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# Does context matter? Exploring the effects of productive structures on the relationship between innovation and workforce skills' complementarity

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**Abstract**

Innovation is often seen as a crucial factor for regional economic growth. Many strands of literature have investigated the role of agglomeration externalities or workers' skills in the innovation capacity of the territory without ever considering their interaction. Using fixed-effects Poisson regression models on official data for 2014–2019 in the Italian regions, this paper aims twofold. First, by controlling for region-specific variables, the paper explores how workforce skills' complementarity (overlapped skills, connected skills, unlinked skills) and productive structure (i.e. MAR specialised or Jacobs diversified structures) foster innovation. Second, the paper investigates how innovation processes depend on the alternative configurations deriving from the interactions between the productive structure and workers' skills. While all types of skills participate in the innovation generation process in MAR specialised contexts, only connected skills positively affect innovation performance in Jacobs contexts. Guidelines are provided to help policymakers and managers who increasingly require regional place-based approaches to stimulate innovation.

**Keywords** Innovation · Patents · MAR specialisation · Jacobs' diversification · Poisson regression · Italy

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## 1 Introduction

Many theoretical strands have recognised the importance of innovative processes for economic growth and aspire to understand the main factors that drive companies to invest in innovation at different levels (Pradhan et al. 2018; Thompson 2018). As with all investments aimed at increasing the competitiveness of companies, the engine of the development of the territory can only pass through the implementation of innovations. Within this field of study, innovation is conceived as the keystone for developing an increasingly competitive and dynamic knowledge-based economy (Kraus et al. 2021).

The high content of creative work and know-how ensure the competitiveness of companies and act as a driving force for the entire economy. Knowledge-intensive activities are, in fact, essential to stimulate employment absorption and to help the transition of traditional business sectors to new sectors with as yet unexplored potential (Papanastassiou et al. 2020). Innovative capacity strongly depends on knowledge and human, structural and relational capital (Podrug et al. 2017; Mariz-Pérez et al. 2012; Lin 2007). Human capital mainly concerns the composition of workers' skills that can contribute, directly or indirectly, to knowledge-generation activities. The ability of local workers to interact with each other can help trigger knowledge spillover processes.

Furthermore, the osmotic process of skills, attitudes, virtue, intellectual agility, and the 'knowledge networks' that develop thanks to labour mobility inevitably affect innovation-oriented activities. However, the role that skills' mobility plays in innovation is still blurred and not universally clear, as this relationship may also depend on the particular productive structure of the territory (Stoyanov and Zubanov 2012; Singh and Agrawal 2011). Each region can develop its innovation model based on specific local conditions that allow the different innovation phases to occur (Capello and Lenzi 2013). Therefore, in-depth knowledge of the main factors determining innovation behaviours would be fundamental for planning targeted innovation policies.

Over the past two decades, a growing number of researchers have aimed to identify the factors that encourage or hinder companies in developing and adopting innovations; however, most of the studies dealt with the relationship between innovative local activities and the productive structure or between innovative local activities and workers' skills. Many studies have shown that industrial specialisation (Lavoratori and Castellani 2021; Vlčková and Stuchlíková 2021; Greunz 2004; Mukkala 2004) or diversification (Dzemydaitė 2021; Duranton and Puga 2000; Ouwersloot and Rietveld 2000; Feldman and Audretsch 1999; Paci and Usai 1999, 2000) may affect the innovative capacity of the territory with a variety of results that have prevented so far from reaching shared conclusions. Some studies have found a weak association (Van der Panne and Van Beers 2006; Var der Panne 2004) or even any association (Massard and Riou 2002; van Oort 2002; Beaudry et al. 2001; Ouwersloot and Rietveld 2000) between propensity for innovation and economic structure. Other studies have shown that the results may depend on the unit of analysis—territory or companies—and, in the latter case, on the firms' size (small vs. large) (Var der Panne 2004; Capello 2002).

Furthermore, researchers highlighted the crucial role of a high degree of cognitive proximity (Nooteboom 2000) and skills connection (Neffke et al. 2017) to trigger local learning and growth processes. Several studies have shown how an efficient matching of skills among related industries leads to productive complementarities, which in turn create new knowledge in the region (Duranton and Puga 2004), and how the existence of high skills' complementarity may imply regional growth (Fitjar and Timmermans 2017; Boschma et al. 2014; Ellison et al. 2010). Recent studies have also highlighted the direct relationship of local skills-related industries with regional economic performance (Diodato et al. 2018; Neffke et al. 2018; Eriksson and Hane-Weijman 2017; Holm et al. 2017; Eriksson et al. 2016; Diodato and Weterings 2015).

In light of the previous literature, the role of agglomeration externalities is worth noting, which can give rise to a specific configuration of the productive structure. The roles played by workers' skills in the innovative capacity of the territory have been chiefly assessed separately, without ever considering the potential effects that their interaction could have on the innovation performance of the territory itself. Thus, there would still be much to add to the debate on the propensity for innovation of the territory and its joint relationship with externalities and labour mobility.

Based on the above, this study aims to contribute to the ongoing debate by providing a comprehensive framework for investigating the main factors that favour or hinder the ability of the territory to generate innovation, jointly considering the type of regional productive structure and the workforce complementarity/diversity, i.e., different types of skills that flow into companies. The key contribution of this paper is to test the existence of a significant link between agglomeration economies (specialisation vs. diversification) and complementarity theories (overlapped skills, unlinked skills, connected skills) and to explore the joint effect of the two forces on the territorial innovation process, using Italy as a case study. To the best of our knowledge, this is one of the first studies that assesses how the interaction of the productive structure with the types of skills' complementarity boosts Italian regions' innovation processes. Fixed-effects Poisson regressions were performed on a balanced panel of 20 Italian regions over 6 years (2014–2019) by changing the dependent variable (i.e., number of patents, trademarks, and designs) used as proxies for innovations. This allowed us to capture the different steps of the innovation process and their dynamics over time.

