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The Specialisation of EU Regions in Fast Growing and Key Enabling Technologies

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Abstract

In the context of the Europe 2020 objective of establishing in the EU a smart, sustainable and inclusive economy, European regions have been called to design and implement national and regional 'Research and Innovation Strategies for Smart Specialisation' (RIS3). The rationale behind the concept of smart specialisation is that, in a context of global competition for talent and resources, most regions can only acquire a real competitive edge by finding niches or by mainstreaming new technologies into traditional industries and exploiting their 'smart' regional potential.

Although the most promising way for a region to promote its knowledge-based growth is to diversify into technologies, products and services that are closely related to existing dominant technologies and the regional skills base, the European Commission puts special emphasis on a set of technologies labelled as 'Key Enabling Technologies' (KETs). Despite the great emphasis on KETs, there is only very limited evidence on the capability of EU regions to specialise in these fields and there are no studies directly investigating the actual impact of these technologies on regional innovation and economic growth. This report aims at filling these gaps by: i) looking at the relationship between KETs and 'Fast Growing Technologies' (FGTs); ii) providing empirical evidence on the EU regional specialisation in KETs and FGTs; iii) relating technological specialisation to regional innovation and economic growth. In particular, the report aims at answering these questions: 1) Which technologies have emerged as the fastest growing ones in the recent decades? 2) Is there a relationship between fast growing technologies and KETs? 3) Which regions are specialised in FGTs and KETs? 4) Are there convergence and polarization phenomena observable in the evolution of EU regions' innovative activities in fast growing technologies and KETs? 5) Do EU regions specialized in fastest growing technological fields and key enabling technologies exhibit higher innovation and economic performances?

The main results of the report can be summarised as follows. First, only a small share of KETs are also fast growing technologies, although the degree of overlapping between KETs and FGTs varies substantially across different KETs fields. Second, while KETs are concentrated in Central Europe, FGTs prevail in Scandinavian countries and the UK. Third, while there is evidence of some regional convergence in KETs and, to a less extent, in FGTs, spatial correlation increases over time, showing that diffusion often occurs across contiguous regions. Finally, the results of the estimations of the effects of FGTs and KETs on innovation (patents) and economic (GDP per capita) growth show that only specialisation in KETs directly affects economic growth, while specialisation in FGTs has an impact on growth only indirectly, that is through its impact on regions' innovation performances. Overall, these results confirm the pervasive and enabling role of KETs pointing to the importance for European regions to target these technologies as part of their RIS3 strategies.

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1. Introduction

In the context of the Europe 2020 objective of establishing in the EU a smart, sustainable and inclusive economy, European regions have been called to design and implement national and regional innovation strategies for smart specialisation (RIS3). More particularly, RIS3 focuses on economic development efforts and investments on each region's relative strengths, exploiting its economic opportunities and emerging trends, and taking action to boost a knowledge-based growth and employment. The rationale behind the concept of smart specialisation is that, in a context of global competition for talent and resources, most regions can only acquire a real competitive edge by finding niches or by mainstreaming new technology into traditional industries and exploiting their 'smart' regional potential.

Although the most promising way for a region to promote its knowledge-based growth is to diversify into technologies, products and services that are closely related to existing dominant technologies and the regional skills base, the European Commission puts special emphasis on a set of technologies labelled as Key Enabling Technologies (KETs). These include nanotechnology, micro- and nanoelectronics, advanced materials, photonics, industrial biotechnology and advanced manufacturing systems (European Commission Communication, 2009). Selection criteria include their economic potential, their value adding and enabling role as well as their technology and capital intensity. In the Commission Staff Working Document (SEC(2009)1257) "Current situation of key enabling technologies in Europe". KETs are defined as "…*knowledge and capital-intensive technologies associated with high research and development (R&D) intensity, rapid and integrated innovation cycles, high capital expenditure and highly-skilled employment. Their influence is pervasive, enabling process, product and service innovation throughout the economy. They are of systemic relevance, multidisciplinary and trans-sectorial, cutting across many technology areas with a trend towards convergence, technology integration and the potential to induce structural change"*.

KETs work as a key accelerator of innovation and the competitiveness of EU industries and are a key policy instrument within the RIS3 strategy to enhance the technology and innovation capacities of regions, but also tackling the broader societal challenges. Despite the great emphasis on KETs, there is only very limited evidence on the capability of EU regions to specialise in these fields (for the state of the art, see European Commission, 2014) and there is no direct evidence on the actual impact of these technologies on regional innovation and economic growth[1]. At the same time, recent works have pointed out the importance of developing comparative advantages in high opportunity technological fields (Meliciani, 2001; Nesta and Patel, 2004) or emerging – fast growing - technologies (OECD, 2013), mainly relying on country level evidence. However, the effects of the specialisation in specific innovation-driven sectors have remained unexplored at the regional level.

This report aims at filling these gaps by providing empirical evidence on the EU regional specialisation in KETs and fast growing technologies (FGTs) and on their economic impact, in order to support the assessment and future implementation of region's smart specialisation strategies.

[1] Montresor and Quatraro (2015) investigate the role of KETs for the development of new comparative advantages in the context of smart specialisation strategies.

More precisely, the main issues addressed in this study can be formulated as follows: 1) Which technologies have emerged as the fastest growing ones in the recent decades? 2) Is there a relationship between fast growing technologies and KETs? 3) Which regions are specialised in FGTs and KETs? 4) Are there convergence and polarization phenomena observable in the evolution of EU regions' innovative activities in fast growing technologies and KETs? 5) Do EU regions specialized in fastest growing technological fields and Key Enabling Technologies KETs exhibit higher innovation and economic performances?

The Report is organised as follows: Section 2 discusses the literature on fast growing and emerging technologies and their economic impact. Section 3 sets up the criteria to identify fast growing technologies and investigates their relationship with KETs. Section 4 reports descriptive statistics on regional absolute and comparative advantages in KETs and fast growing technologies, their evolution over time and their degree of concentration and diversification. Section 5 estimates the impact of KETs and FGTs on regional innovation and economic growth. Finally, Section 6 concludes and draws the main policy implications of this study.

2. State of the art

Schumpeter (1939) observes that technical change, which is the driving force of economic growth, is not evenly distributed over time, but appears discontinuously in swarms. The clustering of innovations leads to the major role being played by specific industries in different waves of development. Every economic cycle receives impulses from specifically determined innovating industries, while other industries are subject to the impulses generated by the innovating ones. The innovating industries are generally new emerging sectors in the economy, and experience very high rates of growth stemming from the exploitation of clusters of related innovations. This idea informs the Schumpeterian literature on techno-economic paradigms (Perez, 1985, 1988; Freeman and Perez, 1988; Freeman and Louca, 2001; Guerrieri and Padoan, 2007) and, to some extent, also the neoclassical literature on General Purpose Technologies (GPTs) (Bresnahan and Trajtenberg, 1995; Helpman, 1998). Perez (1985, 1988) and Freeman and Perez (1988) explain Schumpeter's long cycles as a succession of techno-economic paradigms. A change in paradigm carries with it many clusters of radical and incremental innovations and has pervasive effects throughout the economy, spreading from the initial industries where it takes place to the whole economy. Moreover, it implies not only major product and process innovations but also organisational and social changes. Changes in paradigms lead to periods of high technological opportunity that can be exploited unevenly by different countries on the basis of the match or mismatch between the characteristics of the new technologies and the specific socio-institutional contexts.

Similarly to techno-economic paradigms, GPTs are radical new ideas or techniques having a potential relevant impact on many industries in the economy. Key characteristics of GPTs are: pervasiveness (used as inputs by many downstream industries); technological dynamism (inherent potential for technical improvements) and innovation complementarities with other forms of advancement (meaning that the productivity of R&D in downstream industries increases as a consequence of innovation in GPTs). Thus, as general purpose technologies improve, they spread throughout the economy, bringing about generalised productivity gains.

Overall, the fact that technical change is cumulative and that innovations are clustered, leads to the consequence that it is not indifferent in which technological areas countries or regions are specialised: investing resources in technologies with a high degree of dynamism is more likely to lead to a more rapid rate of technical change. Second, technologies differ in their degree of pervasiveness, i.e. in their ability to affect different economic activities; therefore countries and regions with the same rate of technical change may achieve different economic performances because of their different technological and productive specialization. Both notions of technological opportunity point to its historical character as the degree of dynamism and pervasiveness of technologies varies over time.

