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Fast Growing and Key Enabling Technologies and their impact on regional growth in Europe

by

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Abstract

This paper studies the specialisation of EU regions in key enabling (KETs) and fast growing (FGTs) technologies and assesses whether being specialized in these technological areas has an effect on regional growth. The evidence presented shows that only a small share of KETs are also FGTs, although the degree of overlapping between KETs and FGTs varies substantially across different KETs fields. 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 KETs and FGTs on GDP per capita growth show that only specialisation in KETs affects regional economic growth, while no significant effects are found for FGTs. Overall, these results confirm the pervasive nature and enabling role of KETs pointing to the importance for European regions to target these technologies as part of their smart specialization strategies.

Keywords: Key Enabling Technologies, Fast Growing Technologies, Regional Growth, Technological Specialization.

JEL codes: O30, O47, R10, R58.

1. Introduction

Over 40 years of theoretical and empirical research in the area of the economics of technological change has shown and demonstrated that economic growth and international competitiveness are linked not only to price-cost factors but - increasingly - to the existence and building-up of technological advantages, that is to the capacity of firms, regions and countries to accumulate distinctive sets of technological capabilities and competencies (Dosi et al., 1988; Dosi et al., 1990; Fagerberg, 1994; Cohen, 2010; Dosi et al., 2015). There has also been a large amount of evidence showing that, both at a country and regional level, competencies and capabilities (and the innovative efforts aiming at searching and reinforcing these distinctive competitive factors) are not evenly and randomly distributed among all possible technological areas but tend to be relatively concentrated in specific technological fields (Archibugi and Pianta, 1992a, 1992b; Vertova, 1999, 2001; Meliciani, 2001, 2002; Mancusi, 2003; Peter and Frietsch, 2009). This is largely due to the cumulative nature of innovation processes, the presence of dynamic economies in knowledge production and learning processes, the localized nature of knowledge spillovers and interactions which tend to make technological accumulation developing along sticky and spatially bounded specialization patterns (Jaffe et al., 1993; Jaffe et al., 1999; Evangelista et al., 2002; Maurseth and Verspagen, 2002; Moreno et al., 2006; Antonelli et al. 2013).

Despite the existence of a large amount of literature analysing and mapping the technological profiles of countries, the extent to which "technological specialization" is able to affect the economic performances of innovation systems remains an open issue, one on which empirical results are limited and controversial, a topic that has been progressively marginalized in the theoretical and empirical agenda.

This trend has however been recently reversed by two "new entries" in the EU policy debate: a) the policy discussion revolving around the concept and strategy of "Smart specialization" (Foray et al. 2009, 2011); b) the recent emphasis put on a new branch of pervasive technologies labelled Key Enabling Technologies (KETs) (European Commission, 2009, 2012). In fact, "Smart Specialization" has become a central component of the EU Cohesion Policy 2014-2020 and a key policy process to foster regional growth and structural change. More in particular the "Research and Innovation Strategies for Smart Specialisation" (RIS3) EU strategy encourages EU regions and cities to strengthen their distinctive technological bases, to concentrate the available resources on their actual or potential areas of comparative advantages, to diversify into technologies, products and services that are closely related to existing dominant technologies and the regional skills base (European Commission, 2011, 2014b). At the same time, the European Commission has recently put a special emphasis on KETs - that, because of their pervasive character, may enable process, product and service innovation throughout the economy. These technologies, given their horizontal and systemic nature have a great potential for the exploitation and eventual transformation of the competencies accumulated at the local level over time (Montresor and Quatraro, 2015).

Technological specialization has therefore come back as a key theme in the current policy debate although in new forms: either in a “smart” and less deterministic fashion; or with reference to the centrality attached to a new set of specific technologies, deemed to have a pervasive and systemic character and being able to meet wide social and economic goals. However, this renewed interest and policy concern on the “technological specialization issue” has so far found little reflection/repercussion in the empirical agenda.

This paper aims at providing some empirical support to this renewed interest on the role and economic impact of technological specialization in the EU context adopting a regional perspective. The choice of adopting a sub-national focus is justified both by the explicit regional reference of most recent EU cohesion, science and technology policies and by the very limited literature on technological specialization at a regional level. In particular, in this paper the effects of technological specialization on regional economic performance are empirically examined taking into account two distinct technological macro-classes, namely KETs and technologies characterized by high level of dynamism (FGTs). The rationale behind the selection of these two different groups of technologies will be discussed more in detail in the next section. Here it suffices to anticipate that while the idea of looking at FGTs is consistent with a strict (more traditional) technological opportunity criteria, the focus on KETs arises from the necessity of adopting a broader and more systemic perspective of the technological opportunity concept, one which takes into due account the level of pervasiveness of technologies and their capacity of acting as a technological multiplier/accelerator of the performances of the regional innovation system as a whole.