Italy is an interesting case study. The historical economic gap between Northern and Southern Italy (Ballarino et al. 2014) is reflected in the geography of innovative outcomes, productive territorial structures, and human capital accumulation (Ciccarelli and Fenoaltea 2013). This fits well with the aim of this paper, which is to test the connection between skills' complementarity (as a form of human capital), geographical patterns and innovative outcomes. Italian regions are usually characterised by their productive structure and human capital endowments as strategic factors for their development (Gumbau-Albert and Maudos 2009). The paper can provide guidelines for policymakers, who increasingly require regional place-based approaches to stimulate innovation and for entrepreneurs/managers who need to know the factors that could support their companies in innovation. Although the number of registered patents has increased in recent years,[1] Italy shows a lower patent intensity than the EU-27 average, thus classifying itself as a 'moderate innovator' (European Commission 2014). This is probably because the Italian economy—compared to other European countries—is characterised by a greater incidence of more traditional low-tech sectors with less patent activity (such as textiles, clothing, leather goods, footwear, wood products) than patent-intensive ICT sectors and those most prone to innovation (such as chemistry, medical and precision equipment, office machines, computers) (Bank of Italy 2012).

[1] https://www.epo.org/about-us/annual-reports-statistics/annual-report.html.

The paper is structured as follows. Section 2 shows the theoretical background on which the work is based. Sections 3 and 4 deal with the method and data used to perform the analysis, respectively. Section 5 presents the main results. Section 6 discusses policy implications and Sect. 7 concludes.

## 2 Theoretical background

The innovative capacity of companies is influenced not only by internal resources, whether intangible or financial but also by knowledge sharing and other local factors provided by the external context in which companies operate (Vandavasi et al. 2020; Seo et al. 2017; Hansen and Klewitz 2012; Bröcker 2004). Hence the importance of integrating the analysis of internal resources with external factors to fully understand and support the development of innovations (Cuerva et al. 2014). Since this work aims to analyse the effect on innovation of the interaction between the productive structure and skills' complementarity, it is essential to define these two concepts and discuss the related literature.

Regarding the productive structure, the Marshallian specialisation and Jacobs' diversification approaches are the main theoretical frameworks that help investigate local innovative activities and their determinants from a territorial perspective.

The Marshallian theory of specialisation—proposed by Marshall (1890), Arrow (1962) and Romer (1986) and later formalised as the Marshall-Arrow-Romer (MAR) model by Glaeser et al. (1992)—states that a region's innovative capacity is closely related to its degree of industrial specialisation, i.e., regions with specialised productive structures tend to be more innovative in the industry in which they specialise. Specialisation involves the creation of a local labour market pool supported by a local concentration of production, which allows a large number of skilled workers to have more job opportunities, thus increasing the knowledge spillovers due to the transition of workers from one company to another (Galliano et al. 2015). Moreover, industry-specific knowledge allows companies to develop networks that facilitate the exchange of information and ideas, triggering a process of imitation that could lead to the growth of the innovation capacity of the territory. The specialisation can also reduce transaction costs and facilitate the dissemination of knowledge by intensifying communication among companies in the same industry (Le Blanc 2017; van der Panne 2004) and increasing the stock of knowledge available to each company.

Jacobs' theory of externality (Jacob 1969) states that a diversified local productive structure leads to increasing returns through the exchange of knowledge between complementary industries, based on the assumption that the experience and skills developed by one sector can be applied in others (Capello and Lenzi 2013; Feldman and Audretsch 1999). The productive variety may foster knowledge externalities and, consequently, innovative activities and economic growth. Regions characterised by continuous flows of interactions between heterogeneous agents create new opportunities to share, reproduce and recombine ideas necessary to generate synergistic advantages in innovation (Koster et al. 2020).

In brief, the MAR externality assumes that knowledge externalities occur in highly specialised regions (high concentration of firms in the same industry) with a less competitive environment, facilitating innovation. Jacobs' externality sees local diversification with various industries and competitiveness as the most suitable environment for companies to innovate and adopt new technologies. While agreeing on the existence of territorial effects on the propensity for innovation, the two theories disagree on the impact of industrial concentration (Beaudry and Schiffauerova 2009). Despite many studies on this topic, the debate on which of the two theories might best explain the propensity for innovation remains an unresolved question in the economic literature.

The workforce's skills composition represents the primary source of human capital (Jibir and Abdu 2021) that act on innovation processes (Castillo et al. 2020). However, the role played by human capital depends on the relatedness of workers' competencies with knowledge-generation activities (skills complementarity). Based on the hypothesis of skills complementarity (Neffke and Henning 2013; Neffke et al. 2017), if the skills acquired by workers are the same (new workers have work experience in the same industry that the company specialises in), they could hardly contribute to the improvement of the existing skillset (*overlapped skills*). If the skills are related to existing ones but not exactly the same, there would be real learning opportunities that the new knowledge generated has a positive impact on local growth (*connected skills*). Suppose the skills are not related to existing ones (workers have work experience in sectors other than those in which the company specialises). In that case, they are unlikely to acquire or generate new knowledge (*unlinked skills*).

