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Measuring how the knowledge space shapes the technological progress of European regions

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Abstract

This work aims to investigate the features of the regional knowledge space that are more likely to be conducive to technological progress (TP), either in terms of dimension and relevance. We acknowledge the importance of knowledge assets for new knowledge production and we identify more or less path dependent processes that allow a region to be more competitive in terms of innovation potential. In particular, adopting an evolutionary view of regional development, we consider a regional knowledge space as composed of a knowledge base (KB) and a selection environment (SE), which differently affect the technological progress of the region. Empirical evidence come from a quantitative analysis of 269 European regions, whose data are included in the RegPat database. Results show that the variety of KB impacts positively on the technological progress at large. The variety of SE impacts positively only on the technological progress in terms of relevance, while the size of the SE impacts positively only on the quantitative side of the technological progress. Unrelated variety of KB and SE affects technological progress more widely than their correspondent related variety indicators.

Keywords

Knowledge space, related and unrelated variety, technological progress, learning regions, selection environment, knowledge base.

Introduction

Measuring the regional knowledge space is crucial in order to identify drivers of technological progress, and it is necessary in order to explore the causes of regional inequalities in terms of technological capabilities and innovation outputs. Following the literature on evolutionary economics, innovation processes are essentially linked to knowledge that is often sourced locally (Almeida and Kogut, 1999; Stuart and Sorenson, 2003; Breschi and Lissoni, 2009) and regional technological progress is essentially an endogenous process showing a high degree of path dependency (Iammarino, 2005; Rigby and Essletzbichler, 2006; Frenken and Boschma, 2007). Understanding the features of the regional knowledge space is therefore crucial in order to shape regional policies for enhancing the innovation performance of regions.

The relationship between knowledge and innovation and how this is influenced by the regional context is amply studied by the literature on industrial districts (Brusco 1986; Becattini 1989; Bellandi 1989), innovative milieus (Aydalot 1986; Camagni 1991; Maillat et al. 1993), learning regions (Asheim 1996; Morgan 1997; Hassink 2001) and regional innovation systems (Braczyk et al., 1998; Cooke et al., 1997; Iammarino, 2005; Asheim and Gertler 2005). The learning capacity of regions is anchored on the availability of specific regional assets for the production and dissemination of knowledge (Hudson, 1999). Since the competitive advantage of regions relies more and more on knowledge assets and knowledge management, it is important to ask which are the premises for becoming successful learners. Knowledge-based theories of regional growth and innovation (see for example Maskell, 2001; Maskell and Malmberg, 2002) emphasize the nature of local knowledge (Tallman et al., 2004), the intensity (and frequency) of knowledge transfer processes among local firms (Gordon and MCcann, 2000; Mesquita, 2007), and the variety of knowledge in the region (Jacobs, 1969; Glaeser et al., 1992; Frenken et al., 2007). There is still a knowledge gap on the question if it is specific knowledge from particular technological sources or rather a broad variety of diverse sources that matter for innovation. Moreover, previous research work investigates mostly the innovation performance of regions on a quantitative base (the dimension), disregarding the impact of the innovation efforts (the relevance).

The paper aims to measure the effects of knowledge space characteristics on technological progress, either measured as dimension and relevance of the innovation output. The unit of analysis is the region and the empirical setting is Europe. Theoretically grounded on the evolutionary economic geography literature, this work contributes to the debate on the drivers of technological progress by accounting the marginal effect of the knowledge base and of the environment selection features. We consider a regional knowledge space as composed of a knowledge base (KB) and a selection environment (SE), which differently affect the technological progress of the region. The knowledge base and the environment selection are characterised by two relevant structural parameters: size and variety. Therefore, this work offers an original way to analyse the determinants of regional technological progress.

The paper proceeds as follows. Section 1 reviews the literature on regional space and technological progress, focussing on the features of the regional knowledge base and of the selection environment that are more likely to be conducive to technological progress at the regional level and put forward our hypotheses. Section 2 presents the methodology and illustrates the empirical analysis. Section 3 puts forward some conclusive remarks.

