133***	0,135***	0,135***	0,136***	0,123***	0,125***	0,131***	0,134***	0,146***	0,150***
	(0,023)	(0,022)	(0,023)	(0,022)	(0,022)	(0,022)	(0,022)	(0,022)	(0,025)	(0,024)
Knowledge	3,608***	3,616**							6,982**	7,750***
	(1,545)	(1,415)							(3,298)	(2,830)
Knowledge*European science-based area			3,560**	3,330*						
			(1,637)	(1,756)						
Knowledge*Applied science area			4,086***	4,433**						
			(0,988)	(2,244)						
Knowledge*Smart technological application area			2,725	2,874						
			(2,301)	(2,843)						
Knowledge*Smart and creative diversification area			0,588	1,841						
			(5,699)	(8,190)						
Knowledge* Imitative innovation area			86,011	76,563						
			(90,362)	(70,193)						
Knowledge*EU15					3,732***	3,741***				
					(1,157)	(1,386)				
Knowledge*EU12					310,487***	293,587***				
					(70,988)	(94,636)				
Knowledge*Convergence							-48,493*	-54,339***		
							(27,044)	(20,591)		
Knowledge*Competitive							3,424***	3,384**		
							(1,141)	(1,398)		
Knowledge*Transition							-1,429	-3,488		
							(34,446)	(21,516)		
Knowledge*Megas									-4,283	-5,106*
									(3,409)	(3,027)
Constant	0,401***	0,391***	0,396***	0,385***	0,404***	0,394***	0,408***	0,403***	0,400***	0,388***
	(0,048)	(0,042)	(0,051)	(0,042)	(0,047)	(0,040)	(0,049)	(0,042)	(0,048)	(0,042)
Lagrange multiplier (spatial error)	4,855**		4,189**		3,205*		7,021***		6,108**	
Lagrange multiplier (spatial lag)	0,645		0,587		0,705		0,777		0,827	
Lambda		0,390**		0,381**		0,336*		0,441**		0,422**
		(0,190)		(0,193)		(0,199)		(0,180)		(0,183)
R2 (OLS) – Squared Correlation (SEM)	0,33	0,32	0,33	0,33	0,35	0,35	0,34	0,34	0,33	0,33
Observations	258	258	258	258	258	258	258	258	258	258

* $p < 0,10$, ** $p < 0,05$, *** $p < 0,01$. OLS with robust standard errors. Four outliers dropped from the analysis. The SEM estimates are based on a row-standardised continuous distance matrix.

Table 4.16. Relationship between TFP level and capabilities by regional typologies

