"Bigger, better, faster, more!"
How to increase the intensity and relevance of the technological progress of European regions.

1. Introduction

From a theoretical point of view, many authors have applied the endogenous growth theory to the understanding of the drivers of subnational economic development, either at the city or the regional level (Cheshire and Magrini 2000; MacKinnon et al. 2002; Acs and Armington 2004; Harrison 2006, 2007; Button 2011; Stimson et al. 2011; Plummer et al. 2014). In this article we depart from studies that focus on the importance of endogenous technological progress for growth (Romer 1989; Aghion et al. 1998), and concentrate on, among the various factors influencing technological progress, the role of regional knowledge space in shaping new knowledge production and innovation.
Our first research question (RQ1) is as follows. What types of pre-existing knowledge are best suited for new knowledge creation in European regions? Some recent studies (Kogler et al. 2013; Tavassoli and Carbonara, 2014; Rigby, 2015; Castaldi et al., 2015; Miguelez and Moreno, 2017), grounded on the evolutionary economic geography theory, have tried to investigate the features of the knowledge produced within a region that improve the chance of knowledge recombination and new knowledge creation. In these contributions, the knowledge space is often approximated with measures of innovation input and output (such as R&D expenditures and patents). Main focus in the literature cited above is on the relatedness argument, disregarding other important aspects of the regional knowledge space, such as, for instance, the path dependent processes that shape the technological trajectories of regions. In this realm, it is important to underline that innovation activities have a strong cumulative nature (Fieldman, 1994, Breschi, 2000). The literature on the technological regime (Malerba and Orsenigo, 1996a, 1996b) offers an important point of view to understand how cumulativeness of knowledge could influence the generation of new knowledge, thus opening up to a new set of indicators characterising the knowledge space. Our work aims at responding to this research question through an original perspective, which considers together the more common used indicators of technological relatedness, with less explored indicators of technological knowledge base and technological cumulativeness.

The second research question (RQ2) pertains an evaluation of the output of the knowledge production process: which are the features of the knowledge space that are able to increase the intensity of the technological progress in European regions? Are these the same affecting the relevance of their technological progress? In the literature on regional innovation, the majority of studies focused on the innovation intensity, that is a quantitative measurement of innovation output (Acs, 2002; Rigby, 2015, Paci and Usai, 2009). Recently some research works have devoted attention not only to innovation intensity, but also to the quality of the innovation output, in terms of type of innovation (radical vs. incremental - Castaldi et al. 2015) and technological impact (Jaffe et al, 2017; Miguelez and Moreno 2017) or technological importance (Nemet and Johnson, 2012; Benson and Magee, 2015). We build upon these contributions, sharing the goal of increasing the understanding of differences in the determinants of general innovation and breakthrough innovations.

By answering these research questions, this research work sheds light on the relative impact of the technological knowledge base and cumulativeness, the technological diversification and relatedness, on the capacity of regions not only to be innovative, but to be a high-quality innovator. Since existing research works on the topic adopt different units of analysis (European regions, US States, specific European Countries), thus not helping comparing the empirical evidence provided, due to the variety of capitalism (Hall and Soskice, 2003) and the cultural differences (Hofstede, 1984) arguments, the definition of a unified system of indicators useful to answer the RQs is crucial.

In our work we take in consideration both the two measures of technological progress: innovation intensity (based on the number of patents), which is a stock measure of technological progress, and innovation relevance (based on the number of forward citations), which is a quality measure of technological progress. In more detail, the innovation relevance reflects the adoption and dissemination of innovations, mirroring the technological importance for subsequent technological developments and the economic value of innovations (Trajtenberg et al. 1990; Lanjouw and Schankerman 2004; Hall et al. 2005, Gambardella et al. 2008, Jaffe and de Rassenfosse 2017).

The unit of analysis is the region, and the empirical setting is Europe. Theoretically grounded in the literature of evolutionary economic geography, this study adds to the debate on the drivers of technological progress by 1) accounting for the marginal effect of the different features of a regional knowledge space, and 2) distinguishing between the quantitative and qualitative aspects of the technological progress (intensity and relevance).

The paper proceeds as follows. In Section 2 we review the literature on regional space and technological progress, focusing on features that are more likely to encourage technological progress at the regional level, and present the research hypotheses. In Section 3 we define the methodology and provide the empirical analysis. Results are shown in Section 4. Section 5 offers some concluding remarks.

2. Theoretical framework and hypotheses

2.1 Technological knowledge base and technological progress

The accumulation of technological knowledge creates increasing returns in scale in many contexts (Grossman and Helpman 1990); thus a region with a consistent base of technological knowledge has a better chance of activating learning processes that will increase the capacity to produce new technological knowledge than regions without a consistent base (Arthur 1996). Moreover, technological innovation is commonly understood to be a cumulative process in which most new artefacts are being invented by recombining existing technologies in a new manner (Arthur 2007, Tria et al. 2014; Castaldi et al. 2015). Consequently, the stock of knowledge accumulated in a region increases its future invention/innovation capacity. It follows that the size of the knowledge base is related to the region's technological change (Ahuja and Katila 2001; Fleming 2001). Smith et al. (2005) point out that existing knowledge influences the extent to which new knowledge is created, and new knowledge that is created in turn becomes part of the knowledge stock. A dynamic and self-reinforcing system of knowledge production is in place. The accumulation of knowledge leads to improved performance in terms of technological progress, giving rise to a sort of Matthew effect, in which "the rich get richer" (Merton 1988); that is, regions with a larger knowledge base are more likely than those with a smaller knowledge base to produce new knowledge and to maintain their status of being rich in knowledge assets. A higher innovation potential is typically joined by a larger organizational and institutional thickness of the regional innovation system, able to provide better infrastructures and research support for knowledge transfer, knowledge spillovers and innovation process (Asheim et al. 2011). This leads to the articulation of our first baseline hypothesis.