The paper is organised as follows: Section 2 discusses the existing literature on emerging technologies and KETs, and their economic impact. Section 3 introduces the dataset, describes the methodology used to identify FGTs and explores the extent to which KETs and FGTs classes do overlap with each other. Section 4 contains descriptive evidence on the regional specialization of EU (NUTS2) regions in KETs and FGTs as well as on their evolution over time. Section 5 estimates the impact of KETs and FGTs on regional GDP growth. Finally, Section 6 concludes and draws the main policy implications.

2. State of the art

An important structural dimension of both national and regional systems of innovation has to do with their technological specialization (Archibugi and Pianta, 1992a, 1992b; Lundvall, 1992; Nelson, 1993; Patel and Pavitt, 1994; Meliciani, 2001; Evangelista et al., 2002). While it is widely accepted that "specialization matters" (both for innovation and economic performances) the identification of what would be the most effective or rewarding type of technological specialization remains a debated issue, and one on which we lack robust theoretical bases and systematic empirical evidence. The evolutionary literature on "technological regimes" provides some conceptual and methodological indications in this respect. Technological fields are distinguished on the basis of their intrinsic development potential (i.e. level of technological opportunity). One implication is that being specialized in high opportunity fields might in principle be a good thing, providing the innovation system with a more dynamic technological structure. This is particularly true when high levels of technological opportunity are coupled with favourable appropriability conditions - i.e. presence of steep learning curves, first mover advantages, tacit knowledge or effective Intellectual Property Rights tools (Nelson and Winter, 1977, 1982; Pavitt, 1984; Malerba and Orsenigo, 1996, 1997).

One way of detecting high-technological opportunity sectors is to look at the levels and dynamics of invention or innovation activities in the different technological fields, in turn proxied by the R&D intensity of different industries or by the dynamics of output indicators such as patents and innovation counts (Malerba and Orsenigo, 1996; Meliciani and Simonetti, 1998; Vertova, 2001; Meliciani, 2001, 2002; Huang and Miozzo, 2004; Nesta and Patel, 2004).

Following this methodology, some studies have attempted to relate countries' ability to specialise in high technological opportunity fields to their technological/economic performance finding mixed results. While some studies find a positive effect of specialization in FGTs on growth and/or competitiveness (Meliciani and Simonetti, 1998; Meliciani 2001, 2002), other find no effects (Pianta and Meliciani, 1996) or show that most countries do not have the capability to specialise in the highest technological opportunities, but remain locked into inferior technological paths (Vertova, 2001).

These contributions are characterized by the two following traits: a) they have identified high opportunity technology fields with emerging (i.e. fast growing) technologies, that is adopting a strict perspective on technological opportunity sectors; b) they have measured and assessed the economic impact of technological specialisation exclusively at the country level.

This methodological approach somewhat clashes with the most recent EU cohesion, science and technology policy framework, which on the one hand identifies strategic technologies (KETs) on the basis of their pervasive and systemic character (rather than simply on their degree of dynamism) and, on the other, focuses on regions (rather than countries) as key spatial and socio-economic domains as well as policy targets of cohesion and research and innovation EU policies (European Commission, 2010, 2011; Boschma and Frenken, 2011).

KETs 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. KETs share many of the characteristics of "techno-economic paradigms" (Perez, 1985, 1988; Freeman and Perez, 1988; Freeman and Louca, 2001; Guerrieri and Padoan, 2007) and "general purposes technologies" (Bresnahan and Trajtenberg, 1995; Helpman, 1998; Bresnahan, 2010)[1]. Both streams of literature refer to the strategic role played by specific technologies in different waves of development. These technologies are characterised by their systemic relevance, i.e. their ability to affect directly and indirectly the whole economic system bringing about generalised productivity gains. In particular, KETs have been selected as technologies with a pervasive influence, enabling process, product and service innovation throughout the economy and acting as "key-enabler" of the structural transformation towards a "knowledge-based" and "low-carbon" economy. Therefore, it can be reasonably argued that the aggregate economic impact of these technologies would be stronger than the one produced by FGTs.

KETs can also be seen as a part of an integrated policy framework aiming at enhancing the technological potential of regions and at strengthening the regional distinctive technological comparative advantages. It has been in fact argued that KETs might contribute to the implementation and success of smart specialization strategies by allowing regions to develop new comparative advantages (Montresor and Quatraro, 2015). Their economic impact should, therefore, be better captured by adopting a regional perspective.

Despite the new emphasis on KETs, there is only very limited evidence of the capability of EU regions to specialise in these fields (for the state of the art, see European Commission, 2014a) and even more limited is the evidence on the actual impact of these technologies on regional economic performances (Evangelista et al., 2018). Furthermore there has been so far very little theoretical speculation and empirical investigation regarding the extent to which KETs (and FGTs) can help the

[1] A large body of literature has assessed the impact of General Purpose Technologies on countries' growth and productivity performances (for a review see Bresnahan, 2010). This literature mainly tests the impact of these technologies in the context of the production function and does not refer to technological specialisation.

catching-up process of laggard EU regions or, viceversa, if they might further enlarge existing technological and economic gaps within Europe.