1. Theoretical background and hypotheses

1.1. Regional knowledge base and technological progress

According to the knowledge-based view (KBV) of the firm, knowledge is a key source of firm's competitiveness. Moreover, according to recent economic geography studies, regions are one of the key levels of analysis for understanding the dynamics of learning and innovation (see the debate on regional innovation system and learning region).

The competitiveness of regions is based on the innovation and on the capacity to understand, explore, and exploit the continuous technological progress. In this contest, we are moving increasingly towards a knowledge-based economy in which knowledge is fundamental in order to enhance productivity and economic value (Castells, 1996; Cooke, 2002). Economic activities based on learning, innovation and knowledge creation are increasingly more important as sources of competitive advantage if compared to the processing of physical materials (Castells, 1996). Therefore, knowledge has become, in recent years, a key driver for growth of regions and nations. This in mind, it is important to understand in which way the accumulation of knowledge in a region could influence its capacity to produce new knowledge and thus leading to a technological progress. The studies that focus on the role of knowledge in economic systems consider knowledge as the most important strategic resource and learning the most important process (Lundvall and Johnson 1994). In particular, Lundvall and Johnson argue that know-how has become the key resource for firms to stay abreast of product and process innovation. Alongside this perspective, the literature on innovation pays particular attention on the role of knowledge on incremental (Bierly and Chakrabarti, 1996; DeCarolis and Deeds, 1999) and radical innovation (Hill and Rothaermel 2003; Miller et. all. 2007, Zhou and Li 2009).

In particular, over the years, it has been observed persistent regional inequalities in terms of knowledge space, innovation and technological progress. Geographers, economists and social scientists have tried to investigate the reasons behind these inequalities, stemming from the adoption of the neoclassic model of economic growth, which considered the technological change as an exogenous factor. The neoclassic model is based on the concept of economic equilibrium among regional economies, thanks to self-correcting movements in prices, wages, capital and labor, which finally lead to a regional convergence (Solow, 1956, Williamson, 1965).

However, several studies have demonstrated that regional growth not always converges, even over the long run (Perroux, 1955; Kaldor, 1981), thus, in the 1980s, a new theory emerged, aiming at the explanation of persistent regional inequalities: the endogenous growth theory. The endogenous growth theory considers as endogenous to the growth process those factors that the neoclassic growth model relegates as exogenous, such as the technological change (Romer, 1989). The new growth model proposed highlights the inability of the previous model to adequately account for technological change and innovation as drivers of growth (Boltho and Holtham, 1992). In particular, the purpose of the endogenous growth theory is to understand how technological knowledge and various structural characteristics of the economy and society interplay for generating economic growth (Aghion et al. 1998). Many authors applied the endogenous growth theory to the understanding of the development at a subnational scale, such as at the city or region 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 our work we refer to the studies that enhance the importance of endogenous technological progress for growth focusing, among the various factors that influence the technological progress, on the role of region’s knowledge assets in shaping new knowledge production. In particular, the accumulation of technological knowledge creates increasing returns in scale in many context (Grossman and Helpan, 1990), thus a region with a consistent base of technological knowledge has more chance to activate learning processes oriented towards the growth of the capacity to produce new technological knowledge (Arthur, 1996).

Moreover, it is well known that, traditionally, innovation, invention, and new profitable ideas enlarge the stock of knowledge, which, in turn, increases the innovation/invention capacity of a region. Accordingly, the size of a knowledge base has been related to the region’s technological change (Fleming, 2001; Ahuja and Katila, 2001). Smith et al. (2005) pointed 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. In this way we assist to the creation of path dependent phenomena in which the size of the technological knowledge previously owned influences subsequent new knowledge creation processes (Dosi, 1982; Nelson and Winter, 1982). A dynamic and self-reinforcing system of knowledge production is in place. The accumulation of knowledge leads to better performance in term of technological progress, giving rise to a sort of Metthew effect, in which “the rich get richer” (Merton, 1988), that is the regions with larger knowledge base are more likely to produce new knowledge and keep the status of being rich (in terms of knowledge assets). Following this, a region with a consistent knowledge base could be more inclined to create new knowledge.