Evaluating the relationship between workers' skills and innovation has ancient roots. However, an important drawback of this stream of literature is how to measure skills since they can be proxied through several individual attributes (e.g., education, working experience, competencies) (Gallié and Legros 2012). Many indicators of competencies have been proposed over the years (Antonioli et al. 2011). Since the seminal works of Nelson and Phelps (1966) and Benhabib and Spiegel (1994), education has been considered a proxy of skills and knowledge (e.g., people featuring secondary/tertiary education are considered high-skilled workers). One of their main findings is that education positively influences innovation and productivity growth rates. In other words, high-skilled workers lead to higher levels of innovation. Other authors followed this path. Furman et al. (2002) and Varsakelis (2006) find a positive impact of higher educated workers on new patents development and innovation activities improvement. Acs et al. (2002) considered education a pivotal input to the innovative production function. In sum, these studies recognised skilled workers as a source of new ideas and knowledge that can help push innovation frontiers (Xiao and Mao 2021). However, measuring competencies just with education is not sufficient for explaining their impact on the innovation performance of an economic system (Borghans et al. 2001). The issue with the education-based approach is that knowledge cannot be considered a stock measure.

The workers' education level is just the starting point in shaping individual competencies since skills acquisition (or depreciation) continues after school (Borghans et al. 2001). Thus, other authors focused on the so-called "task approach" (Acemoglu and Autor 2011; Autor and Handel 2013; Antonczyk et al. 2016). The underlying idea of this approach is that a fundamental part of the skills acquisition process occurs during the work activities through the so-called "learning by doing". In other words, skills should be classified according to jobs' core task requirements. The issue is the classification of workers into skilled or unskilled categories. Many authors (Petrongolo and Pissarides 2006; Kok and Weel 2014; Groot et al. 2014; Goos et al. 2014) linked the workers' skills with their remunerations, i.e. high-(low-)paid workers are high-(low-) skilled workers. To justify the match between skills and wages, the authors recurred to the so-called skill-biased technical change hypothesis (see, among others, Borghans and ter Weel 2007; Goos et al. 2014). Nevertheless, the task approach does not allow for the desired improvements in evaluating the relationship between skills and economic/ innovation performance. For instance, Dobbelaere and Vancauteren (2014) compared their task-based skills classification with the education-based classification by Bartelsman et al. (2015), finding that the two classifications are pretty close (especially for the manufacturing sector). The limitation of these measures is that the competencies development process cannot be compartmentalised. It is not only a question of what people studied or their tasks at work; it is also about the workers they meet, the competencies they absorb, and how their skills can interact with those of colleagues. In other words, the interaction and cooperation between economic agents and the collective learning process allow for the accumulation of knowledge (Paci et al. 2014; Cotic-Svetina et al. 2008). It seems necessary to consider how skills combine to overcome the lack of empirical literature on the relationship between skills and innovation.

This work aims to fill this gap by using a skills complementarity measure based on the skill relatedness index by Neffke and Henning (2013) and Neffke et al. (2017). While Cappelli et al. (2019) used this index to evaluate the relationship between firms' survival and skill-relatedness, to our best knowledge, this work is the first attempt to consider the skills complementarity in the innovation field. Companies usually engage new skills made available by worker mobility, as they are linked to the knowledge and skills that companies already possess (Cappelli et al. 2019). This means that the new skills that local companies should absorb must neither be too tied to the same type of knowledge nor too distant. Moreover, there is no clear evidence of the effect of the interaction between skills and agglomeration economies on innovation.

## 3 Method

We performed the fixed-effects Poisson regression (Palmgren 1981; Hausman et al. 1984) to follow the dynamics of innovation intensity over time. Our dataset is a balanced panel of the 20 Italian regions observed during $T=6$ years. Let $N_{\mathrm{it}}$ be the innovation output for region $i$ during year $t$, which is assumed to be Poisson distributed with mean $\theta_i \cdot \lambda_{i,t}$, $i=1, \ldots, N$, $t=1, \ldots, T$. The expected annual frequency of innovation output is given by the product of the static factor $\theta_i$, which accounts for the dependence between observations relating to the same region, and the dynamic factor $\lambda_{i,t}$ for the observable characteristics that may vary over time.

In general, $\lambda_{i,t} = \exp\left(\beta' x_{i,t}\right)$, therefore ln $\lambda_{i,t}$ is a linear combination of the explanatory variables ($x_{it}$) and $\beta'$ is the vector of regression parameters. In fixed-effects models, all not time-varying characteristics are captured by the individual heterogeneity term $\theta_i^{\mathrm{FE}}$, which is treated as a parameter to be estimated for each unit. Fixed-effects models only provide estimates for parameters of time-varying characteristics since all other parameters can be seen as part of the individual term $\theta_i^{\mathrm{FE}}$.

By assuming that $\theta_i^{\mathrm{FE}}$'s have mean $\mu_i = \exp\left(\beta' x_{i,t}\right)$ and variance $\tau_i$, the joint probability function of $N_{i,1}, N_{i,2}, \ldots, N_{i,3}$ is given by:

$$P\left(N_{i,1} = n_{i,1}, \ldots, N_{i,T} = n_{i,T}\right) = \int_0^\infty \left( \prod_{t=1}^{T} \frac{\left(\lambda_{i,t}^{FE}\theta\right)^{n_{i,t}} \exp\left(-\lambda_{i,t}^{FE}\theta\right)}{n_{i,t}!} \right) f\left(\theta | \mu_i, \tau_i\right) \mathrm{d}\theta \quad (1)$$

where $f\left(|\mu_i, \tau_i\right)$ denotes the probability density function. Parameter estimation is performed using maximum likelihood estimators considering for $f$ the Gamma density.