The main focus of this paper is to start filling this gap by providing evidence on the level and dynamics of EU regional specialization in KETs and to assess their impact on regional economic growth. We also aim at comparing the potential of KETs with that of FGTs. In particular, the contribution moves from the hypothesis that KETs – when compared to FGTs - are likely to have stronger effects on the aggregate economic performance of regions and this is because of their pervasive nature. FGTs are likely to lead to new discoveries and to a more rapid rate of technical change, while the impact on aggregate regional macroeconomic performance is likely to be negligible due to their limited horizontal/systemic nature.

3. Key enabling technologies and fast growing technologies

KETs 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" (European Commission, 2009). On the basis of their economic potential, that is their contribution in solving societal challenges and their 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, and aeronautics and space, since they are essential for all goods and services incorporating 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 sustainable process alternatives for industrial and agriculture and food processing operations. Finally, advanced manufacturing systems are essential for producing knowledge-based goods and services.[2] As already discussed, the importance attached to KETs derives from the fact that these are science based and R&D intensive technologies characterised by high technological opportunities (in a wide/systemic sense), which can act as "key-enabler" of the structural transformation towards a "knowledge-based" and "low-carbon" economy. Their influence is pervasive, enabling process, product and service innovation throughout the economy.

While there is consensus on the identification of KETs, various studies have used different criteria to identify emerging technologies (OECD, 2013; Dernis et al. 2015; for a review, see Rotolo et al., 2015[3]). 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 paper we focus on this common attribute identifying the technologies that have experienced a relative high rate of growth (what we call FGTs). FGTs are therefore related to patent classes showing a particularly high dynamism, and are in turn selected on the basis of the following criteria.

Patent applications filed at EPO during the 1992-1995, 2000-2003, 2008-2011 periods have been retained from the OECD REGPAT database.[4] Patent activities are attributed to EU NUTS2 regions on the basis of the inventor's residence information, as reported in patent documents. This choice is the most appropriate to localize where technological activities are carried out and knowledge and competences accumulated, providing information on the (regional) system of innovation (de Rassenfosse et al., 2013)[5]. For each IPC code at the four digit level we have calculated the growth rates of patent 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 respectively for the two sub-periods 1992-2003 and 2003-2011 (for all the years within the periods considered); therefore FGTs have been identified for the 1996-2003 and 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 (i.e. taking into account the 1992-2011 period) FGTs is reported in Appendix. Table 1 reports a transition matrix showing the distribution of the rates of growth of patent filings between the first and the second sub-period.

[2] For a complete list of patent codes related to KETs, see Gkotsis (2015).
[3] 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).
[4] The OECD REGPAT database presents patent data that have been linked to regions utilizing the addresses of the applicants and inventors.
[5] For a discussion of problems related to measuring specialization with patent data, see Zeebroeck et al. (2006).

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% of them move to the central part of the distribution and 26% to the last quartile.

(table 1 about here)

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 indicate the unpredictable nature of technological change and that only few technologies have the potential of driving long-term economic growth. The empirical estimations presented in section 5 seem to support this point. But is there a link between FGTs and KETs? Table 2 allows us to provide an answer to this question by showing 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 about here)

The first three columns in Table 2 show that 16% of all patents belong to long term fast growing patent fields and 14% of KETs patents belong to FGTs (a patent is defined as FGTs and KETs if it contains at least one KETs/FGTs code)[6]. This means that KETs related patents are slightly less related with FGTs than other - i.e. non-KETs - patents (for which the share is 16%). Similar results are found when looking at the two sub-periods. However, 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 the correspondence level is very high only in the first period. Finally, the lower correspondence is found in Advanced Materials and in Micro and Nano Electronics.

[6] 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 decreases to 850 in the second period).

4. The technological specialisation of EU regions in KETSs and FGTs

As anticipated in the introduction most of the empirical literature on technological specialization has been carried out at a national level while the sub-national dimension of this important structural dimension of innovation systems has been largely neglected.[7] This is even more so with respect to the role played by relevant technological fields such as those characterised by a high level of dynamism and pervasiveness. This section aims at fulfilling this gap in the empirical literature providing a descriptive analysis of the regional specialization of EU regions in KETs and FGTs as well as on their evolution over time. The empirical analysis is carried out at a NUTS2 level using patent data and taking into account the period 1996-2011. Given the high level of variability of patent counts over time, patents are aggregated over 4 years periods (1996-1999; 2000-2003; 2004-2007 and 2008-2011). Furthermore, in order to strengthen the statistical robustness of the empirical analysis, EU 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.

Technological specialisation is measured with the revealed technological advantage index:

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

where KET indicates the total number of patents in KET related patent fields, PAT is the total number of patents and N is the total number of regions. Values of RTA larger than one indicate relative specialisation (the share of region i in KETs is higher than the same share in total patents). Analogous indicators are computed for FGTs.

Figure 1 reports the EU regions (relatively) specialized in KETs (i.e. with RTA>1) in 1996-1999 and in 2008-2011.