Based on these concepts, few studies have attempted to identify high opportunity fields, to measure countries' ability to specialise in these fields and their impact on technological and economic performance (Pianta and Meliciani, 1996; Meliciani and Simonetti, 1998; Vertova, 2001; Meliciani, 2001, 2002; Huang and Miozzo, 2004; Nesta and Patel, 2004). Pianta and Meliciani (1996) find a positive impact of the degree of technological specialisation (concentration of patents) on economic growth but no impact of specialisation in electronics (which they consider a high opportunity field). Vertova (2001) identifies high opportunity technological fields as those with a growth rate above the average and finds that most countries do not have the capability to specialise in the highest technological opportunities, but remain locked into inferior technological paths. Huang and Miozzo (2004) assess the 'quality' of the technological specialisation by looking at the values of this index in particular technological sectors characterised by high levels of pervasiveness and growth rates. Meliciani and Simonetti (1998) and Meliciani (2001) look at the fastest growing patent classes in the US between the periods 1970–74 and 1990–94 and find that over the 1980s they were mainly Information and Communication Technologies (ICTs). They also find that countries specialised in the fast-growing technological areas or in ICTs-related patent classes experiences above-average rates of growth of per capita GDP. Finally, Meliciani (2002), in a balance of payments constrained growth model, finds that countries specialised in the fastest growing technologies face more favourable income elasticities of demand, resulting in higher international competitiveness and economic growth.

The literature reviewed so far has analysed and assessed the impact of specialisation exclusively at the country level. Moreover, it has focussed on emerging technologies (mostly identified as the new fact growing technological fields), while no study has related specialisation in key enabling technologies to technological and economic performances. The value added of this report is to measure specialization in fast growing technologies and in KETs at the regional level and to assess their technological and economic impact.

3. Key enabling technologies (KETs) and fast growing technologies (FGTs)

Key enabling technologies have been identified by the European Commission in its Communication "Preparing for our future: Developing a common strategy for key enabling technologies in the EU" (COM(2009)512). On the basis of their economic potential, contribution to tackle societal challenges, and knowledge intensity, the following technologies have been identified: 1) Nanotechnology, 2) Micro- and nanoelectronics, 3) Photonics, 4) Advanced materials, 5) Biotechnology, 6) Advanced manufacturing systems.

In particular, nanotechnology should lead to the development of nano and micro devices and systems affecting vital fields such as healthcare, energy, environment and manufacturing. Nano-electronics, including semiconductors, have wide applications in various sectors including automotive and transportation, aeronautics and space since they are essential for all goods and services which need intelligent control. Photonics is a multidisciplinary domain dealing with light, encompassing its generation, detection and management. Among other things it provides the technological basis for the economic conversion of sunlight to electricity which is important for the production of renewable energy, and a variety of electronic components and equipment such as photodiodes, LEDs and lasers. Advanced materials offer major improvements in a wide variety of different fields. Moreover, they facilitate recycling, lowering the carbon footprint and energy demand as well as limiting the need for raw materials that are scarce in Europe. Biotechnology develops cleaner and more sustainable process alternatives for industrial and agriculture and food processing operations. Finally, advanced manufacturing systems are essential for producing knowledge-based goods and services.

While there is consensus on the identification of KETs, various studies have used different criteria to identify emerging technologies (Dernis et al. 2015; for a review, see Rotolo et al., 2015[2]). However, the relative fast rate of growth of a technology is one of the most frequent attributes considered as a condition for emergence. In this report we focus on this common attribute identifying the technologies that have experienced a relatively high rate of growth (what we call FGTs). In order to identify the Fast Growing Technologies (FGTs) we apply the following methodology.

Patent applications filed at EPO during the 1992-1995, 2000-2003, 2008-2011 periods have been retained from the OECD REGPAT database.[3] For each IPC code at the four digit level we have calculated the growth rates of filings between consecutive periods (that is 2000-2003 versus 1992-1995 and 2008-2011 versus 2000-2003).The IPC codes with growth rates above the 75% percentile are considered FGTs for all the years within the periods considered; therefore FGTs have been identified for the 1996-2003 and

[2] As put forward by Rotolo et al. (2015), there are multiple definitions and methodologies in the literature to identify emerging technologies. The authors have suggested a reconciling definition of an emerging technology as "*a radically novel and relatively fast growing technology characterised by a certain degree of coherence persisting over time and with the potential to exert a considerable impact on the socio-economic domain(s) […].Its most prominent impact, however, lies in the future and so in the emergence phase is still somewhat uncertain and ambiguous.*" (Rotolo et al. 2015, page 1828).

[3] The OECD REGPAT database presents patent data that have been linked to regions utilizing the addresses of the applicants and inventors.

2004-2011 sub-periods. Finally, long term FGTs have been defined as those IPC which are fast growing in both sub-periods. A list of the long term fast growing technologies is reported in Appendix 1.

Table 1 reports a transition matrix showing the distribution of the rates of growth of patents between the first and the second sub-period.

The table shows a relatively high degree of mobility in fast growing technology fields. Among the technologies in the first quartile (top 25%) in terms of rate of growth between 1992-1995 and 2000-2003, only 32% of them remain in the first quartile also between 2000-2003 and 2008-2011, while 41% move to the central part of the distribution and 26% to the last quartile.

Table 1:Transition matrix for the patents growth rates

Growth		Second period		
		Bottom 25	Middle 50	Top 25
First period	Bottom 25	31.8%	43.9%	24.3%
	Middle 50	21.1%	57.1%	21.8%
	Top 25	26.4%	41.2%	32.4%

Note: calculated for the 1992/95 to 2000/03 and 2000/03 to 2008/11 periods on EPO patent applications as reported in REGPAT.

The correlation coefficient between the rate of growth in the two periods is not very high (0.16) and the Spearman rank correlation rejects independence only at a 10% statistical significance level. These results seem to suggest that only few technologies have the potential of driving Schumpeterian long-term technological cycles or sustain the emergence of new techno-economic paradigms.

But is there a link between fast growing technologies and KETs? Table 2 shows the relationship between KETs and FGTs in the long period and in the two sub-periods for all KETs together and for each enabling technology separately.

Table 2 - Fast growing technologies and key enabling technologies

	Long term FGTs			FGTs (1992-95 to 2000-03)			FGTs (2000-03 to 2008-11)		
	Others	Fast Growing	Total	Others	Fast Growing	Total	Others	Fast Growing	Total
KETs	*86*	*14*	*100*	*55*	*45*	*100*	*73*	*27*	*100*
Nano	0	100	100	0	100	100	0	100	100
Ind. Bio	83	17	100	8	92	100	82	18	100
Photonics	63	37	100	36	64	100	42	58	100
MNE	90	10	100	68	32	100	84	16	100
Adv. Mat.	94	6	100	77	23	100	86	14	100
AMT	84	16	100	44	56	100	61	39	100
All patents	84	16	100	45	55	100	71	29	100

Source: *Authors' own calculations on EPO patent applications as reported in REGPAT.*

The first three columns in Table 2 show that 16% of all patents belongs to long term fast growing patent fields and 14% of KETs patents belongs to FGTs (a patent is defined as FGTs and KETs if it contains at least one KETs/FGTs code). This means that KETs related patents are slightly less related with fast growing technologies than other patents (for which the share is 16%). Similar results are found when looking at sub-periods. It is also worth observing that in the first sub-period 55% of patents are related to FGTs while the percentage decreases to 29% in the second sub-period (fast growing technologies are larger in terms of patents in the first period when the average number of patents for FGTs is 1402 while it drops to 850 in the second period). The overall lack of correlation between FGTs and KETs hides strong differences across the six different KETs. In fact, the correspondence is complete in the case of Nanotechnology and it is high also in the case of Photonics. Moreover, in the case of Industrial Biotechnology and in the case of Advanced Manufacturing Technologies the correspondence level is high in one of the two periods (the first for Industrial Biotechnology and the second for AMT).