Hypothesis 1a: The larger the technological knowledge base, the higher the intensity of technological progress in a region

The relationship between the size of the technological knowledge base and the regional innovation relevance is not clearly defined in the literature. Some authors highlighted the absence of a significant impact of the technological knowledge base on innovation relevance. More in details, analysing the relationship between level of R&D at the firm level and quality of patents from panel data on manufacturing firms in the US for the period 1980–93, Lanjouw and Schankerman (2004) did not find any significant correlation. Thus suggesting that the magnitude of the innovative effort does not show any impact on the relevance of the technological progress of a region. Nevertheless, following a process of technological exhaustion, which could undermine the ability to reach for radically new technologies it is likely to observe negative impact of the size of the technological knowledge base on the relevance of the innovative output (Fleming, 2001). The assumption of bounded rationality and local search (March, 1991) explains the tendency of inventors to recombine knowledge within a familiar set of technology components, or refine previous combinations, thus locking in the innovation process within an innovation pattern that is more oriented to the exploitation of local knowledge spaces rather than the exploration of distant knowledge spaces. Accordingly, inventive certainty is preferred to inventive uncertainty (Fleming, 2001), favouring a technological exhaustion process, where most of the possible relationships between a set of components have already been tried.

Hypothesis 1b: The size of the technological knowledge base negatively affect the relevance of technological progress in a region

2.2. Technological cumulativeness and technological progress

The generation of technological progress is linked to a region's ability to explore, select and use existing knowledge. This ability is a specific feature of the regional technological regime (Malerba and Orsenigo, 1996b), and is widely addressed by evolutionary literature as cumulativeness. The cumulativeness of technological advances is the degree to which new technology builds on existing technology (Nelson and Winter, 1982). Technological cumulativeness is related to the fact that one innovation can generate a stream of subsequent innovations that improves upon the original or creates new knowledge that is used for other innovations in related areas (Breschi, 2000; Breschi et al., 2000; Lee et al., 2017; Peneder, 2010, Malerba and Orsenigo, 1996a). The process of knowledge selection, and the recombination of existing knowledge into new knowledge, become relevant steps in shaping the region's potential for technological progress. Accordingly, the analysis of the knowledge sources used by the region is essential to determine the relative adoption of different technologies over time and influences the path of technological progress generated by any given invention (Banerjee and Cole 2010). Following a pre-existing trajectory could be easier, less expensive and resource saving, because of the use of capabilities that already exist and are well managed in the region. Therefore, the selection and recombination of a higher number of knowledge sources allows a wider knowledge pool, where each component can be recombined to create new knowledge and might lead to technological progress, especially in terms of innovation intensity. Building on the Schumpeterian tradition, and aligning with Malerba and Orsenigo (1996), Breschi et al. (2000), Lee and Lim (2001), we consider two main patterns of innovations: a *creative distruction* pattern in which innovation are less related to the previous innovations and a *creative accumulation* pattern where new innovations are highly related to the previous innovation and could be defined as an exploitation of the existing technologies. In particular, our Hypothesis 2a, which describes the technological trajectory of regions dominated by Schumpeter Mark II technologies (Schumpeter, 1942), are traditionally developed by scale intensive firms (Pavitt, 1984), within routinized innovation regimes and high concentration of innovative activities.

Hypothesis 2a: A high technological cumulativeness positively affects the intensity of the technological progress of the region.

In addition, the identification and measurement of which knowledge sources are recombined to create new knowledge can help to assess the degree of novelty of new inventions and may be informative of the intrinsic dynamics of the technological process. Considering backward citations of patents as a measure of cumulativeness of technological advances, Trajtenberg et al. (1997) highlighted that more trivial inventions are more extensively rooted in what has come before, while more basic inventions are less incremental in nature and thus have fewer identifiable antecedents. Therefore, the extent of knowledge sources, which a patent refers to, may signal the innovation to be more incremental in nature (Lanjouw and Schankerman 2004) and also mirrors the existence of a regional innovation strategy aimed at following the inventive trajectory to which it is tied (Jaffe and de Rassenfosse 2017). We build upon the argument put forward by Winter (1984) and Malerba and Orsenigo (1996), who claimed that low technological cumulativeness is linked to the activities of small firms alongside entrepreneurial regimes. We therefore expect that regions dominated by Schumpeter Mark I technologies (Schumpeter, 1934), characterised by low technological cumulativeness, might be able to produce more impactful and relevant innovations.

Hypothesis 2b: A low technological cumulativeness positively affects the relevance of the technological progress of the region

2.3. Technological diversification and technological progress

Knowledge that is not oriented to new directions could lead to closure and increase the risk of lock-in into a specific technological domain, allowing only the exploitation of existing knowledge. The exploration of new knowledge in different technological domains may open up new opportunities and expand the technological possibilities (Boschma and Lambooy 1999; Martin and Sunley 2006, 2010; Rosenzweig, 2017). Therefore, new knowledge is created predominantly by processes of recombination of knowledge from different technological classes, which represent different knowledge sources. These types of knowledge sources tend to be specific forms of scientific and applied knowledge related to technology, markets and organizational aspects (Grillitsch et al. 2015). Regions accumulate know-how across a variety of disciplines and heterogeneous market domains through extensive processes of knowledge exploration (Prabhu et al. 2005). Processes of new knowledge creation and innovation in a region are influenced not only by the size of the technological knowledge base, but also, and maybe more importantly, by the diversification of this knowledge base (Audretsch and Vivarelli 1996; Saviotti 1996; Rodan and Galunic 2004; Frenken et al. 2007; Tavassoli and Carbonara 2014). The exposure to heterogeneous knowledge allows for new recombination opportunities and spillovers, which sustain the creativity of firms in the region, leveraging on their opportunity recognition and recombinant abilities, and boosting their capacity to develop new knowledge and innovation (Kogut and Zander 1992; Rodan and Galunic 2004). A diversified knowledge base is more likely to be conducive to novelties and expands regional learning capabilities, avoiding lock-in and path-dependent processes, which are particularly critical in case of external economic shocks (Sedita et al. 2017). Some studies have shown that regional knowledge heterogeneity influences positively knowledge creation and innovation performance (Jacobs 1969; Phene et al. 2006), providing opportunities for novel linkages and associations. The diversification of knowledge augments the selection opportunities and decreases the likelihood of technological dead-ends (Singh and Fleming 2010). Following this line of reasoning, a region that recombines broader pre-existing knowledge could be more inclined to create new knowledge and actively contribute to technological progress, in terms of innovation intensity, than a specialized region.

Hypothesis 3a: The technological diversification positively affects the intensity of the technological progress of the region.