Hyp. 1: The larger the size of the knowledge base of the region, the higher the contribution to the technological progress

The accumulation of knowledge in a localized area, such as the region, leads to a comparative advantage due to a cumulative and collective learning process embedded in the regional context (as it was well explained by Morgan, 1997, who introduced the notion of "learning regions"). However, it is not uncommon that the regional accumulation of knowledge is highly specialised in a one specific technological field. In this situation, a specialised region can become locked into rigid development trajectories. The accumulated knowledge does not assure the ability to explore new knowledge in new fields and to sustain technological progress. The adoption of this point of view leads to the observation that the creation of new knowledge and the innovation capacity of a region are influenced not only by the size of the knowledge base, but also, and maybe more importantly, by the variety of this knowledge base (Audrethsch and Vivarelli, 1996; Saviotti, 1996; Rodan and Galunic, 2004; Frenken e al. 2007).

Knowledge variety implies that firms in a region develop heterogeneous and maybe complementary knowledge alongside various technology classes. Accordingly, the exposure to heterogeneous knowledge should improve both the creativity of the firms in the region and their ability to develop new knowledge and innovation (Rodan and Galunic 2004).

Regions with a broad knowledge base have a greater potential to recombine different elements of the knowledge possessed in order to improve opportunity recognition and creative potential (Kogut and Zander 1992).

Heterogeneous knowledge generates novelty and affects the learning capabilities of the region economies. Dismissing this diversity of knowledge means destroying parts of the economy's stock of knowledge and reducing the possibilities for communication and interaction between different kinds of skills, knowledge, and competence, thus reducing learning possibilities.

Some studies have highlighted that the variety of knowledge inside a region influences the knowledge creation and the innovative performance (Jacob, 1969; Saviotti, 1996). Knowledge that is technologically distant provides opportunities to make novel linkages and associations (Phene et al. 2006), thus achieving superior knowledge creation performance.

Furthermore, we follow a recent literature that distinguishes between related and unrelated variety (Frenken et al., 2007), and, in particular, we are interested in investigating the influence of each type of variety on regional technological progress.

On the one side the regional related variety of knowledge indicates the balance between cognitive proximity and distance across technological classes in a region. This balance is needed for knowledge to spill-over effectively between technological classes (Castaldi et al., 2015). Instead, on the other side, unrelated variety measures the extent to which a region is diversified in very different technological classes.

The benefit of related variety of knowledge for innovation-related measures has been shown both at the firm-level (Breschi et al, 2003) and at the regional-level (Feldman and Florida, 1994; Feldman and Audretsch, 1999; Ejermo, 2005).

According to Frenken et al. (2007), both related and unrelated variety have a positive impact on regional technological progress, but the related variety has a greater influence. In particular, the authors highlight that the higher the number of technologically related sectors in a region, the higher inter-sectorial knowledge-spillovers between those related sectors, and, presumably, the more learning opportunities for them. Related variety "improves the opportunities to interact, copy, modify, and recombine ideas, practices and technologies across industries giving rise to Jacobs externalities" (Frenken et al.,2007, p. 687),

Therefore, if the knowledge base of a region is characterized by a large number of related technological classes, the region is more likely to host regional knowledge spillovers between these related technological classes, providing venues for creating new knowledge.

Generally speaking, the related variety measures a technological variety that might be more conducive to knowledge transfer and cross-fertilization processes between different sectors than the unrelated variety, which does not assure per se any knowledge spillover or combinative knowledge process.

Hyp. 2: The impact of related variety of the knowledge base on the regional technological progress is higher than the impact of unrelated variety.

1.2. Selection environment and technological progress

The generation of technological progress is linked to the ability of a region to explore, select and use prior knowledge, and, as we stated before, the size and the variety of the owned knowledge base is particular relevant for the regional technological progress. Moreover, the selection among different sources of knowledge, and the recombination of that knowledge in new knowledge become relevant steps in the definition of the potential for technological progress of a region.

The evolutionary theory of the firm developed by Nelson and Winter (1975, 1977) proposes a definition of the selection environment at the firm level. In particular, the authors point out that the diffusion of new technologies starts from the firm search routines aimed to identify and evaluate potential changes in their ways of doing things (Malloy et al. 2004). In this perspective, the selection environment is characterized by the features of the socio-economic system, in which firms operate, that determines the path of technology diffusion over time (Nelson and Winter 1977). The selection environment influences the path of productivity growth generated by any given innovation (Nelson and Winter 1977).