4. The technological strength and specialisation of EU regions in KETs and FGTs

4.1 Data and indicators

The empirical analysis uses patent data referring to a sample of European Union regions at the NUTS 2 level, and taking into account the period 1996-2011. Due to problems with variability of patents data over time, patents are aggregated over 4 years periods (1996-1999; 2000-2003; 2004-2007 and 2008-2011). Finally, in order to reduce problems of small numbers, regions with less than twenty patents in the first period are dropped from the sample. Thus, we end up with a sample of 227 NUTS2 European Union regions.

The technological strength of EU regions in KETs and FGTs is captured by the 'absolute technological advantage' indicator, measuring the share of each region *i* in the total number of patents in KETs or FGTs:

$$ATA_i = \frac{KET_i}{\sum_{i=1}^{N} KET_i}$$

where KET is the number of patents in Key Enabling Technologies for region *i* and N is the total number of regions. Technological specialisation is measured by the revealed technological advantage index:

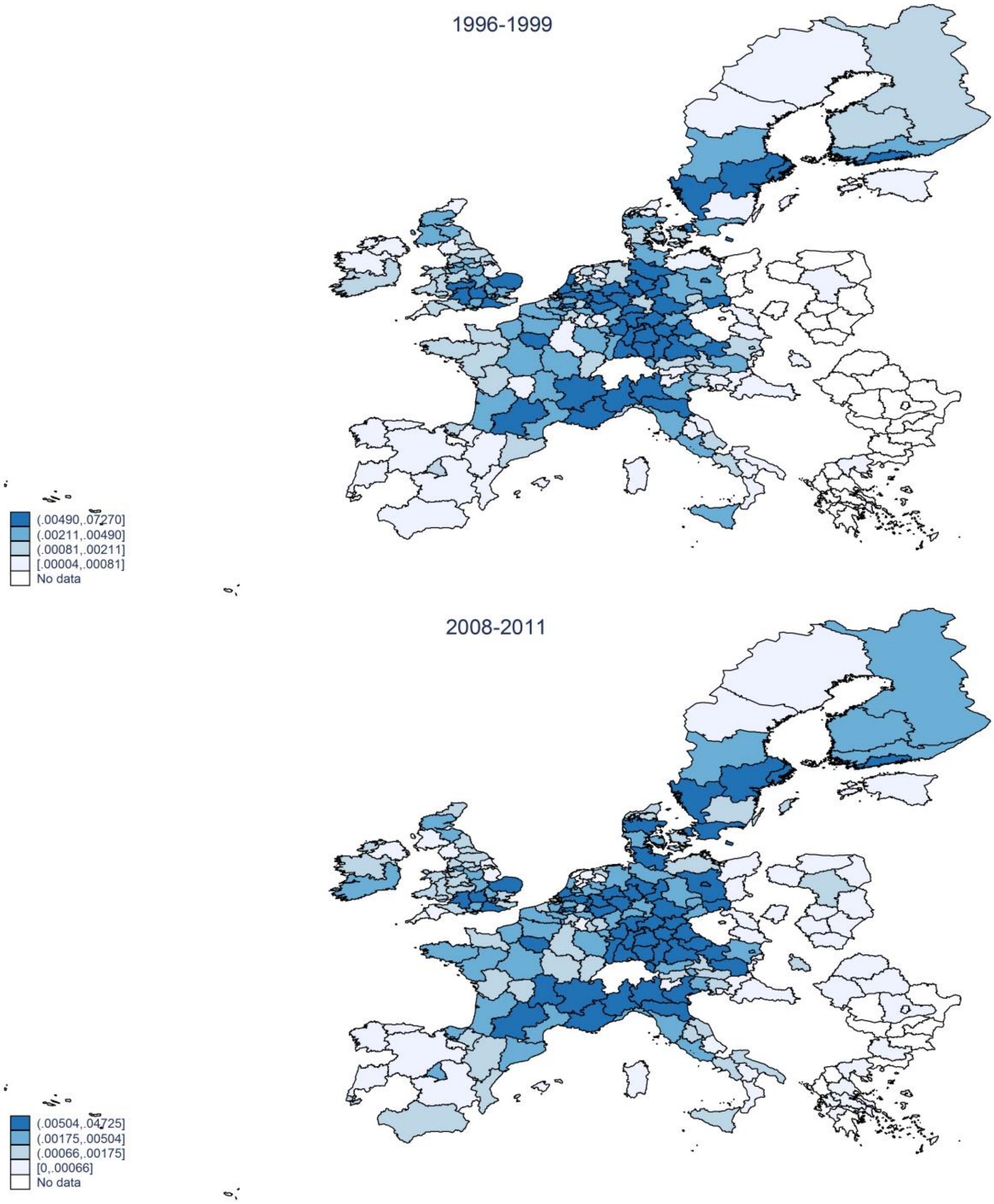
$$RTA_i = \frac{KET_i}{\sum_{i=1}^{N} KET_i} / \frac{PAT_i}{\sum_{i=1}^{N} PAT_i}$$

where PAT indicates the total number of patents. Values of RTA larger than one indicate relative specialisation (the share of region *i* in KETs is higher than the same share computed for total patents). Analogous indicators are computed for FGTs.

4.2 Regional absolute and comparative advantages in KETs

Figure 1 shows two maps reporting the indicators of absolute advantage in KETs (quartiles) for the sample of NUTS2 regions in the first (1996-1999) and last period (2008-2011) respectively.

Figure 1: Regional strength in KETs: 1996-1999 and 2008-2011



Source: *Authors' own calculations on EPO patent applications as reported in REGPAT.*

The maps show that in both periods patents in KETs are concentrated in Central Europe. However, there are some signs of cross-regional diffusion of these technologies over time. In particular, while in 1996-1999 the ten regions with the highest absolute advantages (7 German regions, plus Ile de France and Rhone-Alpes in France and Noord Brabant in the Netherlands) accounted for 40% of total patents in KETs, this share decreases to 35% in 2008-2011. Moreover, the standard deviation of the absolute advantage index decreases from 0.0098 to 0.0079 and the kurtosis index from 22.68 to 15.59.