Moreover the recombination of widely diversified knowledge is likely to lead to impactful innovation (Benson and Magee 2012; Nemet and Johnson 2012), with high economic value (Fleming and Soreson 2004; Kaplan and Vakili 2015), which can lead to complete new operational principles, functionalities and applications (Fleming 2001; Saviotti and Frenken 2008; Castaldi et al. 2015). The combining of diverse technological components generates unique and thus genuine innovation (Van de Vrande 2013) that could enable further combinations (Nemet and Johnson 2012). A diversified knowledge base allows the combination of ideas that had not been brought together before, thus leading to increased innovation performance (Ahuja and Lampert 2001; Singh and Fleming 2010; Rosenzweig 2017). In this perspective, we hypothesize a positive relationship between technological diversification and the relevance of the technological progress.

Hypothesis 3b: The technological diversification positively affects the relevance of the technological progress of the region.

2.4. Technological relatedness and technological progress

Despite the role of the diversified knowledge base in fostering technological progress being well recognised in the literature, we have to take into consideration that high diversification is often accompanied by high risks and switching costs, because of the limited capabilities of firms and the peculiarities of their business models, which clearly hinder their possibilities to move their technological frontier in completely different knowledge domains (Boschma et al. 2014). The recombination of diversified knowledge sources requires strong abilities of firstly recognising the value of distant knowledge, secondly assimilating it, and thirdly exploiting it for technological and commercial ends (Cohen and Levinthal 1990).

Fornahl et al. (2011), stemming from the concept of cognitive proximity of Nooteboom (2000), introduced the definition of an "optimal cognitive distance", which characterizes knowledge that is neither identical (hence it can be usefully exchanged) nor too distant (therefore it can still be effectively absorbed), but related. Relatedness can therefore be associated with knowledge transfers that occur across industries because of their optimal cognitive distance. Some degree of cognitive proximity is desirable because it ensures effective communication and common understanding, while guaranteeing to avoid cognitive lock-in.

As for the industrial structure, Frenken et al. (2007) introduced the concept of related and unrelated variety, highlighting that regional variety impacts on regional development only if regional sectors are technologically related to each other. Other authors have applied these concepts to different regional contexts: The Netherlands (Frenken et al. 2007), Italy (Boschma and Iammarino 2009; Quatraro 2010), Sweden (Boschma et al. 2009), Great Britain (Bishop and Gripaios 2010), Germany (Brachert et al. 2011), Spain (Boschma et al. 2012), Finland (Hartog et al. 2012), European Regions (Cortinovis and Van Oort 2015), confirming that related variety tends to contribute positively to regional growth in terms of employment or productivity.

Shifting from the analysis of the features of the regional industrial structure to the determinants of the regional innovation performance, the concept of relatedness is applied to the technological trajectories of the innovation process. By doing so, the measure of technological relatedness proposed by Breschi et al. (2003) at the firm level has been borrowed by scientists from the realm of economic geography. In particular, previous research proved that technologically related variety affects positively the regional innovation performance in general, while the technologically unrelated variety affects positively the creation of radical/breakthrough innovations (Tavassoli and Carbonara 2014; Castaldi et al. 2015).

Technological relatedness at a regional level measures how regions' diversification possibilities are affected by the degree to which technologies are connected to one another, where the link between two technologies is usually measured by how much they share in terms of common scientific knowledge, technical principles, heuristics, and common needs in general (Petralia et al. 2017). Several studies have confirmed the role of relatedness in fostering technological or industrial development – through "branching processes". Regarding the industrial diversification of regions, Neffke et al. (2011) and Essletzbichler (2015) highlighted that regions are more likely to enter into industries that are related to those already existing. Similarly, Kogler et al. (2013), Boschma et al. (2015) and Rigby (2015), focusing on regional technological diversification, found that technologies related to pre-existing technologies in U.S. cities or metropolitan regions increase the possibility of entering those regions and that they are crucial for technological change. Quatraro and Usai (2017) found that as the trajectory becomes more familiar, innovating agents learn to move across the knowledge space and are more likely to undertake organized searches directed towards the combination of technologies that are close to one another. Therefore, if the knowledge space of a region is characterized by a patenting activity alongside a large number of related technological classes, the region is more likely to host regional knowledge spillovers between these related technological classes, which provide venues for new knowledge creation. Following this line, a region that recombines related pre-existing knowledge could be more inclined to create new knowledge and actively contribute to technological progress, both in terms of innovation intensity and relevance.

Hypothesis 4a: The technological relatedness positively affects the intensity of the technological progress of the region

Hypothesis 4b: The technological relatedness positively affects the relevance of the technological progress of the region

3. Methodology

This study investigates the relationship between regional knowledge space and technological progress by exploring the relative impact of the size, reliance, diversity and relatedness of the regional knowledge space. The sample involves N=269 regions in 29 countries (European Union plus Norway). NUTS2 (Nomenclature of Territorial Units for Statistics) is used to define the regional level. Data concerning patents, patent citations, technological classes and inventors were collected from the Organisation for Economic Co-operation and Development (OECD) REGPAT database (version released 02/2016). Patent data have been regionalized on the basis of the inventors' address. Fractional counting is applied in case of multiple inventors per patent coming from different regions (De Noni et al. 2017a). Technological classification refers to International Patent Classification (IPC) classes at the 4-digit level. The final panel dataset covers the time period from 1996 to 2012. Explanatory variables (x) about regional knowledge features are measured on the previous five-year moving average in order to mitigate the effect of time fluctuations. Differently, the dependent variables (y) are computed on the following three-year moving time-windows, lagged one period with respect to the explanatory variables. The time lags are introduced to minimize endogeneity and reverse causality issues. To sum up, if y is operationalized gathering data from t to t+2, x is defined from t-1 to t-5. In addition, the control variables, which concern the economic and demographic regional features and are provided by the statistical office of the European Union (Eurostat), are measured in t-1. Therefore, because of these variables' structure, the number of time series in the panel dataset is limited to T=9.[1]

Finally, spatial modelling with individual fixed effects is implemented to control for potential spatial dependence of innovation and for a number of unobserved factors at the regional level, such as institutional setting or policy differences (Cortinovis et al. 2017).