(Figure 1 about here)

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

[7] The study by Peter, V., Frietsch, R. (2009) represents a notable exception. Studies looking at the spatial-regional dimension of technological activities within the EU area and adopting a sectoral perspective include Breschi (2000), Paci and Usai (2000), Montresor and Quatraro (2015). For a study comparing the distribution of innovative activity across regions across main OECD economies see Usai (2011).

concentrated. However, there are cases of regions specialised in KETs also in Northern European, UK and even in laggard and peripheral EU regions in the south of Italy, Spain and in the Czech Republic[8]. 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 regions of new specialisation. All in all the comparison of the two maps reveals a relatively high degree of mobility. More in particular it is possible to observe on the one hand an increase in the number of German regions specialised in KETs and, on the other, a pattern of KETs related competencies and regional strengths diffusion towards the East of Europe. Overall, despite the increasing number of regions specialised in KETs, spatial correlation in RTAs, measured with the Moran index, rises from 0.10 in 1996-99 to 0.13 in 2008-11, suggesting that technological diffusion occurs more easily among spatially contiguous regions.

Figure 2 shows the regions specialised in FGTs (with RTA>1) in 1996-99 and 2008-11.

(Figure 2 about here)

In 1996-1999, 71 regions were specialised in FGTs. When compared to KETs, FGTs appear to be more spatially scattered. 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 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 specialization. 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.

We might also wonder if technological specialization in KETs or FGTs is broadly associated to the overall level (or more broadly to the stage) of technological development of EU regions. To shed some light on this issue, table 3 reports the RTAs values for KETs and FGTs computed for four distinct EU regional groups each one characterized by a different level of technological development. The regional classification reported in table 3 is drawn by the Regional Innovation Scoreboard (European Commission, 2014b), which classifies EU regions into four innovation performance groups: 1) Leaders, 2) Followers, 3) Moderate, 4) Modest. The classification is obtained using a wide

[8] The relative strength shown by some laggard and peripheral EU regions in KETs can be explained by various factors. The limited amount of patent activities in these regions can lead to an aleatory distribution of patents across the different technological fields; moreover, the presence of foreign affiliates of Multinational Enterprises, often located in high innovative sectors, can account for a relevant share of total regional patents in laggard regions.

array of technological indicators measuring the ability of each region to produce and assimilate knowledge.

(Table 3 about here)

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 specialization of Leader regions decreases (while the specialization of the other regions tends to increase), in the case of FGTs, Leader regions keep their specialisation increasing over time (while the specialization of the other regions tends to decrease). The table seems to suggest some convergence in KETs specialization in contrast with an increasing polarization in FGTs. Whether the capability of Follower and Modest regions to move towards KETs is also related to their overall economic performance is an issue that will be investigated in the econometric analysis.

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

1) regions specialised in KETs are concentrated in Central Europe, while FGTs specialization prevails in Scandinavian countries and in the UK.
2) Over time, Follower and Modest regions increase their specialization in KETs at the expense of Leader regions; on the other hand, Leader regions increase their specialization in FGTs.
3) The signs of convergence in KETs specialization are coupled with an increase of spatial correlation in KETs over time. This finding suggests that (spatial) technological diffusion often occurs across contiguous regions. In the case of KETs, in particular, a pattern of technological diffusion from Germany towards East Europe has taken place.

5. Specialization in FGTs and KETs and the growth performance of EU regions

5.1 *The empirical specification*

A major empirical objective of this paper consists of testing whether the level of specialization in KETs and FGTs affects regional per capita GDP growth. The econometric specification used is consistent with a technology-gap framework and the recent developments on the spatial nature of innovation processes and their economic effects. The technology-gap approach highlights the country-specific character of technical change and the limited possibility of transferring technological capabilities across countries (Fagerberg, 1987; 1994; Dosi et al., 1988, 1990; Verspagen, 1993, 2010; Fagerberg and Verspagen, 2002; Castellacci and Natera, 2013). Such an approach can be effectively translated on (and it is likely to maintain its validity when applied to) a regional scale. In fact, the difficulties of technology diffusion across different spatial and institutional contexts applies to countries as well as regions and derive from the tacit and cumulative character of knowledge that is deeply embedded within firms and organisations (Nelson and Winter, 1982; Lundvall, 1992; Nelson, 1993; Archibugi and Castellacci, 2008) and develop through interactions within spatially and institutionally bounded contexts (Crescenzi, 2005).

Within this framework economic development at the regional level is the result of a disequilibrium process characterised by the interplay of two conflicting forces: innovation, which is responsible for increasing economic gaps across regions; imitation which acts in the direction of reducing the gaps. At an empirical level the regional innovation performances may be measured by the rate of growth of R&D activities or patents (see, e.g. Acs and Audretsch, 1989; Archibugi and Pianta, 1992a, 1992b; 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 “spatial proximity” 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 (Bottazzi and Peri, 2003; Peri, 2004; Moreno et al., 2006; Rodriguez-Pose and Crescenzi, 2008; Crescenzi and Rodriguez-Pose, 2011; Vinciguerra et al., 2011; Basile et al., 2012; Chapman and Meliciani, 2012; Meliciani, 2016).