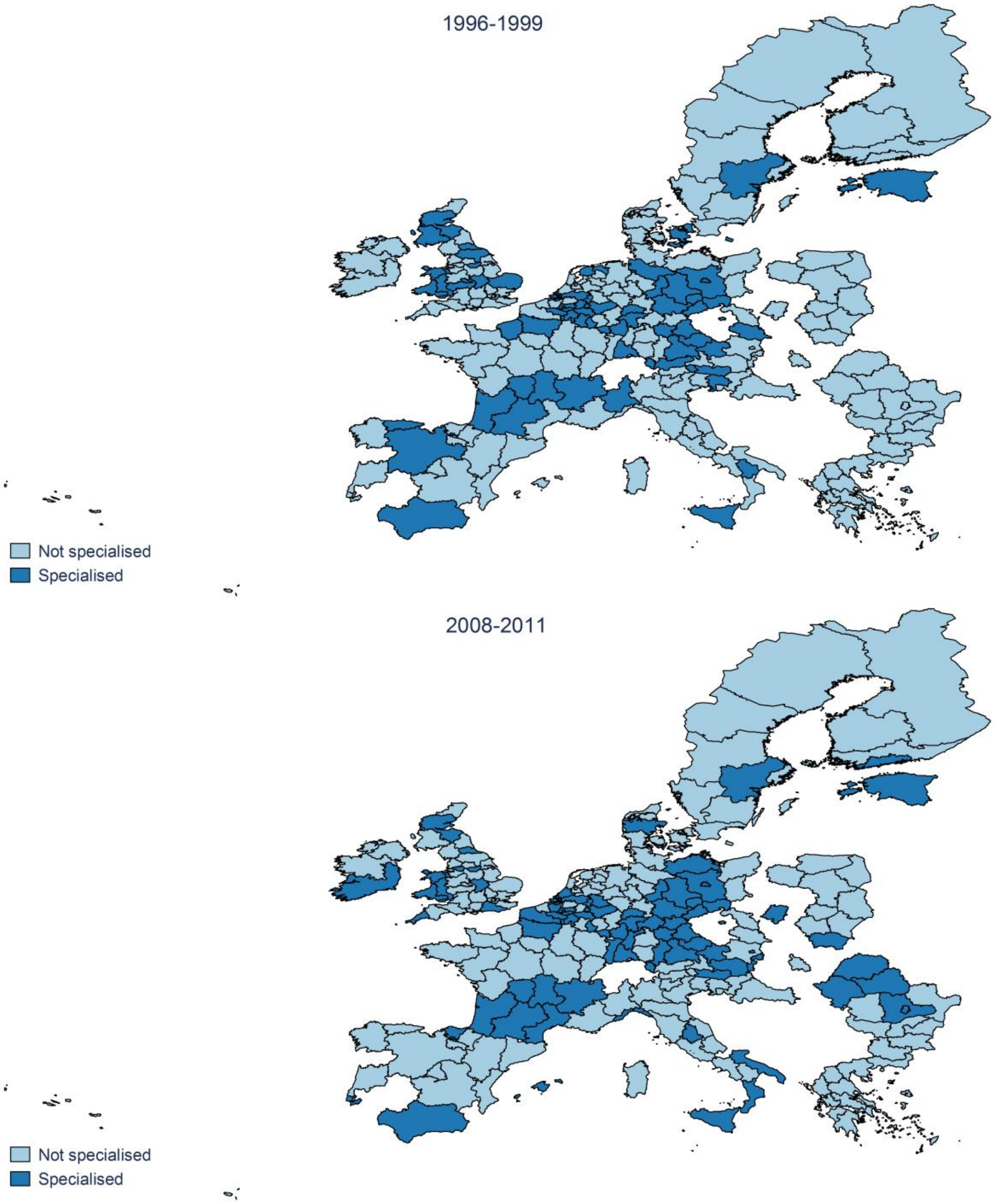
Overall KETs at the beginning of the period are more concentrated than total patents. In fact the standard deviation of the share of total patents is 0.0085 and the ten regions with the highest shares account for 35% of total patents. At the end of the period the levels of concentration for total patents and KETs are much closer to each other (the standard deviation of the share of total patents is 0.0074 and the ten regions with the highest shares account for 31% of total patents). Interestingly, diffusion occurs often among contiguous regions so that, despite the decrease in the cross-regional variability, spatial correlation increases. The Moran coefficient[4] computed on the absolute advantage in KETs increases from 0.10 to 0.13 between 1996-99 and 2008-11.

The indicator of absolute technological advantage is strongly linked to the overall technological capability of the region. In order to have indications on the relative strength of the regions in Key Enabling Technologies, Figure 2 reports the EU regions (relatively) specialized in KETs (i.e. with RTA>1) in 1996-1999 and in 2008-2011.

In 1996-1999 68 regions are specialised in KETs. Most of them are located in Central Europe (19 in Germany, 8 in Belgium, 7 in France, 5 in the Netherlands and 4 in Austria) and tend to be spatially concentrated. However, there are cases of regions specialised in KETs also in Italy, Spain, UK, Czech Republic and Northern European countries, but without a clear geographical pattern. In 2008-2011 the number of regions specialised in KETs increases from 68 to 82. Out of these 82 regions, 48 were already specialised in KETs in the previous period while 34 are new entrants. All in all, the comparison of the two maps reveals a relatively high degree of mobility.

[4] The Moran coefficient is a measure of spatial autocorrelation and takes values from −1 (indicating perfect dispersion) to +1 (perfect grouping). The Moran coefficient is similar but not equivalent to a correlation coefficient. In particular, a positive coefficient indicates that similar values occur near one another, where a negative one indicates that dissimilar values occur near one other. Finally, a zero value indicates a random spatial pattern.

Figure 2: Regions specialised in KETs: 1996-1999 and 2008-2011



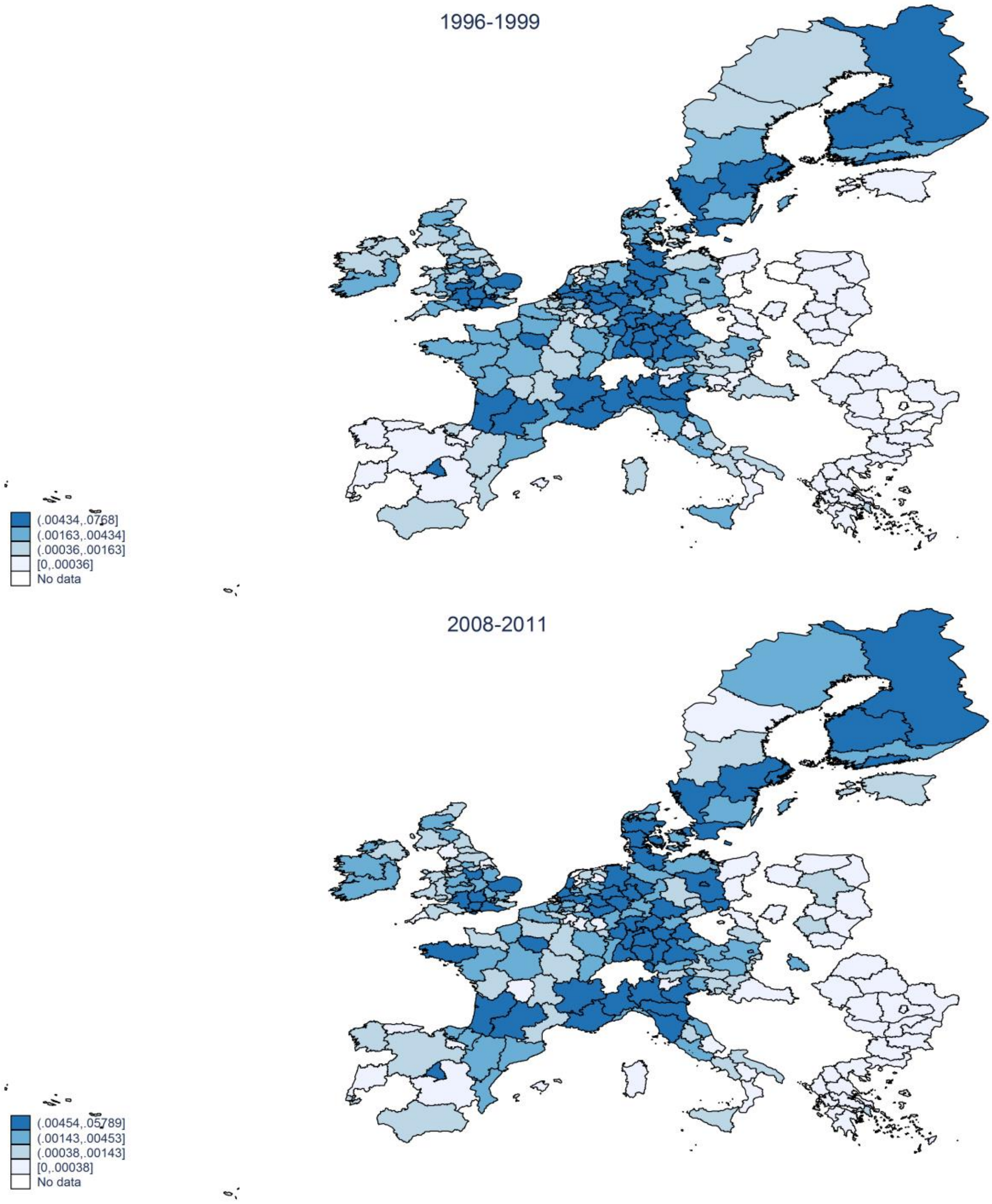
Source: *Authors' own calculations on EPO patent applications as reported in REGPAT.*

Looking at the localisation of regions specialized in KETs in the last period, we can observe on the one hand an increase in the number of German regions specialised in these technologies, on the other, a pattern of diffusion towards the East of Europe. Overall, despite the increase in the number of regions specialised in KETs, spatial correlation in RTAs, measured with the Moran index, increases from 0.10 in 1996-99 to 0.13 in 2008-11, exactly the same result found for the ATA index.

4.3 Regional absolute and comparative advantages in FGTs

Figure 3 shows the maps of the indicator of absolute advantage in FGTs (quartiles) in the first (1996-1999) and last period (2008-2011).