In literature, we find different attempts to adapt the principles of evolutionary economics to the field of Economic Geography (Stainer and Belschan, 1991; Grabher, 1993; Feldman and Florida, 1994; Hudson, 1999, Storper, 1997; Boschma and Lambooy, 1999), with particular regards on the role of technological innovation and learning in a specific territory and on the ways some factors (such as habits, routines, conventions, path-dependencies, variety in the selection environment) influence the space and direction of regional learning and adaptation dynamics.

We adopt a general interpretation of the selection environment definition identifying the technological environment in which the production of new technologies starts from, assuming that there is an underlining pattern of prior knowledge selection that gives rise to subsequent knowledge recombination and affects the future technological progress. Moreover, we extend the level of analysis at the regional level, investigating in which way the selection environment influences the regional capacity to grasp and exploit the knowledge either produced inside or outside the region.

The selection environment determines the relative use of different knowledge and different technologies over time and influences the path of regional knowledge productivity.

The identification of the regional opportunities derives from the abilities to identify potentially fruitful combinations of pieces of knowledge that seem related or unrelated to their existing knowledge bases – this idea is associated to Schumpeter's (1934) idea of "novelty by combination".

The selection of a higher number of knowledge source allows having a wider knowledge pool, where each component can be recombined to create new knowledge and might lead to a technological progress.

Hyp. 3: The broader the size of the selection environment of the region, the higher the contribution to the technological progress

As we stated for the knowledge base, also for the selection environment, variety plays a fundamental role in the determination of regional technological progress.

The prevalent way in which new knowledge is created is from re-combination processes of knowledge coming from different technological classes, which represent different knowledge sources. These types of knowledge sources tend to represent specific forms of scientific and applied knowledge related to technology, markets and organizational aspects (Grillitsch et al. 2015). Regions have accumulated know-how across a variety of disciplines and heterogeneous market domains, through extensive processes of knowledge exploration (Prabhu et al. 2005). Laursen and Salter (2006) highlight that diverse knowledge sources (which therefore are components of a specific selection environment) may stimulate a variety of ideas.

The variety of the selection environment allows avoiding the risk of lock-in into a specific technological domain and increases the chance to exploit different knowledge into new technological domains. We also assume that using a differentiated selection environment particularly requires strong regional knowledge capabilities to absorb and recombine a variety of knowledge sources.

Hyp. 4: The higher the variety of the selection environment of the region, the higher the contribution to the technological progress

2. Methodology

The study investigates the relationship between regional knowledge space and technological progress by exploring the relative impact of the size and the variety of knowledge base on one side, and the number and the variety of knowledge sources (which compose the SE) on the other side. The analysis focuses on regions of EU-27 countries (plus Norway). Data concerning patents, patent citations, *International Patent Classification* (IPC) classes and inventors are collected from the OECD *RegPat* database (version release 02/2015), while economic and demographic information are derived by Eurostat database. In order to organize a balanced panel dataset from 2002 to 2008, the final sample is reduced to 269 European regions (because of missing data).

2.1. Variables

In this study, technological progress is defined by looking at the dimension and the relevance at regional level. Differently, exploratory variables involve data on knowledge base size and variety and knowledge source size and variety. Finally, R&D capacity, human capital, inventors' productivity, manufacturing specialisation and population density are introduced as controls.

Dependent variables

Technological progress relevance (*TCN.RLV*). We use the number of citations a given patent receives in the subsequent 5-years window (forward citations) as a proxy of the technological importance of the patent for the development of subsequent technologies (Hall, et al., 2005; Harhoff et al., 2003). The more the citations of the patent by future patents, the more the value and the potentiality of patents are estimated. Based on findings of Hall et al. (2005), the measure also includes self-citations, which are as valuable as citations from external patents. An average value is calculated at regional level for each 5-years window.

Technological progress dimension (*TCN.DIM*). The number of patents is the more widely adopted measure in literature to capture the technological progress. Thus, it is operationalized by using the average number of patents per 1000 capita in the subsequent 3-years window of time. Patents have been found to be a good proxy for innovative activity at a regional-level (Acs et al., 2002) and 3-years' lag is a good proxy to measure the lagged effect of the invention process. For instance, R&D expenditure in 2008 is expected to produce effects on regional innovation performance in the subsequent lapse time, i.e. from 2009 to 2011. An average value is calculated at regional level for each year. The higher the index, the higher is the regional capacity to innovate.