Among the different localized factors and processes affecting the capability to absorb and translate available knowledge into (endogenous) economic growth, the innovation system approach emphasizes the role of human capital and learning processes. 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.

Building upon this literature we estimate the following equation for the rate of growth of per capita GDP:

$$GrGDP_i = \alpha_1 GDP_i + \alpha_2 GrPat_i + \alpha_3 Edu_i + \alpha_4 R\&D_i + \alpha_5 KET_i + \alpha_6 FGT_i + u_i \quad (1)$$

where $GrGDP_i$ is the rate of growth of per capita GDP of region i over the period 2000-2011, GDP_i is the level of per capita GDP in 2000 (in logs), $GrPat_i$ is the rate of growth of patents between 1996-1999 and 2004-2007, Edu_i is the share of population with tertiary education in 2000, $R\&D_i$ is the share of R&D over GDP for the first available year (starting from 2000) and KET_i and FGT_i denote the regional share of, respectively, KETs and FGTs patent fields in 2000-2003 over total regional patents.[9] The rate of growth of patents is lagged with respect to the rate of growth of GDP in order to reduce endogeneity problems. Knowledge spillovers between regions are captured by the spatial specification described in the next paragraph.

After estimating these equations on the whole sample of EU NUTS 2 regions, we test whether the impact of KETs differs over regions according to their overall level of technological development (Leaders; Followers, Moderate; Modest).

5.2 *The econometric approach*

In order to take into account spatial spillovers, a spatial model is adopted. 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 all set of spatially lagged independent variables:

$$Y = WY\rho + X\beta_1 + WX\beta_2 + \varepsilon \quad (2)$$

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 (where 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

[9] 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). Alternatively, one could use the symmetric index as in Dalum et al. (1998; 1999) in the case of trade data; see also Laursen (2015).

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 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 $\beta_2 = -\rho\beta_1$ yields the spatial error model (SEM) that allows only for spatial dependence in the disturbances. Imposing the restriction 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 ρ=0 and β_2 =0 leads to a non-spatial regression model. We will choose the appropriate model by testing the restrictions using likelihood ratio tests[10].

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 effect 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; LeSage and Pace (2009) label this effects as the *average total impact from an observation* (see also Le Sage and Fischer, 2008). In the following section, in presenting the results of our empirical estimates, we will report both the direct and indirect effects and their statistical significance.

In the estimations, we adopt a row standardised NxN inverse distance matrix where the bandwidth reflects the median geographical distance between regions' centroids[11]. Row standardization implies

[10] Lagrange Multiplier tests and their robust versions are used to test the OLS versus the SAR and SEM; Likelihood ratio (LR) tests are used for testing the SAR and SEM versus the SDM while the test of the SLX versus the SDM is a t-test on the coefficient of the spatial lag of the dependent variable in the SDM. If the (robust) LM tests point to another model than the LR tests, then the spatial Durbin model is adopted. This is because this model generalizes both the spatial lag and the spatial error model.

[11] Inasmuch as space is not isotropic, this represents a limitation. A more accurate measure should be based on time distance. However, data on travel time are not easily available and the majority of studies still currently rely on simple geographic distance. [11] Exceptions are Crescenzi and Rodríguez-Pose (2011) and Le Gallo and Dall'erba (2008). Crescenzi and Rodríguez-Pose (2011) use information (provided to them by the European Commission) on road travel

that the elements of the distance matrix measure the fraction in a region's overall spatial effect that is attributable to each neighbour. Consequently, in the growth model the spatial lag of the dependent variable has the intuitive appeal of being a weighted average of neighbours' growth rates.

5.3 *Empirical results*

The results reported in Table 4 support the technology gap approach to economic growth (although in this case applied and tested at a sub-national scale) and the important role played by spatial proximity for the dynamics of innovation processes and their economic effects: per capita GDP growth 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, while R&D is not significant. The lack of significance of R&D intensity can be partly related to a certain degree of collinearity with the human capital variable (the correlation coefficient is 0.38) or to the presence of catching-up processes of technologically laggard regions (not fully captured by the GDP per capital indicator). The strong evidence of spatial effects gives support to the existence of localised knowledge spillovers (Peri, 2004; Bottazzi and Peri, 2003; Moreno et al 2006; Rodriguez-Pose and Crescenzi, 2008; Crescenzi and Rodriguez-Pose, 2011). 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. The lack of significance of FGT can be explained both considering that they have been defined adopting a strict perspective on technological opportunity (looking only at technological dynamism) and referring to their high variability over time (see Section 3).

Finally, it is 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.

(table 4 about here)

time across EU regions computed by the University of Dortmund for the calculation of peripherality indicators (IRPUD, 2000). Le Gallo and Dall'erba (2008) construct a weights matrix based on travel time by road (as a measure of accessibility) from the most populated town of a region to the one of another region using data coming from the web site of Michelin. They find very similar results when using this matrix and a matrix based on geographical distance.