Figure 3: indicator of absolute advantage in FGTs (quartiles) in the first (1996-1999) and last period (2008-2011)

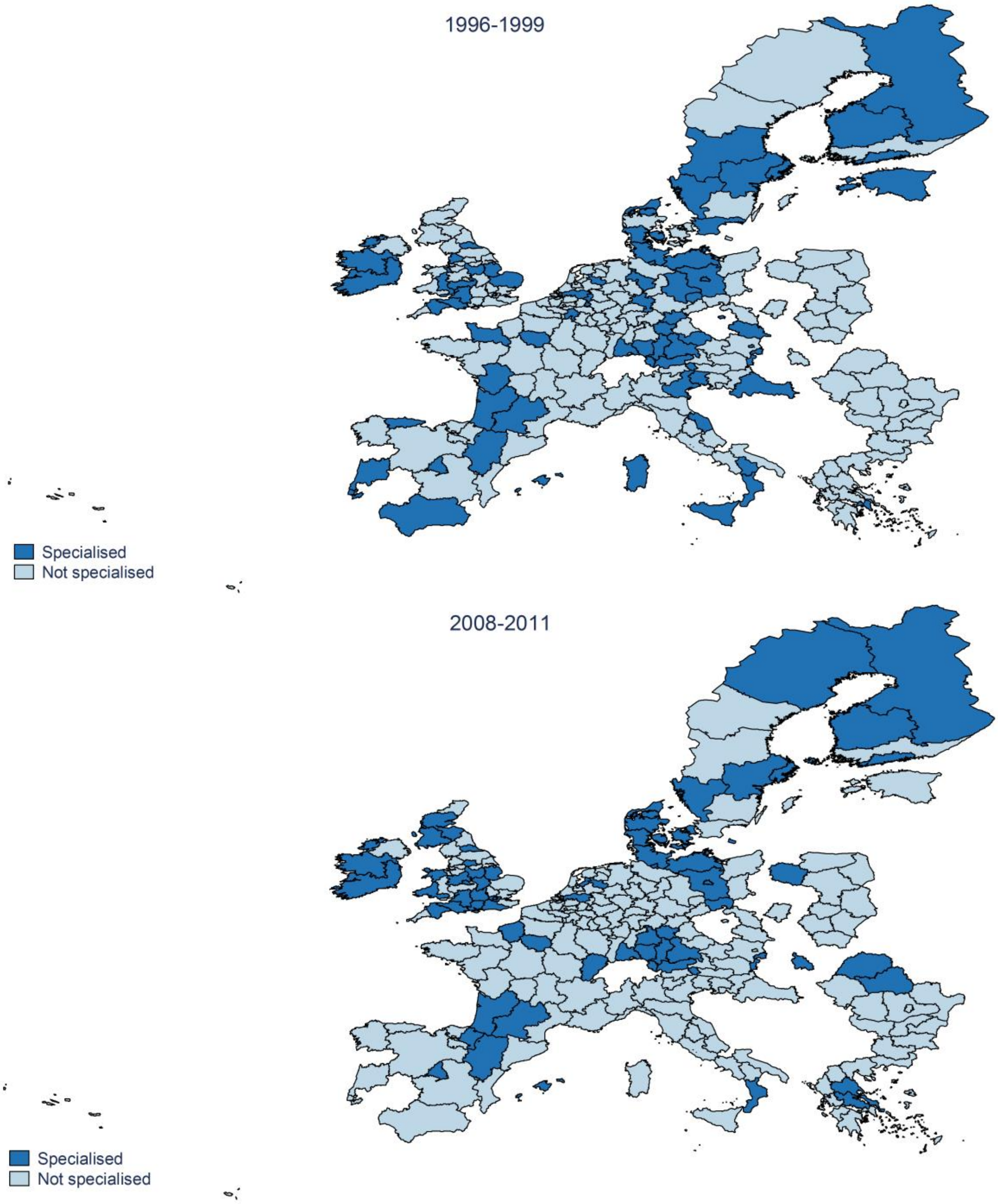


Source: *Authors' own calculations on EPO patent applications as reported in REGPAT.*

When compared to KETs, fast growing technologies appear less concentrated in Central Europe and largely present in Northern Europe (the Moran coefficient of spatial correlation is only 0.056). In fact, among the ten regions with the highest patent shares in FGTs we find 5 German regions, Ile de France (FR), Noord Brabant (NL), Lombardia (IT) but also Helsinki-Huusimaa (FI) and Stockolm (SW). At the beginning of the period, the degree of concentration of FGTs is slightly lower than that of KETs: the top ten regions account for 39% of all patents in FGTs and the standard deviation is 0.0092. As in the case of KETs, also for FGTs the level of concentration decreases over time but less markedly: in 2008-2011 the share of the top ten regions decreases to 36% (among the top ten regions Lombardia is replaced by Rhone-Alpes) and the standard deviation to 0.0084. Finally, spatial correlation slightly increases (from 0.056 to 0.062).

Figure 4 shows the regions specialised in FGTs (with RTA>1) in 1996-99 and 2008-11.

Figure 4: Regions specialised in fast growing technologies 1996-1999 and 2008-2011



Source: *Authors' own calculations on EPO patent applications as reported in REGPAT.*

In 1996-1999, 71 regions are specialised in FGTs. When compared to KETs, they appear to be less spatially concentrated. In particular, Central Europe is not the prevalent location of regions specialized in FGTs (as in the case of KETs). Many regions specialised in these technologies can in fact be found in the UK and in Northern EU countries. In 2008-2011 the number of regions specialised in FGTs decreases from 71 to 67. Out of these 67 regions, 38 were already specialised in FGTs in 1996-1999 while 29 are regions of new specialisation. Looking at the localisation of regions specialised in FGTs in the last period, we can observe an increase in the concentration in Northern Europe and the UK.

4.4 Absolute and comparative advantage in KETs and FGTs by groups of regions

In order to have a more synthetic picture of absolute and relative strengths in KETs and FGTs, table 3 reports absolute and comparative advantage indicators computed for groups of regions characterized by different levels of technological development and belonging to four different macro-regional areas. The first grouping criteria is drawn from the Regional Innovation Scoreboard (2014) which classifies regions into four innovation performance groups: 1) Leaders, 2) Followers, 3) Moderate, 4) Modest. The classification is based on a wide array of indicators measuring the ability of each region to produce and assimilate knowledge. The second way of grouping regions responds to the geographical location of their country. In particular we distinguish between Central European countries (which are divided into two groups, the first including France and Benelux and the second Germany and Austria), Great Britain (including Ireland), Scandinavian countries, Southern countries (Italy, Spain, Portugal, Greece, Cyprus and Malta) and Eastern countries (Czech Republic, Slovak, Romania, Bulgaria, Slovenia, Poland, Hungary).

Table 3 - absolute and comparative advantage in KETs and FGTs by regional groups

	Patent Share		KETs share		KETs RTA		FGTs share		FGTs RTA	
Technology groups	**1996-99**	**2008-11**	**1996-99**	**2008-11**	**1996-99**	**2008-11**	**1996-99**	**2008-11**	**1996-99**	**2008-11**
Leader	0.623	0.589	0.658	0.604	1.056	1.025	0.646	0.642	1.037	1.090
Follower	0.267	0.281	0.254	0.293	0.953	1.044	0.264	0.259	0.991	0.923
Moderate	0.107	0.123	0.086	0.097	0.798	0.789	0.087	0.093	0.811	0.761
Modest	0.002	0.005	0.001	0.004	0.557	0.745	0.002	0.004	1.198	0.779
Country groups										
France and Benelux	0.242	0.237	0.248	0.256	1.026	1.080	0.226	0.221	0.933	0.935
Germany and Austria	0.450	0.445	0.500	0.489	1.111	1.100	0.419	0.425	0.931	0.955
UK and Ireland	0.118	0.100	0.100	0.081	0.846	0.813	0.115	0.107	0.980	1.079
Northen countries	0.091	0.095	0.072	0.077	0.797	0.816	0.154	0.150	1.689	1.578
Southern countries	0.094	0.107	0.075	0.085	0.797	0.790	0.081	0.083	0.863	0.780
Eastern countries	0.005	0.017	0.004	0.012	0.932	0.726	0.004	0.013	0.944	0.779

The table shows that the group of Leader regions is specialised in KETs and FGTs in both periods. However, while in the case of KETs the specialisation of Leader regions decreases and the one of Follower regions increases, in the case of FGTs, Leader regions increase their specialisation over time. Looking at country groups, Central European countries are specialised in KETs but not in FGTs where the higher index of specialisation is found in Scandinavian countries. Finally, in the case of FGTs Scandinavian countries lose some of their initial advantage, while Great Britain acquires a positive specialisation in the final period (2008-2011).