Average TFP level 2005-2007	(1) OLS	(2) SEM	(3) OLS	(4) SEM	(5) OLS	(6) SEM	(7) OLS	(8) SEM	(9) OLS	(10) SEM
LQ in manufacturing sector	-0,184***	-0,192***	-0,196***	-0,203***	-0,187***	-0,197***	-0,174***	-0,183***	-0,181***	-0,187***
	(0,039)	(0,034)	(0,037)	(0,033)	(0,038)	(0,034)	(0,036)	(0,034)	(0,037)	(0,034)
Trust	0,106*	0,145*	0,126**	0,182**	0,106*	0,147**	0,108*	0,140*	0,105*	0,138*
	(0,063)	(0,075)	(0,061)	(0,076)	(0,062)	(0,075)	(0,063)	(0,073)	(0,063)	(0,074)
EU12	0,079***	0,079*	0,110***	0,119***	0,092***	0,099***	0,079***	0,081**	0,063**	0,061*
	(0,029)	(0,033)	(0,029)	(0,034)	(0,030)	(0,034)	(0,028)	(0,032)	(0,026)	(0,035)
Megas	0,156***	0,161***	0,149***	0,151***	0,154***	0,158***	0,147***	0,152***	0,158***	0,163***
	(0,022)	(0,021)	(0,022)	(0,021)	(0,022)	(0,021)	(0,022)	(0,021)	(0,022)	(0,021)
Capabilities	0,014	0,021							0,028*	0,032**
	(0,013)	(0,013)							(0,014)	(0,014)
Capabilities*European science-based area			-0,123***	-0,118***						
			(0,028)	(0,039)						
Capabilities*Applied science area			-0,040	-0,040						
			(0,030)	(0,029)						
Capabilities*Smart technological application area			0,007	0,014						
			(0,014)	(0,023)						
Capabilities*Smart and creative diversification area			0,041**	0,046***						
			(0,018)	(0,016)						
Capabilities* Imitative innovation area			0,040	0,070						
			(0,047)	(0,047)						
Capabilities*Convergence					0,029	0,034*				
					(0,024)	(0,020)				
Capabilities*Competitive					-0,012	-0,002				
					(0,018)	(0,018)				
Capabilities*Transition					0,048*	0,054**				
					(0,026)	(0,023)				
Capabilities*EU15							0,017	0,025*		
							(0,013)	(0,013)		
Capabilities*EU12							-0,077	-0,079		
							(0,067)	(0,053)		
Capabilities*Megas									-0,057**	-0,050**
									(0,024)	(0,023)
Constant	0,371***	0,363***	0,356***	0,343***	0,363***	0,357***	0,359***	0,356***	0,369***	0,361***
	(0,046)	(0,045)	(0,044)	(0,045)	(0,045)	(0,045)	(0,044)	(0,044)	(0,045)	(0,045)
Lagrange multiplier (spatial error)	6,164**		4,647**		3,14*		6,668***		3,816**	
Lagrange multiplier (spatial lag)	0,355		0,087		0,013		0,667		0,201	
Lamba		0,454**		0,464**		0,420**		0,411**		0,472**
		(0,199)		(0,196)		(0,211)		(0,203)		(0,187)
R2 (OLS) – Squared correlation (SEM)	0,31	0,31	0,36	0,36	0,33	0,33	0,32	0,32	0,33	0,33