3.1 Variables

In this study, we define technological progress by looking at its intensity and relevance at the regional level. Explanatory variables involve data on technological knowledge base, technological cumulativeness, diversification and relatedness. Finally, we introduce R&D capacity, human capital, manufacturing specialization and population density as controls.

Dependent variables

[1] We also test five-year moving time-windows of dependent variables. However, since this procedure further decreases the times of panel dataset from T=9 to T=7 and does not change the findings significantly, we only report the models concerning the five-year lagged dependent variables in appendix A.

Technological progress intensity. Despite the limitations[2] for measuring technological knowledge (Alcacer and Gittelman 2006; Lane et al. 2006), patents have been found to be a good proxy for computing innovation performance at a regional level (Acs et al. 2002) and are widely used today. In addition, since patents refer to the output of a lagged invention process (Paci and Usai 2009; Crescenzi et al. 2012), using a lag window larger than three years is typically recommended (Marrocu et al. 2013; Paci et al. 2014). To sum up, technological progress intensity is here measured as the logarithmic transformation of the cumulated regional patent contribution per million inhabitants over a shifted three-year window[3]; the higher the index, the higher the regional capacity to innovate.

Technological progress relevance. This study uses the citations a given patent spawns (forward citations) as an indicator of its technological impact and economic value (Jaffe and de Rassenfosse, 2017). The forward citations refer to the technological descendants of an invention and its extent suggests the technological importance of a patent for the development of subsequent technologies (Harhoff et al. 2003; Hall et al. 2005, Namet and Johnson, 2012). The number of forward citations in the following five years from application is automatically provided per patent by the OECD REGPAT database. Then, we computed the logarithm of the average number of forward citations associated with the cumulated regional patent contribution over three-year moving time-windows[4]. The more citations of a patent by future patents, the greater is the likelihood of being adopted for exploiting a technological trajectory and the higher the estimation of its potentiality or relevance. On the basis of the findings of Hall et al. (2005), the measure also includes self-citations, which are as valuable as citations from external patents.

Independent variables

Technological knowledge base. The size of the technological knowledge base of a region represents the regional capacity to produce and accumulate knowledge stock, which may potentially be exploited to create technological progress. Based on Dettori et al. (2012), this index is operationalized as the logarithmic transformation of cumulative patent stock of the region in the previous five years over the total population. The larger the knowledge stock of a region, the higher the recombination potential and expected innovation performance are. The use of this variable on the regional *technological progress intensity* corresponds to running a dynamic panel model.

[2] Although patent data are typically used to measure knowledge outputs and innovation, they do not represent the overall knowledge production of a region (Rigby, 2015)
[3] To check the robustness of our results, we operationalized also a 5-year time window instead of a 3-year time window for our dependent variable (see Appendix A).
[4] Also in this case we operationalized an additional 5-year time window instead of a 3-year time window (see Appendix A).

Technological cumulativeness. Backward citations inform about the technological antecedents of an invention. The basic idea is that the extent to which inventions rely on antecedents proxies the degree of path-dependency between new and pre-existing knowledge, notifying their novelty or radicalness (Jaffe and de Rassenfosse 2017). Thus, technological cumulativeness is operationalized as the logarithm of the average number of regional backward citations (within or outside the region) reported by patents filed by the region over five-year moving time-windows.

Technological diversification. Technological diversification of a region is supposed to be strongly related to the extent of knowledge sources that inventors of a region can acquire, exploit and transform into new knowledge (Zahra and George 2002). Thus, it's not just a matter of diversified structure of internal knowledge base but mainly of the regional capacity for accessing to and using diversified knowledge in the invention process. Nevertheless, since absorptive capacity strongly depends on cognitive proximity (Noteboom, 2000), the diversity of the regional knowledge base can positively impact on the heterogeneity of the regional knowledge sources. In other words, the more diversified the knowledge of a region, the higher is the opportunity for that region to access to and use differentiated knowledge sources. In order to measure this type of technological diversification, we refer to backward citations rather than patents and specifically apply the Patent Originality Index, provided by OECD REGPAT, which refers to the breadth of the technology fields on which backward citations of a patent rely on (Jaffe and de Rassenfosse 2017). Based on Hall et al. (2001), the originality index measures the degree of heterogeneity of the backward citations across patent classes (IPC4-level). The higher the index, the larger the number of diverse knowledge sources a patent exploits, and therefore the higher the probability to obtain original results. Conversely, the lower the value, the higher the concentration of the citations within few technological fields, and therefore the higher the probability that the patent mirrors an incremental innovation. An average value is calculated at the regional level on the patent stock of a region over five-year moving time-windows.

Technological relatedness. Following Balland et al. (2015), we firstly compute T incidence regions-technologies matrices based on the relative distribution of regional patents across 438 IPC4-level technological classes over five-year moving time-windows. A dichotomized matrix of Revealed Comparative Advantage (RCA) is further defined by considering the technologies with a location quotient[5] higher than 1. Secondly, we construct T network matrices of the technology space in order to measure the degree of relatedness across all technologies by computing a technologies-

[5] The location quotient is applied by comparing the share of each technology in a given region to the share of this technology in overall sampled European countries.

technologies matrix based on normalized co-occurrences of technological classes[6] over five-year moving time-windows. Following Boschma et al. (2014), we dichotomize the relatedness matrix by considering as related only to the top 5% technology pairs. Finally, the average relatedness density within the regional portfolio is computed by integrating the technological space matrix and RCA matrix (Balland 2017). The higher the value, the higher the relatedness across the most relevant technologies of a region.

Control variables

R&D expenditures. Gross domestic expenditure on Research & Development (R&D) as a percentage of gross domestic product is an indicator of high political importance at the EU, national, and regional levels. R&D intensity is expected to have a positive impact on innovation, assuming that there exists a positive correlation between technological input and output (Gilsing et al. 2008).

Human capital. Since the attitude of a region to innovate depends on the average level of human capital within the local economy (Lee et al. 2010), tertiary educational attainment is used as a proxy for human capital. The higher the educational level, the higher the potential number of inventors. This indicator, provided by Eurostat, is specifically based on the EU Labour Force Survey. It is defined as the percentage of the population aged 25-64 who have successfully completed tertiary studies (e.g. university, higher technical institution, etc.). Educational attainment is defined with reference to the International Standard Classification of Education 1997 levels 5-6 for data up to 2013.