Regions with different technological capabilities (characterized by a different level of technological development) may not only show a different propensity to develop KETs but might also benefit differently – through different mechanisms - from being specialised in these technologies. In fact, while the most advanced 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. In particular, for laggard regions, specialised in traditional sectors, KETs might contribute to the implementation and success of smart specialization strategies by allowing them to develop new (or upgraded) comparative advantages (Montresor and Quatraro, 2015).

In order to disentangle whether KETs have a different impact on regional growth depending on regional technological level, Table 5 reports the results of the estimation of equation (1) allowing for the impact of specialisation in KETs to differ across technology groups (1=Leader regions; 2=Follower regions; 3=Moderate regions and Modest regions)[12]. We also allow the intercept to vary among the three regional groups.

(Table 5 about here)

The table shows that the benefits of being specialised in KETs are higher for technology backward regions (when compared to more innovative regions). 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) and Follower regions to Moderate and Modest regions[13]. These results suggest that investing resources in KETs facilitates the catching up process, thus supporting the inclusion of KETs related targets as part of smart specialisation strategies for catching up 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.

[12] The regional classification used is the one elaborated by the EU regional Innovation Scoreboard - European Commission, 2014b. Moderate and Modest regions are taken together due to the low number of Modest regions in the sample which includes regions with at least 20 patents at the beginning of the period.

[13] While there is no statistical difference in the estimated impact of KETs on growth between Leader and Follower regions, there is a significantly higher impact for Moderate and Modest regions.

6. Conclusions

The main results of this contribution can be summarised as follows. First, only a small share of KETs are also FGTs, 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 in the UK. Third, over time, the group of less innovative regions increase their specialization in KETs at the expense of the most innovative regions; on the other hand, technologically leading regions increase their specialization in FGTs. Finally, the results of the econometric estimations show that only specialisation in KETs affects economic growth, while being specialized in FGTs does not seem to exert any significant impact on regional long-term growth. These last results are consistent with our expectation and provide some support to the importance attached to KETs in the recent EU policy framework. In fact, differently from FGTs, KETs have been selected for their pervasive and wide in scope nature, systemic relevance and potential socio-economic impact. They are supposed to enable the development of new goods and services and the restructuring of industrial processes, fundamental ingredients and preconditions to modernise EU industry, strengthening the research, development and innovation base of EU regions and (most important) facilitating regional cohesion. These technologies are multidisciplinary in terms of knowledge basis, multi-sectoral in terms of use and cutting across many technology areas, thus facilitating technological and industrial convergence and integration. The results of our regressions confirm the important role that KETs can play for regional growth. Moreover, the results of our estimates show that KETs are of strategic importance especially for laggard regions playing an enabling role in the catching up process.

Drawing policy implications from the results of this study is not an easy task. On the one hand, the lack of significance of specialization in FGTs on regional growth suggests that policies aimed at picking up (technology) winners, or at sustaining more dynamic technologies, might prove ineffective. At the same time, identifying emerging technologies is not an easy task since these are surrounded by a high degree of uncertainty. In fact our results show that only a small share of patent classes exhibits above average performances over long time spans. However, policies devoted at targeting specific technologies may still be beneficial especially when complemented by horizontal policies aimed at stimulating regional innovation and absorption capacity. What appears to be important is identifying technologies with a systemic impact, being able to have widespread effects throughout the economic system. The results on the positive impact of KETs on regional growth suggest that these technologies are likely to have these desired characteristics.

As a final policy concern, we might ask whether the results of this study are supportive of the new EU focus on the smart specialization strategy. This strategy seems to suggest that there are no "superior" patterns of specialization since each region has its own set of comparative advantages on which it should build on. However, there is also some 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 are consistent with this view especially when the potentiality offered by KETs in supporting smart specialization (diversification) processes are taken into account. Precisely because of their high degree of pervasiveness, KETs can enhance the possibility of regions to both strengthen their traditional comparative advantages and diversify in a "smart" (related) fashion (Montresor and Quatraro, 2015).

The aggregate approach adopted in this paper does not allow identifying the channels through which KETs affect regional performance and, therefore, does not allow directly testing the link between KETs, processes of related diversification and regional growth. This is a relevant issue with important policy implications that is left for further research.

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Table 1. Transition matrix for the patents growth rates

	Growth	Second period Bottom 25	Middle 50	Top 25
First period	**Bottom 25**	31.80%	43.90%	24.30%
	Middle 50	21.10%	57.10%	21.80%
	Top 25	26.40%	41.20%	32.40%