Observations	258	258	258	258	258	258	258	258	258	258

* *p* < 0,10, ** *p* < 0,05, *** *p* < 0,01. OLS with robust standard errors. Four outliers dropped from the analysis. The SEM estimates are based on a row-standardised continuous distance matrix.

Table 6.17. Relationship between TFP level and innovation by regional typologies

Average TFP level 2005-2007	(1) OLS	(2) SEM	(3) OLS	(4) SEM	(5) OLS	(6) SEM	(7) OLS	(8) SEM
LQ in manufacturing sector	-0,221***	-0,225***	-0,223***	-0,227***	-0,228***	-0,233***	-0,221***	-0,225***
	(0,041)	(0,034)	(0,042)	(0,035)	(0,041)	(0,034)	(0,041)	(0,034)
Trust	0,058	0,102	0,089	0,128*	0,039	0,093	0,061	0,101
	(0,063)	(0,074)	(0,063)	(0,074)	(0,065)	(0,074)	(0,063)	(0,073)
EU12	0,109***	0,110***	0,125***	0,129***	0,142***	0,144***	0,023	0,030
	(0,033)	(0,036)	(0,037)	(0,038)	(0,045)	(0,040)	(0,063)	(0,072)
Megas	0,143***	0,145***	0,133***	0,135***	0,137***	0,137***	0,142***	0,144***
	(0,022)	(0,021)	(0,022)	(0,022)	(0,021)	(0,021)	(0,022)	(0,021)
Innovation	0,167**	0,165*						
	(0,079)	(0,089)						
Innovation*European science-based area			0,201**	0,200*				
			(0,100)	(0,120)				
Innovation*Applied science area			0,076	0,085				
			(0,137)	(0,148)				
Innovation*Smart technological application area			0,082	0,095				
			(0,163)	(0,180)				
Innovation*Smart and creative diversification area			0,170	0,170				
			(0,214)	(0,239)				
Innovation* Imitative innovation area			-0,088	-0,101				
			(0,344)	(0,357)				
Innovation*Convergence					-0,064	-0,113		
					(0,170)	(0,120)		
Innovation*Competitive					0,151**	0,153*		
					(0,074)	(0,088)		
Innovation*Transition					0,019	-0,061		
					(0,121)	(0,119)		
Innovation*EU15							0,126	0,128
							(0,083)	(0,093)
Innovation*EU12							0,459*	0,427*
							(0,246)	(0,225)
Constant	0,360***	0,349***	0,372***	0,360***	0,393***	0,385***	0,375***	0,363***
	(0,050)	(0,047)	(0,077)	(0,072)	(0,054)	(0,049)	(0,052)	(0,047)
Lagrange multiplier (spatial error)	4,214**		3,125*		9,553***		3,408*	
Lagrange multiplier (spatial lag)	0,453		0,278		1,579		0,116	
Lamba		0,372*		0,352*		0,511***		0,348*
		(0,193)		(0,201)		(0,167)		(0,198)
R2 (OLS) – Squared correlation (SEM)	0,32	0,32	0,33	0,33	0,33	0,33	0,33	0,32
Observations	258	258	258	258	258	258	258	258