Overall, the main results of the descriptive evidence presented in this section can be summarised as follows:

1) KETs are concentrated in Central Europe, while FGTs prevail in Scandinavian countries and the UK.
2) Spatial correlation is higher in KETs than in FGTs.
3) In 1996-99 KETs are slightly more concentrated than FGTs but convergence is stronger in KETs than in FGTs.
4) Despite some signs of convergence, spatial correlation in both KETs and FGTs increases over time, showing that (spatial) technological diffusion often occurs across contiguous regions

5. Specialization in FGTs and KETs and the innovation and economic performances of EU regions

5.1 The empirical approach

In this Section, we test whether absolute and comparative advantages in KETs and FGTs affect regional innovation performances (measured by the rate of growth of patents) and per capita GDP growth. The rate of growth of per capita GDP is computed between 2000 and 2011 while the rate of growth of patents, due to problems of variability of patent counts over time, is computed between 1996-1999 and 2008-2011.

The approach adopted is that of the technology-gap theory of growth (Fagerberg, 1987, 1994; Verspagen, 1993, 2010). This approach highlights the country-specific character of technical change and the limited possibility of transferring technological capabilities across countries and regions (Fagerberg, 1987; Dosi et al., 1988; Dosi et al., 1990; Verspagen, 1993). These difficulties of technology diffusion across countries and regions depend on the tacit and cumulative character of knowledge that is seen to be embedded within firms and organisations (Nelson and Winter, 1982; Lundvall, 1992; Nelson, 1993). This leads to define 'systems of innovation' as 'the network of institutions in the public and private sector whose activities and interactions initiate, import, modify and diffuse new technologies' (Freeman, 1987:1). Translated at the regional level, the 'systems of innovation' framework suggests that the process of innovation is embedded in the (various) territorialized processes responsible for the economic performance of each economic space. Innovation thus needs to be linked to the cluster structure of the economy, and the regional innovation system should be understood in terms of the relationships and flows between the various actors and parts of the innovation system itself (Cooke, 1997; Evangelista et al., 2002; Crescenzi, 2005).

Within this framework economic development is the result of a disequilibrium process characterised by the interplay of two conflicting forces: innovation, which is responsible for increasing economic gaps; imitation, which acts in the direction of reducing the gaps. At an empirical level innovation may be measured by the rate of growth of R&D activities or patents (see, e.g. Acs and Audretsch, 1989; Archibugi and Pianta, 1992; Acs et al., 2002), while imitation may be proxied by the initial level of economic or technological development. Regions with a lower level of economic (per capita GDP) or technological (per capita patents) development have (in an initial stage) more possibilities to grow by imitating the technologies developed elsewhere, however this occurs only conditional on investing in absorption capacity (often proxied by human capital).

Due to the tacit character of innovation, imitation may be easier to occur among geographically close regions. Studies in the field of the geography of innovation state that geography matters because it enhances interpersonal relationships and face-to-face contacts, thus making easier to transfer tacit knowledge (Zucker et al., 1998; Almeida and Kogut, 1999; Singh, 2005; Balconi et al., 2004; Breschi and Lissoni, 2009; Mairesse and Turner, 2006). This is confirmed by recent contributions that have investigated the role of geographical spillovers for regional growth (Peri, 2004; Bottazzi and Peri, 2003; Moreno et al., 2006; Rodriguez-Pose and Crescenzi, 2008; Crescenzi and Rodriguez-Pose, 2011; Basile et al., 2012; Chapman and Meliciani, 2012; Meliciani, 2016).

Among the different local factors affecting the capability to absorb and translate available knowledge into (endogenous) economic growth, the innovation system approach emphasizes the role of human capital. Moreover, the level of education of the population also matters for the generation and adoption of organizational innovations (i.e., learning organizations, Lundvall, 1992). Following this approach, Crescenzi (2005) and Crescenzi and Rodriguez-Pose (2011) include human capital as a determinant - together with innovation - of regional growth in the EU (see also Vogel, 2013 and Chapman and Meliciani, 2016). Both studies find that human capital interacts (in a statistically significant way) with local innovative activities, thus allowing them to be more (or less) effectively translated into economic growth.

Overall, following this literature the following equation for the rate of growth of per capita GDP is estimated:

$$GrGDP_i = a_1 GDP_i + \alpha_2 GrPat_i + \alpha_3 Edu_i + \alpha_4 KET_i + \alpha_5 FGT_i + u_i \qquad (1)$$

where $GrGDP_i$ is the rate of growth of per capita GDP of region i over the period 2000-2011, GDP is the level of per capita GDP in 2000 (in logs), $GrPat_i$ is the rate of growth of patents between 1996-1999 and 2000-2011, Edu_i is the share of population with tertiary education in 2000 and KET_i and FGT_i denote the regional share of Key Enabling Technologies and fast growing patent fields in 2000-2003 over the total patents of the region.

Moreover, in order to test whether specialisation in KETs and FGTs affects the overall rate of technological progress, we also estimate an equation for the rate of growth of patents:

$$GrPat_i = \beta_1 Pat_i + \beta_2 RD_i + \beta_3 KET_i + \beta_4 FGT_i + \nu_i \qquad (2)$$

where PAT is the number of patents per population in 1996-99 and RD is the share of R&D on GDP for the first available year.

After estimating these equations on the whole sample of NUTS 2 regions, we test whether the impact of KETs differs in regions classified according to their technology level (leaders; followers, moderate; modest).

5.2 The econometric approach

In order to take into account spatial dependence, we adopt a spatial model. The more general spatial model is the Spatial Durbin model (SDM) which includes amongst the regressors not only the spatial lagged dependent variable, but also the spatial lagged set of independent variables:

$$Y = WY\rho + X\beta_1 + WX\beta_2 + \varepsilon \tag{3}$$

where Y denotes a Nx1 vector consisting of one observation for every spatial unit of the dependent variable; X is a NxK matrix of independent variables; N is the number of regions and K the number of explanatory variables; W is an NxN non negative spatial weights matrix with zeros on the diagonal. A vector or matrix pre-multiplied by W denotes its spatially lagged value ρ, β_1 and β_2 are response parameters, and ε is a Nx1 vector of residuals with zero mean and variance σ^2.

The Spatial Durbin model nests most models used in the regional literature. In particular, imposing the restriction that β_2=0 leads to a spatial autoregressive (SAR) model that includes a spatial lag of the dependent variable from related regions, but excludes these regions' characteristics. Imposing the restriction that $\beta_2 = -\rho\beta_1$ yields the spatial error model (SEM) that allows only for spatial dependence in the disturbances. Imposing the restriction that ρ=0 leads to a spatially lagged X regression model (SLX) that assumes independence between the regional dependent variables, but includes characteristics from neighbouring regions in the form of explanatory variables. Finally, imposing the restriction that ρ=0 and β_2=0 leads to a non-spatial regression model. We choose the appropriate model specification by testing the validity of restrictions using likelihood ratio tests.

In a spatial regression model, a change in a single explanatory variable in region *i* has a *direct impact* on region *i* as well as an *indirect impact* on other regions (see LeSage and Fischer, 2008 for a discussion). This result derives from the spatial connectivity relationships that are incorporated in spatial regression models and raises the difficulty of interpreting the resulting estimates. LeSage and Pace (2009) provide computationally feasible means of calculating scalar summary measures of these two types of impacts that arise from changes in the explanatory variables. There are two possible (equivalent) interpretations of these effects. One interpretation reflects how changing each explanatory variable of all neighbouring regions by some constant amount would affect the dependent variable of a typical region. LeSage and Pace (2009) label this as the *average total impact on an observation*. The second interpretation measures the cumulative impact of a change in each explanatory variable in region *i* over all neighbouring regions, which LeSage and Pace (2009) label the *average total impact from an observation* (see also Le Sage and Fischer, 2008). In the estimations the spatial matrix *W* is a row standardised NxN inverse distance matrix where the bandwidth reflects the median distance (results are robust to choosing different bandwidths). In the following section, in presenting the results of our empirical estimates, we will report both direct and indirect effects and their significance.