Exploratory variables

Knowledge base size (*KB.SIZE*). Knowledge base size of a region represents the regional capacity to produce and accumulate knowledge stocks, which may potentially be exploited to create technological progress. In this direction, patents are typically considered a good proxy of cognitive and technological size for both firms and regional systems. Thus, this index is operationalized as the pro capita cumulative number of regional patents in the previous 5-years window of time. The larger the knowledge stock of a region, the higher are the recombination potentiality and the expected innovation performance.

Knowledge base variety. Technological diversification is adopted as proxy of knowledge variety within regional innovation systems. It measures the distribution of regional patents across the IPC levels using the Shannon entropy index. It would give an indication of the extent to which a region has patents that are distributed over broadly defined technological categories. We use the entropy decomposition theory to calculate unrelated variety (*KB.UNREL)* and related variety (*KB.REL).* Unrelated variety (*KB.UNREL*) is measured as the entropy of the distribution of patents over 1-digit IPC categories, which specify how diversified each region is across the eight broad unrelated technological categories (Castaldi et al., 2015). *KB.UNREL* is operationalized by using the Shannon entropy index at 1-digit IPC level according to the following formula:

$$KB.UNREL_r = \sum_{j=1}^{8} P_j log_2 \left(\frac{1}{P_j}\right)$$

where $P_j = E_{j,s}/E_r$. It is the number of patents guaranteed in each IPC categories within a region r ($E_{j,r}$) related to the overall number of patents guaranteed in the same region r (E_r). Patents relying on multiple IPC categories are homogeneously weighted for the number of categories they are in. The higher the index, the more diversified is the regional patent distribution across the 1-digit IPC categories. Conversely, specialized innovation regional systems should show lower index values.

Related variety (*KB.REL)* is the diversification of the regional patent portfolio at the most fine-grained classification. It is computed using the difference between total entropy at the level of narrowly defined 7-digit IPC subclasses (639 levels) and 4-digit IPC classes (129 levels). The formula is the following:

$$KB.REL_r = \sum_{m=1}^{639} P_m log_2\left(\frac{1}{P_m}\right) - \sum_{l=1}^{129} P_l log_2\left(\frac{1}{P_l}\right)$$

The *KB.REL* compute the within-group variety components and show how diversified a region is within the most fine-grained levels (Castaldi et al., 2015). Moreover, as stressed by Frenken et al. (2007) and Castaldi et al. (2015), related and unrelated variety are not opposites, but orthogonal in their meaning.

Selection environment size (*SE.SIZE*). The number of backward citations is to be considered a proxy of the regional selection environment size. The higher the average number of backward citations either to the patent or to non-patent literature (e.g. scientific papers), the larger is the base of knowledge sources regional inventors may recombine to produce new knowledge. Moreover, even though a large number of backward citations is typically associated to incremental innovation, they have been also found to be positively related to the value of a patent (Harhoff et al., 2003). Thus, this index is operationalized as the average number of regional backward citations in the previous 5-years window of time.

Selection environment variety (*SE.VAR*). Selection environment variety is supposed to be strongly related to the number of different sources can be acquired, exploited and transformed in new knowledge (Zahra and George, 2002). It refers to the Patent Originality Index (POI) defined by OECD RegPat. The POI refers to the breadth of the technology fields on which a patent relies. Looking at backward citations, the patent originality measure operationalises the number of diverse knowledge sources as supposed to lead to original results. The construction of the index is based on the number and distribution of both 4-digit and n-digit IPC technology classes (where n refers to the highest level of disaggregation possible) contained in cited patents. The index value is high if a patent cites previous patents belonging to a wide range of fields. Conversely, if most citations are concentrated in a few fields, the originality index is low and patent may be supposed to be proxy for an incremental innovation. An average value is calculated at regional level for each year.