**Table 1** Descriptive statistics and data sources, Italy, 2014–2019

| Dimensions | Variables | Min | Max | Mean | SD | Source |
|---|---|---|---|---|---|---|
| Innovation outputs | Patents | 0.67 | 1399.53 | 218.582 | 312.30 | RIS |
| | Trademarks | 5 | 2542 | 386.891 | 546.817 | RIS |
| | Designs | 1 | 503 | 90.949 | 120.391 | RIS |
| Demographic structure | Population 15–24 (%) | 0.921 | 71.211 | 7.060 | 14.675 | ISTAT |
| Education achievement | Workforce with tertiary education (%) | 6.63 | 81.62 | 48.308 | 17.942 | RIS |
| Labour productivity | Workers' per capita wage | 11,996.87 | 24,446.99 | 17,890.98 | 3546.92 | ISTAT |
| Industrial Composition | Employment in hi-tech | 17.143 | 162.375 | 90.232 | 35.168 | RIS |
| R&D expenditure | R&D public sector | 12.676 | 150.704 | 71.402 | 26.197 | RIS |
| | R&D business sector | 1.574 | 140.944 | 42.532 | 31.512 | RIS |
| Scientific research | Scientific publications | 37.356 | 164.595 | 102.501 | 18.579 | RIS |
| Agglomeration economies | MAR index | 0.863 | 12.555 | 5.056 | 3.138 | ISTAT |
| | Jacobs index | 0 | 1.265 | 0.968 | 0.195 | ISTAT |
| Skills' complementarity | Overlapped skills | 20.045 | 33.392 | 28.696 | 2.711 | INPS |
| | Connected skills | 39.139 | 56.340 | 49.028 | 3.404 | INPS |
| | Unlinked skills | 11.022 | 19.958 | 15.021 | 1.773 | INPS |

## 4 Data

The data were taken from official sources covering 2014–2019 (Table 1). As the units of analysis, the Italian regions represent the finest territorial level for data availability.

### 4.1 Dependent variables

Three Poisson regression models were estimated with different dependent variables (i.e., number of patents, trademarks, and designs) to capture the final or intermediate step of the innovation process (Edquist et al. 2018). The data on patents, trademarks, and designs were taken from the 2021 Regional Innovation Scoreboard (RIS) dataset. It is provided by the European Commission's Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs. The RIS 2021 dataset covers the 28 EU Member States, plus Norway, Serbia, and Switzerland, and provides information on region-level innovativeness, capturing innovation's input and output sides (European Commission 2021).

In the first model, the dependent variable is the number of patents applied for at the European Patent Office (EPO) by year of filing. The regional allocation of patent applications is based on the inventor's address. The literature has provided evidence that patents represent a reliable proxy measure of the innovative capacity of companies (Braunerhjelm et al. 2020; Sun et al. 2020; Acs and Audretesch 1989) and territories (Innocenti et al. 2020; Acs et al. 1992, 2002).

The number of patents as a measure of innovation performance has ancient roots. About forty years ago, Pavitt (1985) argued that 'national differences in the volume of domestic patenting activity can be expected to reflect national differences in the volume of innovative activities'. However, this variable suffers from limitations (Romijn and Albaladejo 2002). First, patenting aims to protect inventions, but an invention does not necessarily turn into a process or product innovation. That is, not all patents are innovation-related and not all innovations are patentable or patented (Archibugi 1992; Archibugi and Planta 1996). Second, not all innovators can afford the cost of filing patents to protect their innovations from potential imitators (Rivkin 2001). In other words, the patenting activity differs according to territorial characteristics, such as the size and industry of the companies. This point is particularly true in Italy, whose productive structure is characterised by the predominant presence of small and medium-sized enterprises (SMEs), which in 2019 employed almost 80% of total workers and generated about 67% of overall value added in the 'non-financial business economy' (European Commission 2019).

Two other models were estimated using the number of trademarks and the number of designs as dependent variables to address patent-related limitations and to confirm the validity of the first model's results. More precisely, the number of trademarks applied for at EUIPO (European Union Intellectual Property Office) is an important indicator of innovation, especially for the service sector (Gotsch and Hipp 2012), as the Community trademark confers on its owner a uniform right applicable in all the Member States through a single procedure that simplifies trademark policies at European level. Moreover, the indicator fulfils three essential functions: it identifies the origin of goods and services, ensures consistent quality through evidence of the company's commitment vis-à-vis the consumer, and is a form of communication and advertising (European Commission 2021).

Regarding the number of designs applied for at EUIPO, it is worth noting that a design is the outward appearance of a product or part of it resulting from the lines, contours, colours, shape, texture, materials and/or ornaments. A product can be any industrial or handicraft item, including packaging, graphic symbols and typefaces and excluding computer programs. It also includes products consisting of multiple components that can be disassembled and reassembled. Community design protection is directly enforceable in each Member State. It provides both the option of an unregistered and registered Community design right for an area that includes all Member States (European Commission 2021).

## 4.2 Independent and control variables

Variables related to agglomerations economies and workforce skills' complementarity were used as regressors. Two types of agglomeration economies were considered: (1) MAR externalities, proxied by the geographical concentration of industries; (2) Jacobs' externalities, proxied by the heterogeneity of companies' distribution. Following Cainelli et al. (2016), a geographical concentration index was used to measure MAR externalities:

$$\mathrm{MAR} = \ln\left(\frac{N_{ijt}}{A_{kj}}\right) \tag{2}$$

where $N_{ijt}$ is the number of companies in the industry $i$ and region $j$ at time $t$; $A_k$ is the regional surface (km$^2$). Istat provides data on the number of companies; the industries are defined at two digits of the NACE classification (2-digit NACE Rev. 2).

The procedure applied by many researchers (see Aarstad et al. 2016; Simonen et al. 2015; Frenken et al. 2007) was used to capture Jacobs externalities and their heterogeneity, resorting to the Shannon index (SI):

$$\mathrm{Jacobs} = -\sum_{j=1}^{m} s_{ij}\ln(s_{ij}) \tag{3}$$

where $S_{ij} = x_{ij}/\sum_{j=1}^{m} x_{ij}$ and $x_{ij}$ denotes the number of enterprises in the industry $i$ in region $j$; $m$ is the total number of industries.

The greater the number of industries, the more evenly the employment is distributed across these industries, and the higher the SI for a given region. The maximum value of SI is $\ln(m)$. In this case, all high-tech branches are present in a given region and employment is evenly distributed within these branches (Simonen et al. 2015).