Manufacturing specialization. Since sectors have different technology and innovation opportunities, and manufacturing is typically more inclined to innovate than services (Hipp and Grupp 2005) – especially when innovation is measured in terms of patents – manufacturing specialization is used as the control. Specifically, the level of manufacturing concentration is measured as the share of employees operating within the manufacturing industry with respect to the total number of employees in a given region.

Population density. Population density (population divided by land area in square kilometres) is usually applied as a proxy for externalities related to the urbanization process (Mameli et al. 2012). Urbanization is positively associated with the presence of universities, industry research laboratories, trade associations and other knowledge-generating organizations (Frenken et al. 2007). Thus, urban economies may better support regional innovation performance than non-urban economies.

[6] Differently from USPTO patents, EPO patents are not required to identify a priority technological class. Thus, most of them declare multiple technological classes. Technological space defines how often two technologies are found within the same patent. In other words, two technological classes co-occur if they are both cited in the same patent.

3.2 Model estimation

In this study, we used a spatially lagged model based on a 9-panels dataset, since the ordinary least squares (OLS) estimates, though unbiased, are inefficient when spatial dependence is present (Anselin 1988). Spatial lag is suggestive of a possible diffusion process of knowledge creation because of the spatial dimension of social interactions and collaboration processes, which are typically considered as important drivers for innovation and knowledge spillovers. Moreover, fixed effects are typically preferred to random effects in modelling regions because of the distribution of innovation, which is inclined to be influenced by observed and latent time-invariant territorial features. Finally, we introduce individual effects (regional effects in our case) in order to analyze changes at the individual level and control for regional heterogeneity. The use of n-year moving time-windows mitigates the effect of time fluctuations and makes it unnecessary to control for time effects. In addition, a number of statistical tests are applied to verify our choices. Firstly, the F-test is performed by using the *pFtest* function of R[7]'s *plm* package and confirms that both fixed and random effects models better fit than OLS. Secondly, the Moran I test is applied to measure the spatial autocorrelation given a set of features and an associated attribute. The result confirms that regional technological progress is a spatially clustered process. Furthermore, Lagrange Multiplier (LM) and Robust Lagrange Multiplier (RLM) tests confirm that regional technological progress is spatially lagged. Finally, the Hausman test statistically confirms that fixed effect is more consistent than random effect modelling (Greene 2008). The results of the tests are reported in Tables 3 and Appendix A. Moreover, fixed effect models are the safest choice to eliminate possible omitted variables bias such as cultural and social aspects (Nickell 1981). Important differences between regions are the consequences of region-specific effects related to regional systems of innovation and to specific histories of firms and industries across regions.

We used the R package *splm* (spatial panel linear model) to estimate the regressive models with a maximum likelihood approach controlling for spatial lag dependence.

Thus, following Anselin (1988), we defined the expression of the spatial fixed effects lag model as:

$$Y = \lambda W y + X\beta + \varepsilon$$

where Y is a vector of the dependent variables, X is a matrix of the explanatory and control variables, β represents the vector of the coefficients, ε is the vector of the residuals, and W is the spatial weight matrix, showing the strength of the interaction between two regions.

[7] R is an open source software environment for statistical computing and graphics.

4. Results

Tables 1 and 2 present the descriptive statistics and the correlation matrix for all variables. As Table 2 shows, all the explanatory variables tend to be positively correlated with the two dependent variables that measure the technological progress intensity and relevance.

Table 1: Descriptive statistics

Variables	Mean	Sd.	Min.	Max.	Obs.
Tech. progress intensity	0,10	0,12	0.00	0,56	2421
Tech. progress relevance	0,22	0,10	0.00	0,64	2421
Tech. knowledge base	2,31	0,93	0.00	4,20	2421
Tech. cumulativeness	0,76	0,09	0.00	1,16	2421
Tech. diversification	0.63	0.09	0.00	0.92	2421
Tech. relatedness	16.83	10.11	0.00	42.44	2421
R&D expenditures	0.01	0.01	0.01	0.12	2421
Human capital	21.76	8.44	3.70	48.90	2421
Manuf. specialization	18.32	6.82	3.70	36.90	2421
Pop. Density	344.71	859.69	3.30	9839.90	2421

The correlation values are relatively low under the cut-off point of 0.50 (O'Brien 2007). The only exceptions are the correlations between technological knowledge base and technological relatedness, and between technological cumulativeness and technological diversification. For this reason, we entered separately all the explanatory variables in the regression models to avoid any kind of bias due to multicollinearity among explanatory regressors. Moreover, we checked for the existence of multicollinearity (see Table 3) by computing the variance inflation factors (VIFs) and found multicollinearity is not a problem, as the VIFs are well below the suggested cut-off value of 5 (O'Brien 2007).

Table 2: Correlation matrix

	Variables	1	2	3	4	5	6	7	8	9	10
1	Tech. progress intensity	1									
2	Tech. progress relevance	0.34***	1								
3	Tech. knowledge base	0.75***	0.17***	1							
4	Tech. cumulativeness	0.10***	0.09***	0.03	1						
5	Tech. diversification	0.18***	0.18***	0.11***	0.51***	1					
6	Tech. relatedness	0.63***	0.37***	0.55***	0.18***	0.26***	1				
7	R&D expenditures	0.66***	0.34***	0.48***	0.12***	0.24***	0.49***	1			
8	Human capital	0.39***	0.29***	0.25***	0.23***	0.28***	0.41***	0.51***	1		
9	Manuf. specialization	0.17***	0.04*	0.15***	-0.08***	-0.03	0.13***	0.00	-0.33***	1	
10	Pop. Density	0.14***	0.16***	0.10***	0.03	0.09***	0.17***	0.14***	0.30***	-0.21***	1

Notes: Significance levels are *** p<0.001, ** p<0.01, * p<0.10.

In Table 3 we present the results of the spatial panel estimations using individual effects to explain the drivers of technological progress intensity (Models 1a, 2a, 3a, 4a and 5a) and technological progress relevance (Models 1b, 2b, 3b, 4b and 5b) in European regions.