Control variables

R&D intensity (*R&D.INT*). Gross domestic expenditure on Research & Development (R&D) as percentage of gross domestic product (GDP) is an indicator of high political importance at the EU, national and regional level. 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 (*HUM.CAP*). 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. The indicator is defined as the percentage of the population aged 25-64 who have successfully completed tertiary studies (e.g. university, higher technical institution, etc.). The indicator is provided by Eurostat and is based on the EU Labour Force Survey. Specifically, the educational attainment refers to ISCED (International Standard Classification of Education) 1997 level 5-6 for data up to 2013.

Inventors' productivity (*INV.PRD*). Despite the potential attitude of human capital, the regional capacity to innovate also depends on the realized attitude of inventors, which is based on individual competences and creativity. The inventors' realized attitude is measured as the effective yearly productivity of individual and co-invented EPO patents; then, an average value is calculated at the regional level per year.

Manufacturing specialization (MAN.SPC). Since sectors have different technology and innovation opportunities and manufacturing is typically more inclined to innovate than services (Hipp and Grupp, 2005), manufacturing specialization is introduced as the control. Specifically, the manufacturing concentration index is operationalized as the share of regional employees operating within the manufacturing industry with respect to the total number of regional employees.

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

2.2. Model Estimation

In this study a spatially lagged model based on a 7-years panel dataset is implemented, since the ordinary least squares (OLS) estimates are unbiased but are inefficient when spatial dependence is present (Anselin 1988). Spatial lag is suggestive of a possible diffusion process of knowledge creation because spatial dimension of social interactions and collaboration processes are typically considered an important aspect of innovation and knowledge spillovers. Moreover, spatially lagged model with fixed effects is further preferred to model with random effects because the distribution of innovation in the European regions is likely not randomized but influenced by observed and latent time-invariant territorial features. Finally, time effects are introduced at place of individual effects in order to study the impact of knowledge base and knowledge sources across regions and not over time

A number of statistical tests, measured on full models (model 2a and 2b in Table 2), is further introduced in order to support these choices. Moran I, LM (Lagrange Multiplier) and RLM (Robust LM) tests confirm the regional technological progress is spatially lagged. The results of tests are reported in Table 2. F-test (F=3.15 and p<0.001 on model *2a*, F=54.22 and p<0.001 on model *2b*) measured by *pFtest* function of R[1]'s *plm* package) confirms both fixed and random effects panel models better fit than OLS. Then, Hausman test on the two models (X^2=54.92 and p<0.001 on model *2a*, X^2=451.34 and p<0.001 on model *2b* measured by *phtest* function of R's *plm* package) confirms fixed is better than random effects (Greene, 2008). F-test is further used to assess time vs individual effect in the fixed effect panel model. The results on the two models suggest that a time effect is significant (time effect is preferred since F=8.92 and p<0.001 on model *2a*, F=3.72 and p<0.001 on model *2b*).

Thus, following Anselin (1988), the expression of the spatial lag model is defined 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 and it shows the strength of the interaction between two regions.

1.1 *Analysis and results*

Descriptive statistics and correlation matrix are shown in *Table 1*. Data highlight most of the independent variables are inclined to be positively related to both technological progress dimension and relevance.

	Variables	*Mean*	*St.Dev.*	*Min*	*Max*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1	TCN.RLV	61.91	130.49	0.00	1237	1											
2	TCN.DIM	2.04	0.78	-0.75	3.36	.47**	1										
3	KB.SIZE	0.00	0.00	0.00	0.01	.69**	.62**	1									
4	KB.UNREL	2.24	0.72	0.00	2.93	.25**	.63**	.36**	1								
5	KB.REL	0.93	0.55	0.00	2.25	.62**	.67**	.64**	.54**	1							
6	SE.SIZE	2.52	0.79	0.00	10.50	.03	.09**	.09**	-.08**	-.01	1						
7	SE.VAR	0.62	0.14	0.00	0.95	.10**	.33**	.19**	.47**	.35**	-.01	1					
8	R&D.EXP	1.42	1.28	0.06	13.73	.41**	.62**	.62**	.38**	.62**	-.02	.22**	1				
9	HUM.CAP	22.96	8.39	6.10	50.80	.17**	.54**	.43**	.39**	.47**	-.01	.24**	.51**	1			
10	INV.PRD	0.50	0.17	0.00	2.17	.08**	.21**	.10**	.17**	.11**	.42**	.33**	-.00	.010	1		
11	MAN.SPC	18.02	6.79	3.70	36.80	.21**	.04	.12**	.09**	.06*	-.07**	.05*	-.03	-.35**	.07**	1	
12	POP.DEN	344.59	848.49	3.30	9650	.08**	.15**	.10**	.13**	.22**	-.05*	.08**	.10**	.29**	-.02	-.22**	1