* *p* < 0,10, ** *p* < 0,05, *** *p* < 0,01. OLS with robust standard errors. Four outliers dropped from the analysis. The SEM estimates are based on a continuous distance matrix.

6.5. Innovation and GDP growth

The last performance indicator we considered is GDP growth rate. The literature has long emphasized the positive impact of R&D on economic growth; the impact of innovation is instead less documented probably because of limited data availability, especially at the regional level. Therefore, to better understand the (differential) impact of knowledge and innovation on GDP growth rate, we estimated the following model:

GDP_gr_r = F (Employment growth rate in manufacturing$_r$, Trust$_r$, EU12, FDI$_r$, Structural funds$_r$, Functional specialization$_r$, Mega, Capabilities$_r$, Knowledge$_r$, Innovation$_r$,) + ε_r

In our estimates, we control for a series of factors that can affect regional performance, namely: the functional specialization, the settlement structure, the infrastructure endowment, the social capital (i.e. trust), the local attractiveness as captured by the FDI penetration rate, the availability of public funds as captured by the intensity of Structural funds expenditures, the labour market dynamics, human capital and knowledge embedded into capabilities, and the distinction between EU12 and EU15, as growth patterns have been shown to be quite different in New and Old member states (Capello et al., 2008; Capello et al., 2011)
Details on indicators, sources and descriptive statistics are available in Tables 6.1 and 6.2. To better emphasise territorial heterogeneity in knowledge and innovation behaviours we re-run the analysis for specific groups of regions, namely, EU15, EU12 and EFTA4 countries, Convergence, Transition and Competitive regions, Metropolitan and non-metropolitan regions, the five territorial patters of innovation identified in chapter 2. Details on the regional typologies used are available in Table 6.3.

Estimates are reported in Tables 6.19 to 6.21. Table 6.18 reports the elasticity values at the EU level and for specific groups of regions. Elasticity is the measurement of how changing one independent variable affects the dependent variable; in detail, it is the ratio of the percentage change in one variable to the percentage change in another variable, being thus independent of units. The regional elasticity of GDP growth rate to innovation ($E_{GDP\_gr,\ Innovation}$) is obtained by multiplying the innovation estimated coefficient ($\beta_{Innovation}$) times the ratio between the EU average innovation level and the EU average GDP growth rate, as the formula below summarizes:

$E_{GDP\_gr,\ Innovation} = (\%\Delta Innovationr)/(\%\Delta GDP\_gr_r) = \beta_{InnovationEU}*(Innovation_r/GDP\_gr_r)$