Skill-based variables (i.e., overlapped skills, connected skills, and unlinked skills) were used to gain insights into the *skills' complementarity*. To calculate these variables, a multi-step procedure was used. As the first step, the propensity for innovation of the Italian economic sectors was defined (2-digit NACE Rev.2). Following Istat (2019), the composite indicator of the propensity for innovation was built. It is based on three elementary dimensions: product innovations, process innovations and revenue from new products. Once the composite indicator was defined, the activities were classified by quartiles, considering those belonging to the fourth quartile as the ones with a high propensity for innovation (Istat 2019).[2] In the second step, we define the relatedness between skills to grasp which

[2] The following sectors featuring a high innovation propensity were identified: manufacture of motor vehicles, trailers and semi-trailers; manufacture of other transport equipment; manufacture of electronic components and boards; manufacture of irradiation, electromedical and electrotherapeutic equipment; manufacture of watches and clocks; manufacture of electric motors, generators, transformers and electricity distribution and control apparatus; manufacture of machinery and equipment n.e.c.; motor vehicles maintenance and repair; scientific research and development; computer programming, consultancy and related activities; information and communication; wired and wireless telecommunications.

skills are connected (overlapped/unlinked) with those required for the highly innovative activities. To this end, we resort to the skill relatedness index ($SR_{ik}$)—and the resulting skill relatedness matrix—built by Neffke and Henning (2013) to study the Sweden labour market in 2004–2007 [and then applied in other national contexts, see Cappelli et al. (2019), Neffke et al. (2017), Diodato and Weterrings (2015)]. The $SR_{ik}$ index is based on the labour flows between industries because it is likely that individuals who change jobs will remain in industries that value the skills associated with their previous job. Labour flow is defined as an event in which an employee changes job between two plants in two consecutive years. Neffke and Henning (2013) used direct job-to-job flows and omitted job switches where a worker has periods of non-employment between two jobs. In particular, the authors included in the $SR_{ik}$ calculation the employees with the following characteristics: (1) they are between 18 and 65 years of age on the 30th of June; (2) they are in full-time employment; (3) there is no missing information on industry, occupation or region of work. From a methodological point of view, the index $SR_{ik}$ is given by the ratio between the labour flows from the industry of origin $i$ to destination industry $k$ ($F_{ik}$) and the predicted labour flows from industry $i$ to industry $k$ ($\widehat{F_{ik}}$):

$$\mathrm{SR}_{ik} = \frac{F_{ik}}{\widehat{F}_{ik}}$$

The predicted labour flows $\widehat{F_{ik}}$ are estimated through the zero-inflated negative binomial model in which the dependent variable is the observed labour flows ($F_{ik}$) and the covariates are industry characteristics-based variables (e.g., size, employment growth, wage levels, and so on). In the third step, we use the values of Neffke and Henning's (2013) skill relatedness matrix in the Italian context. By using data from INPS (National Institute for Social Security) on the regional composition of the workforce (i.e., the employees' percentage by industry at 2-digit NACE Rev. 2), we classify the occupations' relatedness in this way: if two occupations feature $SR_{ik} > 1$ they are *overlapped skills*; $SR_{ik} < 1$ stands for *connected skills* and $SR_{ik} = 1$ indicates *unlinked skills* (Neffke and Henning 2013). The skills' complementarity variables are expressed in terms of the percentage share of the total workforce.

To test whether (and how) the productive structures contribute to modifying the relationship between innovation and workers' skills, the interaction variables between the MAR/Jacobs structures and the three types of skills' complementarity were also considered.

Finally, region-specific control variables were used: (1) demographic structure, measured as the percentage of the population aged 15–24 (Frosch and Tivig 2009; Poot 2008); (2) education achievement, as the percentage workforce with tertiary education (Rodríguez-Pose and Wilkie 2019; Crescenzi et al. 2007); (3) labour productivity, proxied by the per capita wage (Xu et al. 2017; Cirillo 2014); (4) industrial composition, expressed as the number of employed persons in knowledge-intensive activities in business industries. The knowledge-intensive activities were defined as all at 2-digit NACE Rev.2 classification where at least 33% of employment has a higher education degree (ISCED 5–8) (European Commission 2021); (5) *R&D expenditure,* expressed as the share of GPD dedicated to the development of technological innovations and new products. Both the public and business sides of R&D were considered. These variables (i.e., R&D expenditures in the public sector and R&D expenditures in the business sector) have been commonly used in the literature because R&D is an input for a patent generation. Meliciani (2000) demonstrated the importance of investment activities in contributing to innovation and technical change through longitudinal and multi-country analysis. Many other authors showed the high correlation of patents with the overall level of R&D expenditure (Sun et al. 2020; Buerger et al. 2012; Gumbau-Albert and Maudos 2009;