*Note: Pearson's correlation; Significant levels are ** p<0.01. * p<0.05*

Table n.1 – Descriptive statistics and correlation matrix

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

The only exceptions are the number of knowledge sources that compose the regional selection environment (*SE.SIZE*) and manufacturing specialization (*MAN.SPC*). The former is related to technological progress dimension, the latter to technological progress relevance. Moreover, even though some correlations among independent and control variables are over .60 (such as among *KB.REL*, *KB.SIZE* and *R&D.EXP*) , the values of variation inflation factor (VIF) measured on linear model are always lower than 3. This suggests no serious collinearity problems are expected (O'Brien, 2007).

Table 2 shows the results of the regression analysis using spatial panel estimations to explain the *technological progress relevance* (*TCN.RLV)* and the *technological progress dimension* (*TCN.DIM*) of the European regions.

Dependent variable - Technological progress	*Spatial panel fixed effect models*			
	RELEVANCE		*DIMENSION*	
Explanatory variables	*Mod. 1a*	*Mod. 1b*	*Mod. 2a*	*Mod. 2b*
KB.SIZE		0.075 (0.039)†		0.185 (0.013)***
KB.UNREL		0.173 (0.029)***		0.266 (0.01)***
KB.REL		0.089 (0.038)*		0.151 (0.012)***
SE.SIZE		0.004 (0.025)		0.020 (0.008)*
SE.VAR		0.072 (0.026)**		-0.062 (0.008)***
Control variables				
R&D.EXP	0.007 (0.026)	-0.022 (0.030)	0.214 (0.011)***	0.041 (0.011)***
HUM.CAP	0.083 (0.029)**	0.128 (0.034)***	0.166 (0.013)***	0.087 (0.01)***
INV.PRD	0.089 (0.022)***	0.022 (0.026)	0.058 (0.009)***	0.040 (0.008)***
MANUF	0.107 (0.024)***	0.032 (0.025)	0.097 (0.01)***	0.007 (0.008)
POP.DEN	0.004 (0.023)	-0.025 (0.023)	0.020 (0.009)*	-0.014 (0.007)
Lambda (spatial lag)	0.208 (0.028)***	0.169 (0.028)***	0.709 (0.012)***	0.484 (0.012)***
No. of observationss	1883	1883	1883	1883
EU NUTS-2 regions	269	269	269	269
No. of years	7	7	7	7
GLS redidual variance	0.906	0.860	0.143	0.089
Adj. R squared	0.093	0.140	0.857	0.911
Moran I	4.6431***	4.6431***	18.069***	18.069***
LM-lag	14.726***	5.648*	229.423***	99.700***
LMR-lag	8.563**	26.059***	58.665***	105.491***

Notes: Coefficients are mean centring standardized values. Standard errors are in parentheses. Significant levels are *** p<0.001, ** p<0.01, * p<0.05, † p<0.10

Table n.2 – Spatial regression models with spatial lag

Model 1a and 2a are the control models, whilst Model 1b and 2b are the full models. Control model is only shown in order to validate the higher explanatory power of the full model. Considering the goodness of fit indicators of the models, in fact, it would seem that the full models show lower values of residual variance (Generalised Least Square residual variance) and higher values of adjusted R squared and are inclined to be better compared with the control models.

The analysis of results suggests some main considerations.

First, looking at control variables, even though *R&D intensity* (*R&D.INT*) is confirmed to be significant on the dimension, no effect is observed on the relevance of regional technological progress. *Human capital* (*HUM.CAP*) is positive and relevant across all models. Thus the educational services and structures in a region play a critical role on both relevance and dimension of technological progress. Related to human capital, the significance of *inventors' productivity* (*INV.PRD*) suggests a critical driver of technological progress is the capacity of region to promote and support the development of inventors' relational and innovation competences in order to increase their productivity. Differently, the effect of *manufacturing specialization* (*MAN.SPC*) disappears in the full models, while the urbanization level, measured by *population density* (*POP.DEN*), is inclined to be irrelevant across all models.