As a baseline model (see Models 1a and 1b) to compare our results against, we first present the outcome with only the control variables. Models 1a (tech. progress intensity) and 1b (tech. progress relevance) in Table 3 represent the effect of the control variables on the dependent variables. Models 2a and 2b show the results of the controls after entering the technological knowledge base. Models 3a and 3b introduce the results of the controls plus the technological cumulativeness. Models 4a and 4b present the results of the controls after entering the technological diversification. Finally, Models 5a and 5b introduce the last explanatory variable – technological relatedness.

Generally, the overall fit of the models increases compared to the baseline in terms of lower values of generalised least square residual variance (GLS residual variance) and higher values of adjusted R squared. In other words, the introduction of the four independent terms is important in explaining the intensity and relevance of the regional technological progress, and adding explanatory power to the models.

The analysis of the results in Table 3 on the intensity of the technological progress (see Models 1a, 2a, 3a, 4a and 5a) suggests some main considerations.

First, looking at the control variables, R&D intensity is confirmed to have a significant and positive effect on the intensity of regional technological progress in terms of the number of fractionalized patents in all models (Marrocu et al. 2013; Castaldi et al. 2015). Human capital, even though positive across all models, is not statistically significant. These results seem to confirm the relevant role of mixing R&D investments, highly skilled workers, educational services and structures at a regional level to improve the stock of technological progress (Ponds et al. 2010). Manufacturing specialization shows significant but unexpected effects on the intensity of technological progress. Several authors (Hipp and Grupp 2005; Marrocu et al. 2013) suggest that regions with a large manufacturing base present better levels of patenting activities, because manufacturing is typically more inclined to innovate than other sectors. In contrast, our results show that regions with positive variations of manufacturing activities with respect to their mean value show a decrease in innovative performance, probably due to decreasing return effects. Finally, the urbanization level measured by population density has a positive but not statistically significant impact on the intensity of technological progress. Urbanization economies seem not to confirm the benefits usually associated with the presence of universities, industry research laboratories, trade associations and other knowledge generating organizations (Frenken et al. 2007; Marrocu et al. 2013).

Second, all models confirm the importance of spatial dependence on the intensity of technological progress. The positive and significant *lambda*-coefficient (spatial lag dependence) means that an innovation intensive neighbourhood facilitates and promotes the technological progress of neighbouring regions (Capello 2009; Ponds et al. 2010; Basile et al. 2012).

Third, with respect to our research hypotheses related to the intensity of regional technological progress, we found interesting results.

Model 2a shows that the intensity of technological progress is positively influenced by the size of the technological knowledge base (Model 2a, $p<0.001$), fully confirming Hypothesis 1a.

Model 3a does not support Hypothesis 2a, which claims that technological cumulativeness positively affects the intensity of the technological progress of the region. Even though increments of the dimension of the knowledge sources positively affect the intensity of regional innovation performance, this result is not statistically significant (Model 3a, $p>0.1$).

We found not statistically significant results, also referring to the effect of the technological diversification of the knowledge sources. Model 4a presents a positive but not statistically significant ($p<0.1$) impact of the technological diversification on the intensity of technological progress leading us not to confirm our Hypothesis 3a. Several studies underline that technological diversification is crucial for innovation (Harhoff and Wagner 2009). Inventions relying on a large number of diverse knowledge sources are supposed to lead to original innovations but not to increase the intensity of the regional progress.

Technological progress intensity also depends on the technological relatedness of the knowledge space. More specifically, a region with a higher increment (Model 5a, $p<0.01$) of relatedness in its knowledge space is inclined to report higher technological intensity than a region with low relatedness, thus leading to confirm Hypothesis 4a.

In Models 1b, 2b, 3b, 4b and 5b we present the results of the spatial panel estimations using individual effects to explain the drivers of the relevance of the regional technological progress.

The analysis of the results on the technological progress relevance suggests the following considerations.

Control variables present interesting and sometimes unexpected results. R&D intensity is not statistically significant. Human capital shows significant but negative impacts. The innovation output of regions with higher increments of human capital and R&D investments seem to be of scarce relevance, thus mirroring an inefficient technology diffusion trajectory. Counter to our expectations human capital is negatively associated with the relevance of regional innovations, however there is a rational explanation. This counterintuitive result depends on the operationalization of the human capital variable - the percentage of the population aged 25-64 who have successfully completed tertiary studies and the econometric model specification used. The fixed effects models with individual effects study the deviations from the average value of each single region in order to reduce the bias of the starting knowledge stock. Thus, if we look at the dynamics of our sample related to the distribution of human capital and the relevance of innovations, we can observe that less innovative or peripheral regions show higher increments of human capital (around 27% in the period analyzed) than the so called knowledge-intensive regions (around 16%) in front of an opposite distribution of the number of citations (technological relevance) by patent in which the knowledge-intensive regions have much higher increments. This rationale is also supported by the results of the pooled OLS regression in which the starting regional levels are considered and also by the correlation matrix in Table 2. In the pooled regression models both human capital and R&D investments show positive and statistical significant coefficients. The pooled OLS results are available upon request.

We classified knowledge-intensive regions (Innovation Leaders and Strong Innovators) and less innovative regions (Moderate Innovators and Modest Innovators) using the Regional Innovation Scoreboard (RIS) provided by the European Commission (European Commission, 2016; De Noni et al., 2018).

In contrast, in terms of individual effects, regions with positive variations of manufacturing activities with respect to their mean show a superior technological progress relevance. In regions characterized by the presence of a large manufacturing base, the adoption and diffusion of new technologies seems to be facilitated, because manufacturing is typically more inclined to innovate through the exploitation of new patented technologies than other sectors (Hipp and Grupp 2005; Marrocu et al. 2013). Finally, regions with higher increments of population density report lower levels of technological progress relevance. Even though urbanization economies are expected to better support regional innovation performance, increased urbanization may lead to negative externalities due to congestion costs, unskilled workers and immigrant inflows rather than talents, oversupply of labour, higher cost of living and insufficient infrastructure investments worsening the quality and the value of patents (Dijkstra et al. 2013).

As previously observed in the results coming from the analysis of drivers for technological progress intensity, all models confirm the importance of spatial dependence on the technological progress relevance. The positive and significant *lambda*-coefficient (spatial lag dependence) means that being located in a high-quality innovative geographical context is likely to promote the adoption and diffusion of the technologies coming from neighbouring regions (Castaldi et al. 2015).