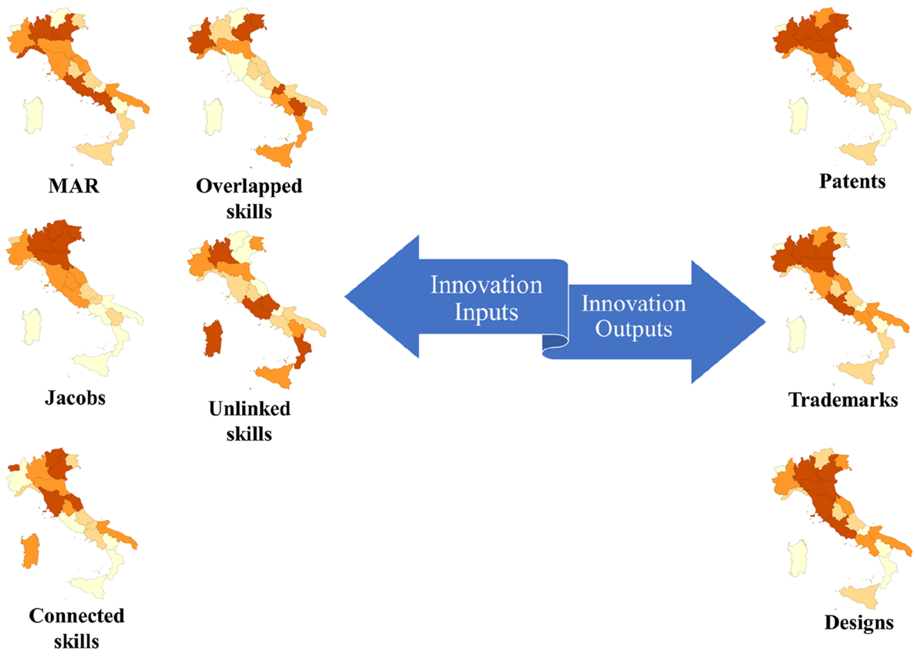


**Fig. 1** Regional distribution of the main variables. Italy, 2019

Piergiovanni and Santarelli 2001); (6) *Scientific research*, proxied by the number of scientific publications among the most cited publications worldwide (Ganau and Grandinetti 2021), as a measure of the efficiency of the research system.

To describe the dataset's characteristics, Fig. 1 shows the territorial distribution of the main variables. For the sake of space, only the data referring to 2019 are plotted. It is worth pointing out that most of the patents were concentrated in northern Italy, in line with ISTAT (2019), which highlighted that three northern regions (i.e. Lombardy, Emilia-Romagna, and Veneto) together covered over 60% of all Italian patents in 2018. Lombardy (one of the most innovative regions in Europe), Emilia-Romagna (the number of patents per million inhabitants was one and half times higher than the national average) and Veneto were characterised by the highest levels of patent applications in technology-intensive activities in machinery manufacturing and the automotive and aerospace sectors, as well as in metal manufacturing and processing. All southern regions were below the national average; in particular, Basilicata, Calabria, Sicily and Sardinia have fewer than ten patent applications per million inhabitants. However, Latium shows more creative, innovative, or high-tech employees (Istat 2019). Table 1 presents the main descriptive statistics and the data sources for the whole dataset.

## 5 Empirical findings

Fixed-effects Poisson regression models were estimated to investigate the role of agglomeration economies and skills' complementarity in generating innovation and their interaction, i.e. how skills can be valued differently in MAR specialised areas rather than in Jacobs' diversified regions. The Hausman test (Hausman and Taylor 1981) allowed testing the advisability to perform the Poisson model with fixed rather than random effects, verifying the orthogonality of individual effects and covariates. The Hausman test determines whether the errors ($u_i$) are correlated with the covariates (the preferred model is fixed effects); the null hypothesis is that they are not (the preferred model is random effects). The null hypothesis cannot be accepted with a statistic test of 111.59 ($p = 0.000$), concluding that the fixed effects model is the most appropriate for this analysis. In other words, the hypothesis that individual effects are uncorrelated with the other covariates was rejected. The reverse causality between firm productivity and agglomeration economies could lead to endogeneity bias (Graham et al. 2010), which was treated through the instrumental variables (IV) and two-stage least squares (TSLS) approach (Green 2003). We used the agglomeration variables and other covariates at the previous time ($t-1$) as instruments of the agglomeration variables (Staiger and Stock 1997; Deng et al. 2010; Reed 2015). With a statistic test of 8.651 ($p = 0.3726$), the Sargan–Hansen $J$ test (Sargan 1958, 1988; Hansen 1982) confirmed the procedure's validity.

Table 2 shows the estimates of the Poisson regression models. For the sake of robustness and for addressing the potential limitations of patent data, three models were estimated by modifying the dependent variable as a proxy for innovation: (1) the number of patents (model 1), (2) the number of trademarks (model 2), (3) the number of designs (model 3). Since models (2) and (3) confirm the results of model (1), we used the patent-based model as reference estimates.

Control variables have the expected signs. Regarding the main variables of analysis, we focus on the skills' complementarity, agglomeration economies, and interaction variables. Workers with *connected skills* will likely improve the region's innovation performance. This confirms the pivotal role of connected skills, highlighting how these workers represent the most important type of human capital and how cognitive proximity allows the generation of new knowledge (Neffke et al. 2017). The results also show the positive contribution of workers with *overlapped skills* in improving the probability of growth in innovation capability, consistent with the literature on the relationship between human capital and economic performance (Cappelli et al. 2019; Leiponen 2005). However, it is worth noting that the magnitudes of the coefficients relating to these two types of skills (connected and overlapped) suggest a similar effect on innovation performance. However, this equivalence deviates from initial expectations about the pivotal role of connected skills as the most important type of human capital in fostering innovation. What emerged is the ability of both overlapped and connected skills to generate new knowledge by using cognitive proximity as the engine of virtuous knowledge networks. Workers with *unlinked skills* are even detrimental to the regions' ability to generate innovation. These workers have gained experience in very different industries from the most innovative ones, and their skills cannot be absorbed in a context of high knowledge exchange (Fitjar and Timmermans 2017; Nooteboom 2000). Consequently, workers with unlinked skills do not represent a real learning opportunity for other workers and cannot generate new knowledge.