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 EU2020 strategy. However, our findings also suggest some caution in the interpretation of this result.
Increasing the average R&D spending at the EU level is certainly beneficial to achieve superior GDP growth rates. **On average, 1 percentage point increase in R&D spending yields a 0.12% increase in GDP growth rate (Table 6.18.). However, this mechanism takes place with different intensity across different groups of regions.**
Not surprisingly, the European science-based area 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%. Applied science area regions, gain higher than average benefits from additional expenditures in R&D being their elasticity higher than the average value (0.177%). Whereas Smart technological application area regions and Smart and creative diversification area regions can benefit from an expansion of their knowledge base (although less than the average, being their elasticity close to 0.09%), Imitative innovation area regions do not look to experience a sizeable impact from extra investments in formal knowledge. All in all, these results support the idea that **further investments in new formal knowledge creation should be concentrated in those regions that are able to take the greatest advantages from it.**
However, the magnitude of the R&D impact tends to vanish once the innovation variable is introduced. The effect of innovation (here measured as the share of firms introducing product and/or process innovation) on GDP growth rate are comparable to that of R&D, although of

larger magnitude and geographical dispersion. The elasticity of GDP growth rate to innovation is, on average, 0.42%, 3.5 times greater than that of R&D. Importantly, the growth benefits stemming from innovation are **spatially more distributed than those stemming from formal knowledge** (Map 4.4.1). In fact, the differences in the elasticity of GDP growth rate to innovation across the five patterns of innovation are not as noticeable as those in the elasticity of GDP growth rate to R&D. Whereas this partly reflects a more spatially distributed nature of innovation in comparison with knowledge (as Maps 1.3.1, 1.3.2, and 1.4.2. show), **this also suggests that the different groups of regions are similarly efficient in translating innovation benefits into higher GDP growth rate**. Nonetheless, the ranking of the GDP growth rate elasticity to innovation is similar to the ranking of the GDP growth rate elasticity to R&D. One difference only stands out. In this case, in fact, also Smart and creative diversification area regions show above the average value of elasticity of GDP growth rate to innovation. This indicates that even in absence of a strong knowledge base, innovation can yield sizeable impact on GDP growth rate. Importantly, 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 regions in the Imitative innovation area have not reached yet a critical mass of innovation to be able to turns its benefits into higher growth rate and, possibly, should implement measures in order to raise innovation levels to engage into faster growth path.

Interestingly, the impact of R&D is greater in EU12 whereas the impact of innovation is greater in EU15. However, especially competitive regions benefit from an increase in both in R&D and innovation, whereas convergence regions little benefit from R&D and, even less, from innovation; similarly to the TFP case, transition regions do not show considerable advantages in expanding their knowledge base. Lastly, GDP growth rate is more responsive to both R&D and innovation in non metropolitan settings than in metropolitan areas.

Table 6.18. 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	0,120	0,419
Competitive regions	0,171	0,411
Convergence regions	0,076	0,256
Transition regions	no impact	0,318
EU15	0,121	0,481
EU12	0,198	0,323
EFTA	0,120	0,419
European science-based area	0,332	0,810
Applied science area	0,177	0,632
Smart technological application area	0,092	0,434
Smart and creative diversification area	0,091	0,425
Imitative innovation area	no impact	no impact
Megas	0,140	0,164
Non megas	0,140	0,551

Note: Elasticity based on SAR models of tables 6.19-6.21 unless stated differently and statistically significant at conventional levels.

Table 6.19. GDP growth determinants (2005-2007)