5.3 Empirical results

Table 4 reports the results for the per capita GDP growth equation, while Table 5 reports the results for the patent growth equation.

The results in Table 4 give support to the technology gap approach to economic growth: growth in per capita GDP is driven by innovation (captured by the rate of growth of patents) and imitation (there is evidence of convergence although at very low rates). Both human capital and geographical proximity to high performing regions, have a positive and significant role for economic growth.

Table 4 - Estimates of the per capita GDP growth equation: spatial Durbin model

	Direct effect	t-stat	Indirect effect	t-stat
Initial level of per capita GDP	-0.008***	-3.527	0.020	0.220
% of population with tertiary education	0.008***	3.892	0.002	0.083
Rate of growth of patents	0.095***	5.340	0.520	0.641
Regional share of patents in KETs	0.031***	2.800	0.492	0.624
Regional share of patents in FGTs	-0.007	-0.448	0.416	0.707
ρ = 0.610***				
R-squared=0.624				

Note: **,**, *** denote respectively significant at 10, 5 and 1%. The Spatial Durbin Model is preferred to the spatial lag and to the spatial error on the basis of likelihood ratio tests.*

Table 5 - Estimates of the innovation equation: spatial Durbin model

	Direct effect	t-stat	Indirect effect	t-stat
Initial level of per capita GDP	-0.024***	-8.213	-0.070	-0.489
R&D share of GDP	0.017***	2.788	0.403	0.663
Regional share of patents in KETs	0.008	0.191	0.898	0.361
Regional share of patents in FGTs	0.170**	2.190	-3.168	-0.542
ρ = 0.697***				
R-squared=0.557				

Note: **,**, *** denote respectively significant at 10, 5 and 1%. The Spatial Durbin Model is preferred to the spatial lag and to the spatial error on the basis of likelihood ratio tests.*

More interestingly, technological specialisation matters for economic growth. Between KETs and FGTs, only the specialisation in KETs has a positive and significant effect on economic performance. The positive impact of KETs on regional growth is consistent with the enabling and pervasive character of these technologies. It is also interesting to observe that although indirect effects of single explanatory variables are not significant, the likelihood ratio test suggests that spatial lags of explanatory variables should be included in the regression.

Looking at the determinants of innovation (Table 5), we get different results. In this case regions initially specialised in fast growing technologies experience higher rates of growth of patents. Consistently with the literature (Bottazzi and Peri, 2003; Di Cagno et al., 2013, 2015) innovation performances are also driven by R&D expenditures and there is evidence of conditional technological catching up.

Finally, being surrounded by regions with high innovation performances positively affects one's region innovation potential; this gives support to the existence of localised knowledge spillovers (Peri, 2004; Bottazzi and Peri, 2003; Moreno et al., 2006; Rodriguez-Pose and Crescenzi, 2008; 2011). Again single indirect effects are not significant but the Spatial Durbin Model is preferred to both the spatial lag and the spatial error models on the basis of likelihood ratio tests[5][6].

Regions with different technological capabilities may benefit differently from specialisation in KETs. While the most technologically developed regions may exploit this type of specialisation to increase their technological strength and forge ahead, backward regions, by moving into enabling technologies may facilitate their catching up.

Table 6 reports the results of the estimation of equation (1) allowing for the impact of specialisation in KETs to differ according to the technological level of the regions (1=leader; 2=follower; 3=moderate; 4=modest). We also allow the intercept to vary among the four regional groups. In this case, due to problems of multicollinearity in estimating the SDM, we report results based on the spatial lag model only.

The table shows that the benefits of being specialised in KETs are higher for technology backward regions than for the other regional groups. In particular, the size of the direct effects of specialisation in KETs on economic growth increases as we move from leader regions (where the impact is positive but not significant) to follower, moderate and modest regions.

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[5] In the regression analysis, we use regional shares rather than RTAs since the RTA is not comparable on both sides of unity (it ranges from zero to one for de-specialised regions and from one to infinity for specialised regions).

[6] Results of the tests are available on request.

Table 6 - Estimates of the per capita growth equation allowing specialisation in KETs to differ across technology groups: spatial lag model

	Direct effect	t-stat	Indirect effect	t-stat
Initial level of per capita GDP	-0.006**	-2.374	-0.059	-0.690
% of population with tertiary education	0.003*	1.734	0.032	0.658
Rate of growth of patents	0.116***	6.064	1.165	0.818
Regional % of patents in FGTs	-0.029	-1.611	-0.298	-0.649
Regional % of patents in KETs leader	0.026	1.274	0.296	0.557
Regional % of patents in KETs follower	0.025*	1.805	0.262	0.649
Regional % of patents in KETs moderate	0.063**	2.339	0.660	0.696
Regional % of patents in KETs modest	0.117***	2.993	1.201	0.735
ρ = 0.862***				
R-squared=0.539				

Note: *,**, *** denote respectively significant at 10, 5 and 1%.

These results signal that investing resources in Key Enabling Technologies facilitates the catching up process and should be part of smart specialisation strategies of less developed regions. This evidence is also in line with the results of Montresor and Quatraro (2015) showing that KETs facilitate regional diversification processes and the achievement of new revealed technological advantages.

6 Conclusions

The main results of the report can be summarised as follows. First, only a small share of KETs are also fast growing technologies, although the degree of overlapping between KETs and FGTs varies substantially across different KETs fields. Second, while KETs are concentrated in Central Europe, FGTs prevail in Scandinavian countries and the UK. Third, there is evidence of some regional convergence in KETs and, to a less extent, in FGTs; however spatial correlation increases over time, showing that diffusion often occurs across contiguous regions. Finally, the results of the estimation of innovation (patents' growth) and economic growth (growth in per capita GDP) show that only specialisation in KETs directly affects economic growth, while specialisation in FGTs affects growth only indirectly, through its impact on innovation. Overall, these results confirm the pervasive and enabling role of KETs pointing to the importance for European regions to target these technologies as part of their RIS3 strategy.

Overall, the results of this study point to the relevance of the composition of technological activities for innovation and growth. Regions investing resources in fields with high technological opportunities are in a position to exploit their advantage in terms of enhanced innovation performances. To the extent that economic growth depends on innovation, selecting the high opportunity fields is indirectly beneficial also for the regional economic performances. However, identifying which will be the fast growing technology fields is not an easy task. Fast growing and emerging technologies are surrounded by a high degree of uncertainty and, as we have shown in Section 3, only a small share of them continue to grow over long time spans. Moreover, the local, firm-specific, tacit and cumulative character of technical progress (Dosi, 1982, 1988; Vertova, 1999; Cefis and Orsenigo, 2001; Mancusi, 2003; Cantwell and Vertova, 2004) makes it difficult for regions lagging behind to move towards emerging technological areas. These considerations are supported by the descriptive analyses showing that only the EU most technological advanced regions are specialised in FGTs and that this regional club increases has increased the specialisation in this dynamic class of technologies over time.

Differently from FGTs, KETs have been selected for their systemic relevance as they enable the development of new goods and services and the restructuring of industrial processes needed to modernise the EU industry, strengthening the research, development and innovation base of EU regions and facilitating regional cohesion. They are multidisciplinary, cutting across many technology areas with a trend towards convergence and integration (see COM(2009)512). The results of the regressions confirm this role by showing that, differently from FGTs, they exert a direct effect on regional growth. Moreover, they appear to be of strategic importance especially for regions lagging behind suggesting an enabling role in the catching up process.