Second, the model confirms the importance of the spatial dependence on the relevance of patents. The positive and significant *lamba*-coefficient (spatial lag dependence) means that to be placed in a high quality innovative geographical context is able to promote the technological progress of the neighboring regions.

Finally, with attention to research hypotheses, we found interesting and different results if we take in consideration the relevance and the dimension of the technological progress.

The model 1b highlights that technological progress relevance in the European regions is not, or in a very poor way, related to the size of the regional knowledge space (*KB.SIZE* and *SE.SIZE*), thus leading to reject Hyp1 and Hyp3.

The technological progress relevance mainly depends on the variety of knowledge base (*KB.REL* and *KB.UNREL*). More in detail, a region with higher level of unrelated knowledge base is inclined to produce more relevant technological progress than regional environments based on related variety thus leading to reject Hyp2. The variety of the selection environment (*SE.VAR*) influences positively the relevance of the technological progress, thus confirming Hyp 4. However, the availability of diversified knowledge base (both related and unrelated) is more critical than the variety of the selection environment a region is able to access.

Differently, model 2b stresses the importance of the size and the variety of regional knowledge base on the dimension of technological progress. As for technological progress relevance, unrelated variety of the knowledge base is more critical than the related variety, thus leading to reject Hyp2. Moreover, the dimension of the technological progress is positive influenced by both the size of the KB and of the SE, confirming Hyp1 and Hyp3. The findings also suggest that, even though the access to a larger number of knowledge sources positively affects the regional innovation performance, the knowledge provided by specific rather than heterogeneous knowledge sources is expected to be even more performing, thus leading to reject Hyp 4.

3. Conclusive remarks

This work aimed to investigate how the composition of the technological space of regions affects the regional technological progress. By doing so, our research contributes to the present understanding of the determinants of regional competitiveness in terms of technology. In order to identify crucial drivers to be pushed for sustaining regional development we explore how technological accumulation, exploration, and diversification affect regional technological progress. Empirical evidence come from original data at the EU level and new indicators included in the Regpat database have been used to test our hypotheses. Moreover, spatial regression techniques help ruling out the effect of geographical proximity and avoid including in the analysis spatial errors. Another element of originality of this work is related to the measures used for catching regional technological progress, which go beyond the count of patents (which, nevertheless, has been included in the analysis). Qualitative metrics of technological progress have been implemented. As a result, some interesting insights on the drivers of regional technological progress are driven.

The first important result concerns the role of the knowledge base of the region on the dimension and relevance of the region technological progress. In particular the variety of the knowledge base influences the technological progress both if measured as relevance and dimension. The second result concerns the crucial role of the technological diversification in shaping the technological progress. Despite the literature affirms the major influence of the related variety, in our case, the unrelated variety appears to have more influence on the technological progress both in terms of dimension and relevance. This result shows an innovative and diversified technological progress. Third, we observe that a wider selection environment, based on a broad portfolio of knowledge sources, influence the technological progress only in quantitative terms, but it is interesting to observe that, the more the selection environment of a region is specialized, the higher is the impact on the dimension of the technological progress. However, the technological progress is more relevant to the development of the regional knowledge space if the knowledge sources are more diversified. In other terms, the specialization increases the magnitude of the new knowledge production process, but this knowledge is more useful if it comes from a more diversified base of knowledge.

We acknowledge some limitations of this work, which mainly concern the specific metrics used to measure the phenomena here investigated, which come from the RegPat database. Nevertheless, we encourage further investigations on the relationship between specific technological investments of the region and the magnitude and impact of its innovation performance, in terms of technological progress. Policy implications can be driven, directing to a smarter analysis of cause-effect relationship between innovation efforts and results. Moreover, in order to move a region on a positive technological trajectory, it is necessary to invest in sustaining specific industries and stimulating eventually cross-fertilization patterns between industries. Innovations often come from combination of distant knowledge, and this work proves the importance of a diversified knowledge base in establishing the technological progress of a region.

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