Dependent variable: GDP growth rate 2005-2007	(1) OLS	(2) SAR	(3) OLS	(4) SAR	(5) OLS	(6) SAR
Employment growth rate in manufacturing (2002-2004)	0,075**	0,079**	0,064**	0,067**	0,068**	0,062**
	(0,033)	(0,031)	(0,032)	(0,031)	(0,033)	(0,032)
EU12	0,043***	0,040**	0,063***	0,059***	0,066***	0,053***
	(0,015)	(0,017)	(0,016)	(0,017)	(0,016)	(0,019)
Trust	0,017**	0,017**	0,018**	0,018**	0,017**	0,014*
	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)
Infrastructure endowment	-0,005**	-0,005*	-0,007***	-0,007**	-0,007***	-0,006**
	(0,002)	(0,003)	(0,002)	(0,003)	(0,002)	(0,003)
FDI	0,005***	0,004*	0,005***	0,005*	0,005***	0,005*
	(0,002)	(0,003)	(0,002)	(0,003)	(0,002)	(0,003)
Structural funds expenditures	0,001	0,001	0,002*	0,002	0,002**	0,002
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
% of blue collars professions	-0,022	-0,020	-0,039**	-0,037**	-0,032*	-0,025
	(0,017)	(0,017)	(0,017)	(0,017)	(0,017)	(0,018)
Capabilities	0,005***	0,005***	0,005***	0,005***	0,005***	0,005***
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
Megas	0,005**	0,005**	0,005**	0,005**	0,005**	0,005**
	(0,002)	(0,002)	(0,002)	(0,002)	(0,002)	(0,002)
R&D	0,318***	0,319***			0,191*	0,198*
	(0,099)	(0,102)			(0,115)	(0,105)
Innovation			0,044***	0,043***	0,039***	0,033***
			(0,009)	(0,009)	(0,010)	(0,010)
Constant	0,019	0,045**	-0,002	0,023	-0,006	-0,009
	(0,012)	(0,019)	(0,013)	(0,020)	(0,013)	(0,016)
Lagrange multiplier (spatial error)	0,852		0,409		2,608	
Lagrange multiplier (spatial lag)	2,979*		2,508*		4,108**	
Rho		-0,665**		-0,604**		0,297**
		(0,289)		(0,284)		(0,147)
R2 (OLS) – Sq. Correlation (SAR)	0,38	0,38	0,41	0,43	0,42	0,43
Observations	262	262	262	262	262	262

* $p < 0,10$, ** $p < 0,05$, *** $p < 0,01$. OLS with robust standard errors. The SAR estimates are based on a row-standardised continuous distance matrix.

Table 6.20. Relationship between GDP growth and R&D by regional typologies

Dependent variable: GDP growth rate 2005-2007	(1) OLS	(2) SAR	(3) OLS	(4) SAR	(5) OLS	(6) SAR	(7) OLS	(8) SAR
Employment growth rate in manufacturing (2002-2004)	0,059*	0,063*	0,074**	0,078**	0,081**	0,084***	0,075**	0,079**
	(0,034)	(0,033)	(0,033)	(0,031)	(0,032)	(0,030)	(0,034)	(0,031)
EU12	0,049***	0,045**	0,035*	0,031*	0,023	0,020	0,042***	0,039**
	(0,016)	(0,018)	(0,018)	(0,019)	(0,015)	(0,017)	(0,014)	(0,017)
Trust	0,018***	0,018**	0,016**	0,016**	0,016**	0,016**	0,017**	0,017**
	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)
Infrastructure endowment	-0,006**	-0,006*	-0,006**	-0,005*	-0,006**	-0,006**	-0,006**	-0,005**
	(0,002)	(0,003)	(0,002)	(0,003)	(0,003)	(0,003)	(0,003)	(0,003)
FDI	0,005***	0,004*	0,005***	0,004*	0,005***	0,004*	0,005***	0,004*
	(0,002)	(0,003)	(0,002)	(0,003)	(0,002)	(0,003)	(0,002)	(0,003)
Structural funds expenditures	0,001	0,001	0,000	0,000	0,000	0,000	0,001	0,001
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
% of blue collars professions	-0,023	-0,020	-0,025	-0,022	-0,019	-0,017	-0,023	-0,021
	(0,017)	(0,017)	(0,017)	(0,018)	(0,017)	(0,017)	(0,017)	(0,017)
Capabilities	0,005***	0,005***	0,005***	0,005***	0,005***	0,005***	0,005***	0,005***
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
Megas	0,005*	0,005**	0,005**	0,005**	0,004*	0,004*	0,009**	0,009**
	(0,002)	(0,002)	(0,002)	(0,002)	(0,002)	(0,002)	(0,004)	(0,004)
R&D							0,392***	0,386***
							(0,114)	(0,113)
R&D*European science-based area	0,424***	0,427***						
	(0,126)	(0,156)						
R&D*Applied science area	0,351***	0,350***						
	(0,127)	(0,130)						
R&D*Smart technological application area	0,205*	0,206*						
	(0,107)	(0,127)						
R&D*Smart and creative diversification area	0,363*	0,364**						
	(0,193)	(0,168)						
R&D* Imitative innovation area	-0,173	-0,148						
	(1,183)	(0,639)						
R&D*Competitive			0,288***	0,291***				
			(0,099)	(0,104)				
R&D*Convergence			0,589*	0,570**				
			(0,324)	(0,265)				
R&D*Transition			0,415*	0,457				
			(0,219)	(0,361)				
R&D*EU15					0,231**	0,235**		
					(0,098)	(0,101)		
R&D*EU12					2,046***	1,992***		
					(0,518)	(0,400)		
R&D*Megas							-0,262	-0,240
							(0,183)	(0,178)
Constant	0,015	0,041**	0,026*	0,052***	0,027**	0,051***	0,019	0,044**
	(0,012)	(0,019)	(0,014)	(0,020)	(0,012)	(0,018)	(0,012)	(0,019)
Lagrange multiplier (spatial error)	0,701		0,831		0,970		0,796	
Lagrange multiplier (spatial lag)	2,953*		2,969*		2,774*		2,898*	
Rho		-0,665**		-0,664**		-0,606**		-0,645**
		(0,288)		(0,289)		(0,282)		(0,289)
R2 (OLS) – Squared Correlation (SAR)	0,39	0,41	0,39	0,41	0,43	0,44	0,39	0,41
Observations	262	262	262	262	262	262	262	262