Finally, with respect to our research hypotheses related to the relevance of regional technological progress, we found the following results.

Model 2b presents a negative and significant ($p<0.001$) impact of the size of the knowledge base on the relevance of technological progress. This means that an increase of the regional knowledge base above the average does not lead to improvements in the relevance of technological progress. Thus, we reject Hypothesis 1b.

Model 3b suggests negative effects ($p<0.001$) of the technological reliance on the technological progress relevance, leading us to reject Hypothesis 2b. Probably reducing the number of regional knowledge sources leads to more original inventions or innovation with higher adoptability and diffusion potentials.

Model 4b shows that a decrease in the variety and complexity of the knowledge sources inside a region can have positive and significant effects ($p<0.01$) on the relevance of inventions. Regions with lower heterogeneity in the knowledge sources are able to produce simpler technologies and this ability supports increased technological relevance. Hence, Hypothesis 3b is rejected.

Technological progress relevance positively and significantly depends on the relatedness of the regional knowledge space. More precisely, a region with higher increments (Model 5b, $p<0.1$) of relatedness in its knowledge space is inclined to produce technologies with a higher adoption rate than a region with a lower technological relatedness. This fully supports Hypothesis 4b.

Finally, we tested the robustness of our results using different time windows of the dependent variables, and alternative model specifications. First, we used a 5-year time window instead of a 3-year time window for our dependent variables. The results of these analyses, reported in Appendix A, are consistent with those presented in Table 3.

Second, we checked the robustness of our results by estimating fixed effects panel models without spatial dependences, but using clustered standard errors at regional and country levels. Also in this case, the results of the analyses were qualitatively similar to those presented here and are available upon request.

Table 3: Spatial fixed effects regression model results (3-year window lag)

Dependent variables	*Spatial panel fixed effects lag models*									
	Tech. progress intensity					*Tech. progress relevance*				
	Model 1a	*Model 2a*	*Model 3a*	*Model 4a*	*Model 5a*	*Model 1b*	*Model 2b*	*Model 3b*	*Model 4b*	*Model 5b*
Lambda (spatial lag)	0.412 (0.022)***	0.411 (0.022)***	0.418 (0.022)***	0.423 (0.022)***	0.422 (0.022)***	0.307 (0.023)***	0.292 (0.023)***	0.307 (0.023)***	0.295 (0.023)***	0.306 (0.023)***
Explanatory variables										
Tech. knowledge base		0.009 (0.002)***					-0.051 (0.010)***			
Tech. cumulativeness			0.002 (0.003)					-0.104 (0.017)***		
Tech. diversification				0.014 (0.011)					-0.120 (0.042)**	
Tech. relatedness					0.001 (0.000)**					0.003 (0.002)*
Control variables										
R&D expenditures	0.920 (0.170)***	0.871 (0.170)***	0.921 (0.170)***	0.918 (0.170)***	0.887 (0.170)***	-0.233 (0.873)	0.060 (0.872)	-0.239 (0.867)	-0.194 (0.872)	-0.328 (0.875)
Human capital	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.015 (0.001)***	-0.011 (0.002)***	-0.013 (0.002)***	-0.014 (0.002)***	-0.016 (0.002)***
Manuf. specialization	-0.001 (0.000)*	-0.001 (0.000)*	-0.001 (0.000)*	-0.001 (0.000)*	-0.001 (0.000)*	0.007 (0.002)***	0.008 (0.002)***	0.007 (0.002)***	0.007 (0.002)***	0.007 (0.002)***
Pop. Density	0.011 (0.028)	0.022 (0.028)	0.011 (0.028)	0.012 (0.028)	0.016 (0.028)	-0.372 (0.147)*	-0.440 (0.147)**	-0.341 (0.146)*	-0.371 (0.147)*	-0.360 (0.147)**
No. of observations	2421	2421	2421	2421	2421	2421	2421	2421	2421	2421
EU NUTS-2 regions	269	269	269	269	269	269	269	269	269	269
No. of panels	9	9	9	9	9	9	9	9	9	9
R squared	0.843	0.855	0.845	0.843	0.851	0.711	0.714	0.715	0.712	0.712
GLS residual variance	0.0067	0.0065	0.0067	0.0067	0.0066	0.0152	0.0150	0.0150	0.0151	0.0151
Moran I	12.99***	12.99***	12.99***	12.99***	12.99***	5.73***	5.73***	5.73***	5.73***	5.73***
LM-lag	321.25***	293.83***	318.93***	317.65***	310.18***	197.47***	177.02***	181.54**	196.49***	197.36***
RLM-lag	12.39***	28.09***	13.99***	15.34***	20.01***	40.85***	25.28***	35.04***	33.12***	46.28***
Hausman χ (df)	268(4)***	240(5)***	278(5)***	268(5)***	178(5)***	238(4)***	276(5)***	157(5)***	205(5)***	231(5)***
Max VIF	1.62	2.17	1.69	1.63	1.75	1.62	2.17	1.69	1.68	1.75

Notes: Standard errors are in parentheses. Significance levels are *** p<0.001, ** p<0.01, * p<0.10.

5. Discussion and conclusions

This study investigates how the knowledge space of regions influences their technological progress. On the theoretical side, the originality of our research resides in 1) accounting for the marginal effect of the different features of a regional knowledge space, and 2) by distinguishing between quantitative and qualitative aspects of the technological progress (intensity and relevance). As for the empirical side, we used original data at the EU level and new indicators included in the REGPAT database to test our hypotheses.