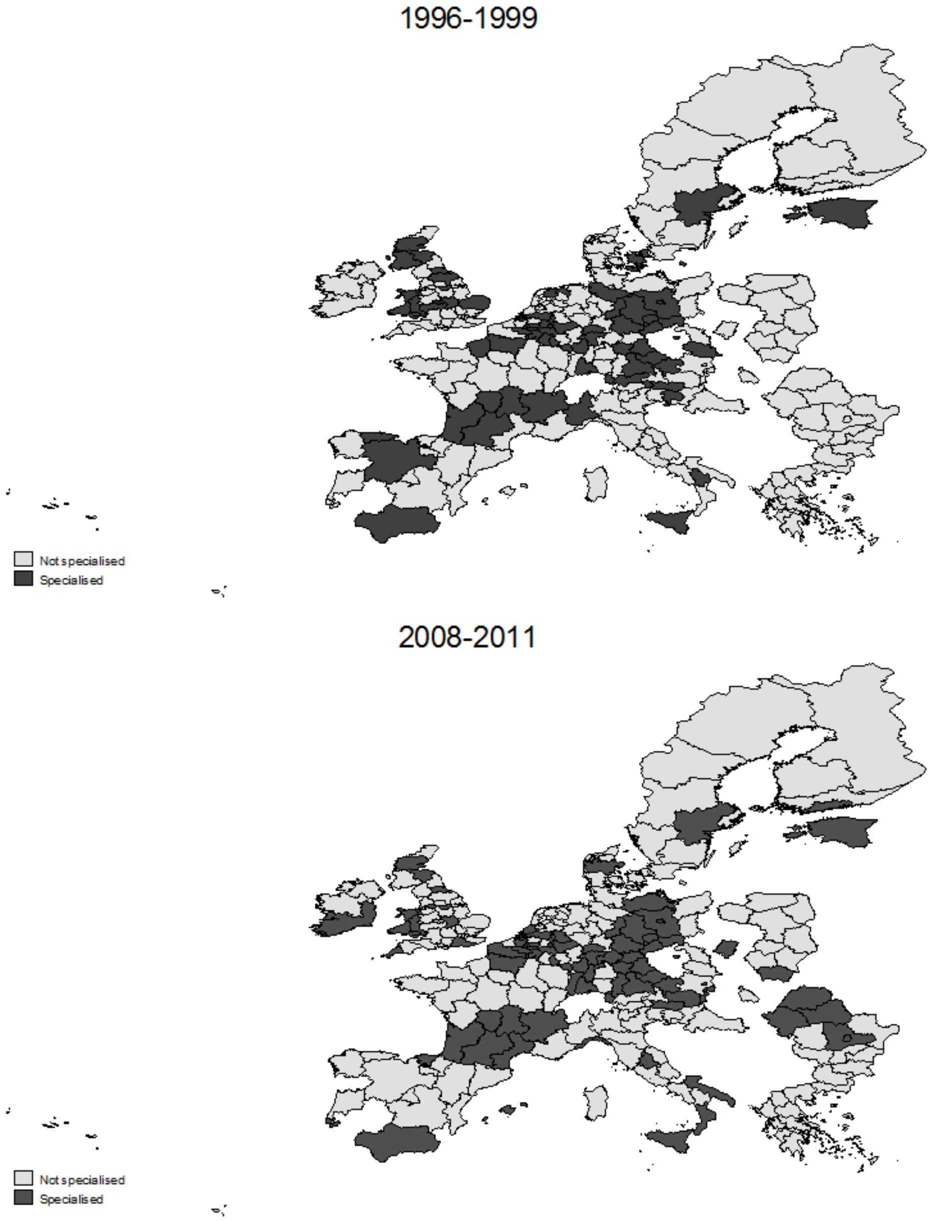
Note: *calculated for the 1992/95 to 2000/03 and 2000/03 to 2008/11 periods on EPO patent applications as reported in REGPAT.*

Table 2. Fast growing technologies and key enabling technologies (% values)

	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
All patents	84	16	100	45	55	100	71	29	100
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