* $p < 0,10$, ** $p < 0,05$, *** $p < 0,01$. OLS with robust standard errors. The SAR estimates are based on a row-standardised continuous distance matrix.

Table 6.21. Relationship between GDP growth and innovation by regional typologies

Dependent variable: GDP growth rate 2005-2007	(1) OLS	(2) SAR	(3) OLS	(4) SAR	(5) OLS	(6) SAR	(7) OLS	(8) SAR
Employment growth rate in manufacturing (2002-2004)	0,048	0,051	0,067**	0,070**	0,062**	0,066**	0,065**	0,068**
	(0,033)	(0,032)	(0,033)	(0,031)	(0,031)	(0,030)	(0,032)	(0,030)
EU12	0,064***	0,060***	0,079***	0,074***	0,050**	0,046**	0,066***	0,062***
	(0,016)	(0,017)	(0,019)	(0,021)	(0,020)	(0,019)	(0,016)	(0,017)
Trust	0,019**	0,019***	0,018**	0,018**	0,017**	0,017**	0,018**	0,018**
	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)
Infrastructure endowment	-0,006***	-0,006**	-0,007***	-0,007**	-0,007***	-0,007**	-0,006**	-0,006**
	(0,002)	(0,003)	(0,002)	(0,003)	(0,003)	(0,003)	(0,002)	(0,003)
FDI	0,005***	0,004	0,005***	0,005*	0,005***	0,005*	0,005***	0,004*
	(0,002)	(0,003)	(0,002)	(0,003)	(0,002)	(0,003)	(0,002)	(0,003)
Structural funds expenditures	0,002*	0,002	0,003**	0,002*	0,002*	0,001	0,002*	0,002
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
% of blue collars professions	-0,036**	-0,034**	-0,037**	-0,035**	-0,039**	-0,037**	-0,043**	-0,040**
	(0,016)	(0,017)	(0,017)	(0,017)	(0,017)	(0,017)	(0,018)	(0,017)
Capabilities	0,005***	0,005***	0,006***	0,006***	0,005***	0,005***	0,005***	0,005***
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
Megas	0,004*	0,004*	0,005**	0,005**	0,005**	0,005**	0,019**	0,019***
	(0,002)	(0,002)	(0,002)	(0,002)	(0,002)	(0,002)	(0,009)	(0,006)
Innovation							0,056***	0,055***
Innovation*European science-based area	0,044**	0,042***						
	(0,021)	(0,013)						
Innovation*Applied science area	0,052*	0,049***						
	(0,028)	(0,016)						
Innovation*Smart technological application area	0,046	0,043**						
	(0,034)	(0,019)						
Innovation*Smart and creative diversification area	0,062	0,059**						
	(0,047)	(0,025)						
Innovation* Imitative innovation area	0,024	0,020						
	(0,078)	(0,039)						
Innovation*Convergence			0,032**	0,031***				
			(0,013)	(0,012)				
Innovation*Competitive			0,048***	0,047***				
			(0,009)	(0,010)				
Innovation*Transition			0,034***	0,034***				
			(0,011)	(0,012)				
Innovation*EU15					0,039***	0,037***		
					(0,007)	(0,010)		
Innovation*EU12					0,076*	0,075***		
					(0,044)	(0,023)		
Innovation*mega							-0,039*	-0,037**
							(0,021)	(0,016)
Constant	-0,004	0,021	-0,013	0,013	0,003	0,029	-0,007	0,017
	(0,017)	(0,020)	(0,015)	(0,022)	(0,013)	(0,020)	(0,014)	(0,020)
Lagrange multiplier (spatial error)	0,816		0,383		0,581		0,455	
Lagrange multiplier (spatial lag)	2,632*		2,499*		2,622		2,378*	
Rho		-0,602**		-0,605**		-0,613**		-0,569**
		(0,283)		(0,284)		(0,284)		(0,282)
R2 (OLS) – Squared Correlation (SAR)	0,43	0,44	0,42	0,43	0,41	0,43	0,43	0,44
Observations	262	262	262	262	262	262	262	262

* *p* < 0,10, ** *p* < 0,05, *** *p* < 0,01. OLS with robust standard errors. The SAR estimates are based on a row-standardised continuous distance matrix.

6.6. References

Bogliacino F. and Pianta M. (2010), "Innovation and employment: A reinvestigation using revised Pavit classes", *Research Policy*, 39: 799-809

Capello R., Camagni R., Chizzolini B., Fratesi Ug. (2008), *Modelling Regional Scenarios for the Enlarged Europe. European Competitiveness and Global Strategies*, Springer-Verlag, Berlin

Capello R., Fratesi U. e L. Resmini (2011), *Globalization and Regional growth. Past Trends and Future Scenarios*, Springer-Verlag

Dettori B., E. Marrocu and R. Paci (2011) Total Factor Productivity, intangible assets and spatial dependence in the European regions, *Regional Studies*, forthcoming, DOI: 10.1080/00343404.2010.529288.

Marrocu E., R. Paci and S. Usai (2010) Productivity growth in the Old and New Europe: the role of agglomeration externalities, *CRENoS WP* 2010/24;

Marrocu E., and Paci R. (2011), "Education or creativity? What matters most for economic performance", *Economic Geography*, forthcoming.

Pianta M. (2005), "Innovation and employment", in Fagerber I., Mowery D.C., and Nelson R.R. (eds.), *The Oxford handbook of innovation*, Oxford: Oxford University Press: 568-598

Spiezia V. and Vivarelli M. (2002), "Innovation and Employment: a Critical Survey", in N. Greenan, Y. L'Horty and J. Mairesse (eds.), *Productivity, Inequality and the Digital Economy: a Transatlantic Perspective*, Cambridge (Mass.): MIT Press: 101-131

www.espon.eu

The ESPON 2013 Programme is part-financed by the European Regional Development Fund, the EU Member States and the Partner States Iceland, Liechtenstein, Norway and Switzerland. It shall support policy development in relation to the aim of territorial cohesion and a harmonious development of the European territory.

ISBN 978-2-919777-11-2