The signs of coefficients of the agglomeration variables are positive, highly statistically significant, and relatively similar in magnitude. Our results align with previous findings that show

**Table 2** Poisson regression with fixed effects estimations. Italy, 2014–2019

| Dimensions | Variables | Model 1 | Model 2 | Model 3 |
|---|---|---|---|---|
| Demographic structure | Population 15–24 (%) | 0.005*** (0.002) | 0.008*** (0.005) | 0.002 (0.002) |
| Education achievements | Population with tertiary education | 0.006*** (0.0001) | 0.001*** (0.0009) | 0.001*** (0.0001) |
| Labour productivity | Workers' per capita wage | 0.0004 (0.003) | 0.001*** (0.0001) | 0.003*** (0.0002) |
| Industrial Composition | Employment in hi-tech | 0.036*** (0.001) | 0.008*** (0.0004) | 0.011*** (0.0006) |
| Research | Scientific publications | 0.002*** (0.0004) | 0.001*** (0.0002) | 0.001*** (0.0002) |
| R&D | R&D public sector | 0.005*** (0.0001) | 0.001*** (0.0001) | 0.021*** (0.0001) |
| | R&D business sector | 0.006*** (0.0001) | 0.001*** (0.0001) | 0.013*** (0.0007) |
| Agglomeration | MAR index | 0.655*** (0.098) | 0.109* (0.056) | 0.294*** (0.058) |
| | Jacobs index | 0.671*** (0.028) | 1.596** (0.641) | 0.345*** (0.055) |
| Skills' complementarity | Overlapped skills | 8.825*** (1.208) | 2.706*** (0.729) | 9.298*** (0.665) |
| | Connected skills | 6.064*** (1.344) | 8.165*** (0.660) | 8.811*** (0.651) |
| | Unlinked skills | −1.916** (1.105) | −2.108*** (0.837) | −8.278*** (0.961) |
| Interaction | MAR*overlapped skills | 0.949*** (0.108) | 0.261*** (0.084) | 0.047*** (0.008) |
| | MAR*connected skills | 1.195*** (0.091) | 0.861*** (0.051) | 0.603*** (0.054) |
| | MAR*unlinked skills | 0.453*** (0.147) | 0.134** (0.064) | 0.096** (0.056) |
| | Jacobs*overlapped skills | −2.723*** (1.066) | −0.928*** (0.086) | −0.411*** (0.083) |
| | Jacobs*connected skills | 1.234*** (0.361) | 4.411*** (0.831) | 4.928*** (0.846) |
| | Jacobs*unlinked skills | 0.682 (0.147) | 0.865 (0.922) | 0.165 (0.221) |

***; **; *Significance level at 1%, 5%, 10%; Model 1: patent; model 2: trademark; model 3: design how both agglomeration economies could positively impact the territories/firms' performance, albeit with different intensities (Becchetti and Rossi 2000; Beaudry and Schiffauerova 2009; Damijan and Konings 2011). According to these authors, the firm's size seems to greatly influence agglomeration economies' impact on performance. In particular, MAR appears to favour the smaller firms more than the largest ones. Their lack of resources and organisational structures may be reduced from a highly agglomerated area (Cainelli et al. 2014). Anyway, the debate on the Mar/Jacobs duality remains unsolved.

The results showed that the direction and intensity of the impact of skills on innovation depend on the type of skills. Beyond this first insight, it is of great interest for research to investigate whether there are differences in the impact of skills' complementarity on innovation when the productive structure is considered. To this end, the third group of variables made it possible to capture the interaction between workers' skills and local productive structures and thus to investigate whether the effects of connected skills (as well as overlapped and unlinked skills) on innovation capability are greater (lower) in the MAR specialised or Jacobs' diversified structure.

The *connected skills* interaction variables are significant and positively impact innovation in the specialised and diversified structure. It appears that workers with connected skills are more valued in diversified areas than in specialised areas. A possible explanation could resort to knowledge networks. Since these networks are based on the complementarity and sharing of skills that generate new knowledge, it seems that diversification presents the best combination of skills capable of triggering the most significant positive effects on innovation activities.

The *overlapped skills* interaction variables are significant, although a closer examination of these interaction effects reveals that the nature of the relationship changes according to the productive structure. The MAR specialised structure highlights the positive contribution of workers with overlapped skills in improving the probability of growth in innovation capability. In Jacobs' diversified structure, the effect of this type of skill is negative, which can be partly explained by the fact that the diversified areas are more sensitive to the lock-in effect. That is, workers with the same or similar skills are unable to create new knowledge because the regions close in on themselves, becoming isolated and impermeable, and preventing knowledge and innovative ideas from the outside from flowing in Cappelli et al. (2019). The interaction term related to *unlinked skills* is significant only in specialised areas. This is a result of great interest as the nature of this effect deviates from the expectation of a negative impact on innovation (as shown by the estimate of the coefficients for the *unlinked skills* variable). In MAR specialised contexts, these workers may play a role in innovation activities probably due to their low diffusion within the macro-area (compared to the rest of the country), allowing easier absorption of their skills. The same cannot be said for Jacobs' diversified areas, where the role of workers with unlinked skills appears negligible.

In summary, the interaction-based analysis shows that all types of skills in the MAR specialised regions can stimulate innovation activities. This highlights how the MAR productive structure may improve workers' skills and increase the capacity of knowledge networks to generate new ones. On the other side, Jacobs' diversified context appears to be less favourable as only connected skills may improve the capability for territorial innovation.

## 6 Policy implications

We found significant effects of skills' complementarity/diversity on innovation performance. In line with expectations, workers with unlinked skills negatively affect innovation, confirming the theory that this type of skill does not generate new knowledge because the highly innovative regions cannot absorb it. Significant positive relationships emerged between the propensity for innovation with connected skills and overlapped skills.

By taking the analysis to a deeper level of detail, the scenario changes and other significant results were obtained. We found interesting interaction effects between the different sources of skills-related variables and the productive structure of the territory. The valorisation of skills deeply changes depending on whether workers operate in MAR specialised structures or Jacobs' diversified ones. In MAR contexts, all types of skills form new ideas and the innovation generation process; in Jacobs' contexts, only the connected skills positively affect innovation performance while the unlinked skills play no significant role. Not negligible, in Jacobs areas, overlapped skills seem to suffer from lock-in problems, also playing a negative role in innovation development.