The first important result concerns the effect of the composition of a regional knowledge space on the intensity and relevance of technological progress. In particular, the factors influencing the innovation intensity are not the same as those impacting on the innovation relevance, except for technological relatedness. It appears, in fact, that technological relatedness is the key factor influencing the technological progress of regions, either measured in terms of intensity or relevance. This evidence provides support for the interpretative framework put forward by the Utrecht school, led by members of the Department of Human Geography and Planning (Ron Boschma, Koen Frenken, Frank van Oort – among others), who in the early 2000s started to devote attention to the neglected relationship between variety and economic development in regions. By claiming that not only the stock of inputs affects growth, but also the precise composition in a qualitative sense, this pool of scholars introduced a disruptive research line. While the large majority of previous research works was mainly focused on the impact of relatedness on the economic growth of regions (stemming from Frenken and Boschma, 2007; Frenken et al. 2007), scattered contributions were centred on economic resilience (Holm and Østergaard 2015; Sedita et al. 2017), and on innovation performance (Tavassoli and Carbonara 2014; Castaldi et al. 2015) – nevertheless the latter seems an exploding research agenda. Our results, by proving that technological relatedness contributes not only to innovation intensity but also innovation relevance, launch, together with Castaldi et al. (2015), an interesting new venue of research. Consequently, an immediate policy implication concerns the direction of the R&D expenditure in regions, which might be chosen coherently with the industrial structure and the possible areas of interactions across sectors. Specific infrastructures could be created that provide information on the cognitive proximity between technologies, a sort of revised version of a patent office, in charge of monitoring possible cross-fertilization between technologies, with the final objective of illuminating firms on potential partnerships and/or merger and acquisition processes for acquiring complementary knowledge and capabilities.

That said, no one-size-fits-all solution exists, and, as the smart specialization agenda claims (Foray 2009), our results confirm that the technological trajectories of regions must be shaped around past and present resource endowments and future objectives. In particular, an accurate reading of the empirical evidence informs of a twofold technological trajectory, which might discriminate knowledge-intensive territories by lagging-behind ones. Since it has been theorized that more socio-economically developed regions are more conducive to knowledge-intensive, innovative activity (Rodriguez-Pose and Wilkie 2017), they might be more suited to capitalize on their past R&D expenditure, by exploiting core capabilities alongside a technological trajectory that follows a related-specialization strategy. This is the recommendation that is spawned by the statistics illustrated in the previous section, which show how the technological specialization, together with the relatedness, boosts the technological progress relevance. Stemming from the observation that more is not better or, similarly, quantity is not relevant, a developed region with a consolidated technological trajectory should deploy its knowledge base not by increasing the number of patents, but by maximizing the diffusion of the innovations that depart from the application of its patents. In contrast, lagging-behind regions should invest more in R&D in order to establish a feasible knowledge space and reach a level of technological progress intensity that allows them to compete with knowledge-intensive regions, as also claimed by Rodriguez-Pose (2001). For lagging-behind regions, this aligns with the EU prioritization of R&D expenditure, which is also based on a linear model of innovation. Nevertheless, our results suggest using caution when adopting the same policy for developed regions, because, in this realm, the marginal effects of an increase in innovation output might be lower than that of investing in expanding the potential for new applications of pre-existing inventive output. Moreover, since the proximity to knowledge-intensive regions contributes positively to innovation intensity and relevance – as the spatial parameters inform – a cross-regional technological fertilization pattern is desired, where knowledge flows from developed to lagging-behind regions is enhanced (De Noni et al. 2017b).

Appendix A: Spatial fixed effects regression model results (5-year window lag)

Dependent variables	*Spatial panel fixed effects lag models*									
	Tech. progress intensity					*Tech. progress relevance*				
	Model 1c	*Model 2c*	*Model 3c*	*Model 4c*	*Model 5c*	*Model 1d*	*Model 2d*	*Model 3d*	*Model 4d*	*Model 5d*
Lambda (spatial lag)	0.430 (0.024)***	0.422 (0.024)***	0.429 (0.024)***	0.429 (0.024)***	0.420 (0.024)***	0,358 (0,025)***	0,335 (0,025)***	0,344 (0,025)***	0,358 (0,025)***	0,357 (0,025)***
Explanatory variables										
Tech. knowledge base		0.005 (0.003)*					-0,044 (0,009)***			
Tech. cumulativeness			0.003 (0.004)					-0,077 (0,013)***		
Tech. diversification				0.011 (0.009)					-0,058 (0,032)*	
Tech. relatedness					0.002 (0.001)**					-0,001 (0,002)
Control variables										
R&D expenditures	0.708 (0.192)***	0.698 (0.192)***	0.710 (0.192)***	0.706 (0.192)***	0.695 (0.192)***	0,266 (0,656)	0,385 (0,653)	0,235 (0,651)	0,280 (0,655)	0,274 (0,656)
Human capital	0.001 (0.000)*	0.000 (0.000)	0.001 (0.000)*	0.001 (0.000)*	0.000 (0.000)	-0,011 (0,001)***	-0,009 (0,001)***	-0,010 (0,001)***	-0,011 (0,001)***	-0,011 (0,001)***
Manuf. specialization	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0,006 (0,002)***	0,006 (0,002)***	0,006 (0,002)***	0,006 (0,002)***	0,006 (0,002)***
Pop. Density	0.016 (0.041)	0.023 (0.041)	0.016 (0.041)	0.017 (0.041)	0.018 (0.041)	-0,554 (0,143)***	-0,626 (0,143)***	-0,561 (0,142)***	-0,558 (0,143)***	-0,555 (0,143)***
No. of observations	1883	1883	1883	1883	1883	1883	1883	1883	1883	1883
EU NUTS-2 regions	269	269	269	269	269	269	269	269	269	269
No. of panels	7	7	7	7	7	7	7	7	7	7
R squared	0.711	0.713	0.718	0.718	0.737	0.843	0.845	0.846	0.843	0.843
GLS residual variance	0.0152	0.0151	0.0150	0.0150	0.0147	0.0067	0.0066	0.0065	0.0066	0.0067
Moran I	13.10***	13.10***	13.10***	13.10***	13.10***	7.79***	7.79***	7.79***	7.79***	7.79***
LM-lag	264.82***	242.39***	262.78***	261.39***	244.64***	237.12***	198.57***	217.60***	234.35***	236.48***
RLM-lag	23.61***	68.53***	25.27***	26.15***	56.54***	49.03***	44.94***	44.48***	44.31***	48.28***
Hausman χ (df)	74(4)***	145(5)***	76(5)***	75(5)***	698(5)	216(4)***	251(5)***	188(5)***	207(5)***	210(5)
Max VIF	1.60	2.15	1.64	1.66	1.74	1.60	2.15	1.64	1.66	1.74

Notes: Standard errors are in parentheses. Significance levels are *** p<0.001, ** p<0.01, * p<0.10.

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