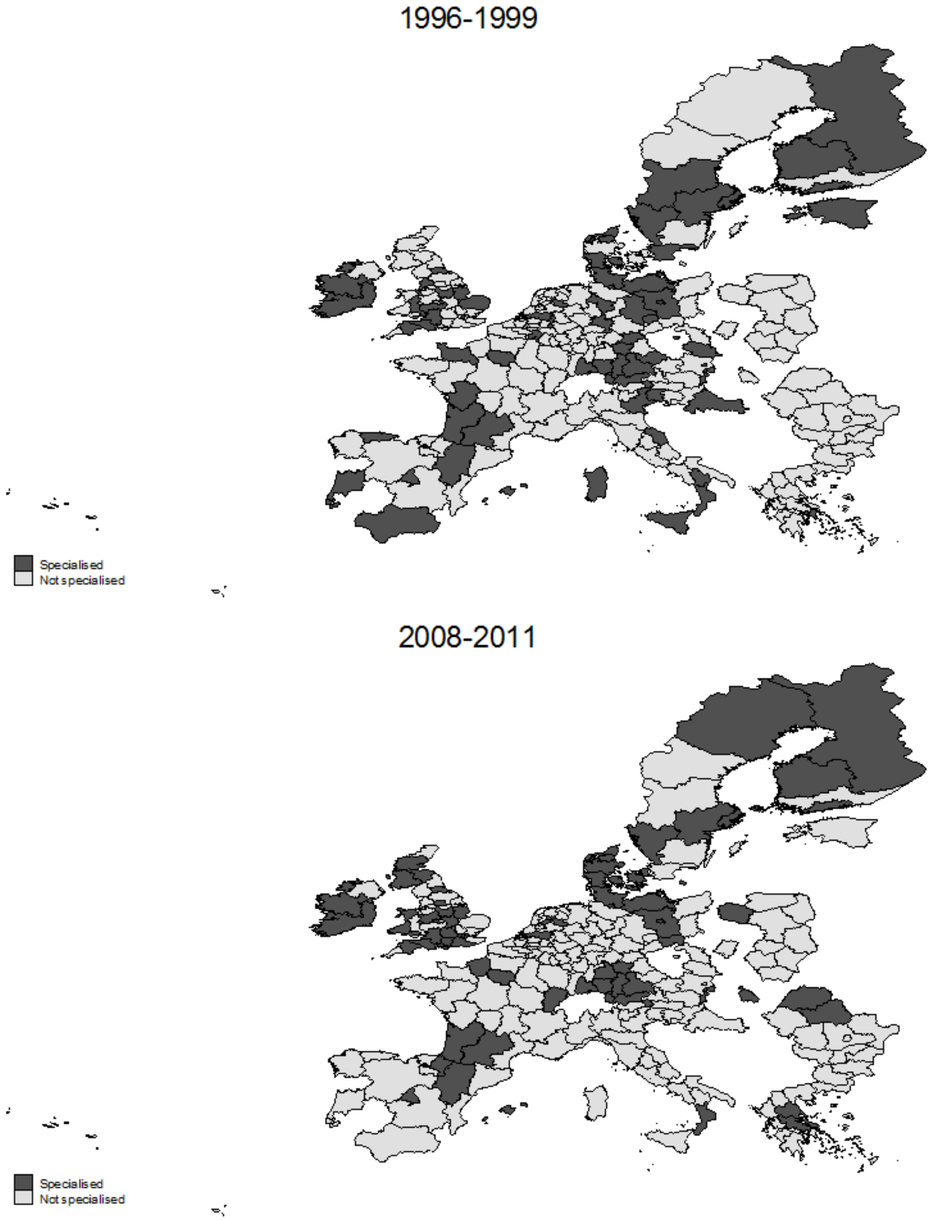
Source: *Authors' own calculations on EPO patent applications as reported in REGPAT.*

Figure 1. Regions specialised in KETs: 1996-1999 and 2008-2011



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

Figure 2. Regions specialised in fast growing technologies, 1996-1999 and 2008-2011.



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

Table 3. Specialization in KETs and FGTs by regional groups

Regional groups	Specialization (RTA) in KETs		Specialization (RTA) in FGTs	
	1996-1999	2008-2011	1996-1999	2008-2011
Leaders	1.056	1.025	1.037	1.090
Followers	0.953	1.044	0.991	0.923
Moderate	0.798	0.789	0.811	0.761
Modest	0.557	0.745	1.198	0.779

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

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	-0.007***	-2.621	0.029	0.472
% of population with tertiary education	0.008***	3.892	0.000	0.003
Rate of growth of patents (lagged)	0.047***	3.950	0.254	0.775
R&D over GDP	-0.0005	-0.631	0.031	0.493
Regional share of patents in KETs	0.030***	2.474	0.180	0.814
Regional share of patents in FGTs	-0.003	-0.166	0.338	0.503

R-squared=0.537 ρ = 0.539***

LM(lag)= 124.70*** R-LM(lag)= 11.18*** LM(error)= 135.14*** R-LM(error)= 23.49*** LR(lag)=33.94*** LR(error)= 17.44***

Note: **,**, *** denote respectively significant at 10, 5 and 1%. LM and R-LM denote the Lagrange Multiplier test and its robust version. LR indicate likelihood ratio tests.*

Table 5. Estimates of the per capita growth equation allowing specialisation in KETs to differ across technology groups: spatial error model

	Direct Effect	t-stat	Indirect effect	t-stat
Initial level of per capita GDP	-0.005**	-2.229	0.005	0.291
% of population with tertiary education	0.009***	3.777	-0.0134	-1.535
Rate of growth of patents (lagged)	0.044***	3.822	0.340***	2.951
R&D over GDP	-0.001	-1.288	0.003	0.315
Regional % of patents in FGTs	0.009	0.538	0.290*	1.803
Regional % of patents in KETs leader	0.024	1.179	0.323	1.361
Regional % of patents in KETs follower	0.022*	1.707	0.092	0.837
Regional % of patents in KETs moderate & modest	0.084***	3.784	0.161	1.040

R-squared=0.620   ρ = -0.008

LM(lag)=124.46*** R-LM(lag)=44.24*** LM(error)=77.12*** R-LM(error)=0.48

LR(lag)=30.73***   LR(error)= 36.49***

Note: **,**, *** denote respectively significant at 10, 5 and 1%. LM and R-LM denote the Lagrange Multiplier test and its robust version. LR indicate likelihood ratio tests.*

Appendix

Table A1 - 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.*
** Labels reported in the IPC classification edited by the authors, n.o.p. stands for " not otherwise provided"*