Therefore, the productive structure plays a key role in the knowledge network and the development of new ideas by activating innovation processes. On the one side, although skills diversity can involve the risk of relational, communication, and skills complementarity problems in the specialised areas, this diversity can have important knowledge-developing advantages. In particular, people with different skills (and work experience) are likely to adopt different thinking styles (e.g., pragmatic vs enthusiastic or strategic vs. operational) or behavioural modes (e.g., exploitation focused vs. exploration-focused, questioning vs executing), which may complement each other in innovative projects. From this perspective, skills' complementarity/diversity seems to be a resource in MAR areas. On the other side, the Jacobs structure is less receptive to improving the diversity of the workforce, emphasising that skills diversity could trigger relational problems (e.g., socialising problems between more skilled and less-skilled workers or redundancy of skills).

These findings have relevance to policymakers. The key question seems to be how to improve the innovation performance of the areas characterised by Jacobs' diversification. From what emerges in this analysis, to increase innovation performance in diversified areas, policymakers could act on two sides: (1) encouraging the development of more specialised productive structures where skills diversity/complementarity can create knowledge networks and new ideas; (2) enhancing the workers' skills endowment to meet the needs of innovative companies.

Network contracts can be an important measure to foster the development of a productive specialisation area. In Italy, network contracts were established by Law n. 33/2009 to improve collaboration between companies and increase the innovative capacity and market competitiveness of each company and the entire network. The introduction of network contracts—as a form of aggregation to optimise resources and as a means for achieving the strategic objectives of companies—stems from the need to keep up with a globalised market and, consequently, to compete on quality and innovation, making use of horizontal technologies and sharing of knowledge and resources. To this end, entrepreneurs undertake to collaborate based on a joint program, exchanging information or services of an industrial, commercial, technical or technological nature and jointly carrying out one or more activities. While from a theoretical point of view, network contracts and business networks could be a powerful tool to increase knowledge sharing between companies, their effectiveness remains unclear. Networking is often a requirement for participating in

European or national funding programmes. The risk is that these collaborations are underused to become a vehicle for reaching funding rather than a means of sharing knowledge, skills, and competencies. Therefore, monitoring activities at supranational, national, and local levels is crucial to unlocking this tool's full potential and controlling network activities and compliance with the stated objectives for access to funds. Increasing the monitoring operations to verify the correct use of the network tool could be a proper solution to increase the productive specialisation of the areas and improve their potential as generators of innovations.

Investing in human capital to improve the matching between workers' skills and the needs of innovative companies is another measure that could help underperforming areas to increase their performance. Since changing the skills composition of the regions is a complex task, local governments could focus on reskilling the workforce in Jacobs' diversified contexts. Reskilling represents a process of retraining workers' skills to allow them to occupy a different job roles. While this practice is widely used to reconvert the workforce by avoiding the firing of workers with no longer required skills, it has a twofold advantage in the field of innovation: (1) it allows workers' skills to be improved and to cope with the lack of talents to be recruited; (2) it facilitates skills' complementarity, avoiding the lock-in effect due to the overlapping of skills or the difficulty of activating knowledge networks due to unlinked skills.

It is no coincidence that reskilling has been identified as one of the central themes of the coming years by the World Economic Forum (2018). In some cases, the costs of these efforts have also been estimated: for the United States, for example, it is planned to invest 34 billion dollars in reskilling activities. The strategies that can be used to drive this reskilling require the commitment of different agents (i.e., governments, companies, individual workers). The role of public and private agents (i.e., companies and workers) is undoubtedly critical, as financial support is required to retrain the workforce. On the one side, local governments and private companies should finance reskilling and upskilling courses designed for workers who need to recalibrate their skills; on the other side, the commitment of individual workers is required to use part of their extra-working time to follow these courses and explore career transition options. These efforts will not be easy. People will need to be adequately supported and incentivised. They will need to see the potential benefits of ongoing reskilling in rewarding career transition paths. In summary, in Jacobs' areas, reskilling could help train the workforce by considering the skills necessary to foster knowledge networks that activate sharing skills, leading to gains in innovation performance.

## 7 Conclusions

While previous research on the driving forces of innovation has focused separately on workers' skills or productive structure, we have helped to fill this research gap by investigating the main effects on innovation performance of the interaction between workforce complementarity/diversity and productive systems. We clearly distinguished three sources of skills' complementarity (i.e., overlapped, connected, unlinked) and two sources of production-related diversity (i.e., MAR specialisation, Jacobs' diversification). The territorial polarisation that characterises Italy in terms of innovation activities and socio-economic and productive structures has been revealed as the ideal context in which to set the research framework.

The results obtained have led to different thoughts. First, productive specialisation (MAR externalities) plays a more decisive role in fostering innovation activities with respect to more diversified productive structures (Jacobs externality). Second, both connected and overlapped skills positively affect innovation performance, unlike unlinked skills, which negatively affect innovation. Third, as regards the joint action of agglomeration externalities and skills' complementarity on innovation performance of Italian regions, it is worth noting that all types of skills are more valorised in the specialised areas, while only the connected skills positively affect innovation performance in diversified contexts.

The interaction between workers' skills and the productive structure on innovation performance calls for further research developments. The use of data at the company level, for example, would allow additional insights to be provided into the role played by the skills composition of the workforce in the different productive structures. Another research enhancement could be the use of data at a finer territorial level (e.g., provinces or municipalities). This may allow more accurate control of territorial dependencies between economic agents and local knowledge networks. Finally, innovation generated by SMEs could be considered. We excluded this important agent of the innovation process from our analysis due to the lack of data on the number of innovative SMEs. Future works could be called upon to outline a more complete picture of the output side of innovation.

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