Drawing policy implications from the results of this study is not an easy task. It could appear that the main implication of our analysis would be to suggest policy makers to target areas of strong technological opportunity and KETs. However, there are several arguments against this strategy. First, it is not possible by definition for all regions to be specialised in the most promising technological fields; second (and this applies especially to FGTs) identifying the most promising technologies is not an easy task given the inherent uncertainty that characterises technical change; finally, and most importantly, regional patterns of specialisation tend to be sticky and competencies tend to grow with experience over relatively long time periods, therefore the attempt to modify the pattern of regional comparative advantages can be a hard and counter-productive task.

The observation that not all regions can specialise in the same activities is however somewhat misleading. Although not all regions can be specialised in the same technological fields, there is no impediment for all regions to increase their share of activities in the most promising technological areas. Moreover, the new technologies can be used for producing different goods according to the prevailing competitive advantages of the various regions. Coming to the issue of stickiness in specialisation patterns, the literature has emphasised that when diversification takes place within a firm, it occurs mostly in the neighbourhood of the prevailing areas of technological strength, since firms do not search by exploring the whole set of existing knowledge but build upon their existing technological competencies (Nelson and Winter, 1982; Pavitt, 1988; Patel and Pavitt, 1994). What takes place at the level of the firm also has an impact at the level of the region, and this is one of the explanations of why regional patterns of technological specialisation are sticky or evolve smoothly over time. These considerations are also at the core of the smart specialisation strategy advocating that policies should be devoted to deepening the linkages within the region in the relevant fields of specialization, helping to foster a related diversification process and developing interregional networks focussing on a region's most connected activities while at the same time maximising local knowledge diffusion and learning networks (Foray et al., 2009, 2011; Frenken et al., 2007; Frenken and Boschma, 2007; Barca, 2009; Boschma and Frenken, 2011; Boschma and Iammarino, 2009). Overall, this approach overcomes the debate on what are the most promising technology fields by recognising that each region has its own set of comparative advantages on which it should build on. However, there appears to be consensus on the fact that more (relatedly) diversified regions have better opportunities with respect to strongly specialised regions (Frenken et al., 2007; Boschma and Iammarino, 2009; Boschma et al., 2012). Our results further qualify these arguments by pointing to the fact that key enabling technologies enhance the possibility of regions to both further strengthen their traditional comparative advantages as well as to diversify in a smart fashion, and this precisely because of their high degree of pervasiveness. Therefore, the effort to acquire competencies in these technologies is not inconsistent with a concern for the areas of regional long-term comparative advantage so that European regions should target KETs as part of their RIS3 strategy.

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Appendix

Table 7: List of long run fast growing patent classes

IPC 4-digit	Label*	Patents 1st period	Patents 2nd period	Growth rank 1st period	Growth rank 2nd period
B82Y	Specific uses or applications, measurement or analysis, manufacture or treatment of nano-structures	28	201	4	4
F21Y	Indexing scheme relating to the form of the light sources	114	456	3	8
F03D	Wind motors	353	2259	9	6
H04W	Wireless communication networks	5076	15172	12	15
B60W	Conjoint control of vehicle sub-units, control systems specially adapted for hybrid vehicles, road vehicle drive control systems	428	1202	15	20
B82B	Manufacture or treatment of nano-structures formed by manipulation of individual atoms, molecules	62	152	13	25
G04D	Apparatus or tools specially designed for making or maintaining clocks or watches	15	35	10	28
F21W	Indexing scheme relating to uses or applications of lighting devices or systems	62	131	2	37
B25F	Combination or multi-purpose tools (n.o.p), details or components of portable power-driven tools	137	376	28	21
F21K	Light sources (n.o.p.)	29	346	50	3
B63J	Auxiliaries on vessels	15	31	16	41
F03G	Spring, weight, inertia, or like motors, mechanical-power-producing devices or mechanism (n.o.p.)	73	238	47	12
B81C	Processes or apparatus for the manufacture or treatment of micro-structural devices or systems	140	270	6	55
F01D	Non-positive-displacement machines or engines (e.g. steam turbines)	1091	2384	27	35
F03B	Machines or engines for liquids	122	580	63	7
G21G	Conversion of chemical elements, radioactive sources	34	66	21	53
F23B	Methods or apparatus for combustion using only solid fuel	4	47	102	2
F21S	Non-portable lighting devices or systems (n.o.p.)	312	749	77	30
E21F	Safety devices, transport, filling-up, rescue, ventilation, or drainage in or of mines or tunnels	21	36	31	79
H04S	Stereophonic systems	164	300	68	63
H01M	Processes or means (e.g. batteries) for the conversion of chemical energy into electrical energy	3795	5946	35	98
F02N	Starting of combustion engines, starting aids for such engines (n.o.p.)	207	319	42	106
F02G	Hot-gas or combustion-product positive-displacement engine plants, use of waste heat of combustion engines	71	121	70	80
B62J	Cycle saddles or seats, accessories peculiar to cycles and n.op. (e.g. article carriers or cycle protectors)	264	436	66	85
B64D	Equipment for fitting in or to aircraft, flying suits, parachutes, arrangements or mounting of power plants or propulsion transmissions in aircraft	408	1025	127	24

G04B	Mechanically-driven clocks or watches, mechanical parts of clocks or watches in general, time-pieces using the position of the sun, moon, or stars	306	528	82	72
F41H	Armour, armoured turrets, armoured or armed vehicles, means of attack or defence in general (e.g. camouflage)	189	387	112	43
F25C	Production, working, storing or distribution of ice	92	184	114	46
B62K	Cycles, cycle frames or steering devices, rider-operated terminal controls specially adapted for cycles, cycle axle suspensions, cycle sidecars, forecars, or the like	325	529	86	87
F01N	Gas-flow silencers or exhaust apparatus for machines or engines in general, gas-flow silencers or exhaust apparatus for internal-combustion engines	1150	1753	62	111
F21L	Lighting devices or systems, being portable or specially adapted for transportation	30	51	95	81
F02C	Gas-turbine plants, air intakes for jet-propulsion plants, controlling fuel supply in air-breathing jet-propulsion plants	521	891	108	74
H04R	Loudspeakers, microphones, gramophone pick-ups or like acoustic electromechanical transducers, deaf-aid sets, public address systems	1313	1893	48	136
G01C	Measuring distances, levels or bearings, surveying, navigation, gyroscopic instruments, photogrammetry or videogrammetry	1041	1733	107	83
F25B	Refrigeration machines, plants, or systems, combined heating and refrigeration systems, heat pump systems	830	1289	92	102
F23R	Generating combustion products of high pressure or high velocity (e.g. gas-turbine combustion chambers)	281	533	136	59
A61B	Diagnosis, surgery, identification	8779	13439	87	109
A01H	New plants or processes for obtaining them, plant reproduction by tissue culture techniques	270	419	93	105
A47L	Domestic washing or cleaning, suction cleaners in general	1191	1926	111	88
C12M	Apparatus for enzymology or microbiology	595	841	58	145
F24C	Other domestic stoves or ranges, details of domestic stoves or ranges, of general application	577	1002	133	70
H02M	Apparatus for conversion of electrical power, and for use with mains or similar power supply systems, conversion of input power into surge output power, control or regulation of	1255	2137	130	77
H05B	Electric heating, electric lighting (n.o.p.)	1978	3155	122	92
G01T	Measurement of nuclear or x-radiation	365	545	126	117
C11C	Fatty acids obtained from fats, oils or waxes, candles, fats, oils or fatty acids obtained by chemical modification of fats, oils or fatty acids	90	128	105	142
A61N	Electrotherapy, magnetotherapy, radiation therapy, ultrasound therapy	1621	2433	134	114
B25J	Manipulators, chambers provided with manipulation devices	489	717	124	125
G01S	Radio direction-finding and navigation, determining distance or velocity with radio waves, locating or presence-detecting by use of the reflection or reradiation of radio waves, analogous using other waves	1979	2806	106	144

Source: *calculated for the 1992/95 to 2000/03 and 2000/03 to 2008/11 periods on EPO patent applications as reported in REGPAT. n.o.p. stands for not otherwise provided for.*

** Labels reported in the IPC classification edited by the authors.*

List of abbreviations and definitions

KETs – Key Enabling Technologies

GPTs - General Purpose Technologies

FGTs - Fast Growing Technologies

IPC - International Patent Classification

ICTs – Information and Communications Technologies

RIS3 - Research and Innovation Strategies for Smart Specialisation

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