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How Do Agglomeration Externalities and Workforce Skills Drive Innovation? Empirical Evidence from Italy

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Abstract
Based on four research hypotheses, this paper investigates whether and how the propensity for innovation of a territory depends on (*i*) agglomeration externalities (specialisation vs. diversification); (*ii*) the interaction between skills complementarity (overlapped, unlinked, connected skills) and agglomeration externalities; (*iii*) inter-regional workers' mobility; (*iv*) workers' mobility in both intra- and inter-regional flows. Although these factors have been explored from a one-by-one perspective, there is little evidence of their joint actions on a location's propensity for innovation. To propose new insights into how these factors work together, we perform the Spatial Durbin Model (SDM) using data on Italian provinces from official sources. The SDMs are estimated globally on all the Italian provinces and separately on the two macro-areas of northern and southern provinces to compare the effects of intra- and inter-regional workers' mobility on innovation. The results can be summarised as follows: (*i*) specialisation plays a more decisive role in fostering innovation than diversification; (*ii*) the interaction between skills complementarity and specialisation has a strong impact on innovation activities; (*iii*) the contribution to the innovation of workers' mobility with overlapped skills is greater when the mobility occurs between provinces of the same macro-area; (*iv*) geographical proximity improves the territory's ability to absorb the related skills regardless of its productive structure. The provided evidence may help policymakers with the appropriate information to foster innovation.

Keywords Innovation propensity · Patents · Agglomeration externalities · Workers' skills · Spatial Durbin Model

JEL Classification C31 · C38 · J24 · O31 · O32 · R12

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Introduction

Innovation is a key factor in the growth of worldwide economies. The relationship between entrepreneurship, innovation, and economic growth (Lerner, 2010) implies that a positive shock in innovation activities leads to greater economic growth, especially in economic boom times (Ahmad & Zheng, 2022). With this in mind, it is pivotal to adopt actions to stimulate investments in research and innovation (Aho et al., 2006). The European Union had recognised the importance of innovation as an engine of development since the early 2000s when the 'Lisbon Strategy' proposed several plans to foster Member States' economic growth. Therefore, strengthening innovation is a cornerstone of the EU strategy to make the knowledge-based economy more competitive and dynamic (European Communities, 2009).

The literature debate on the commitment to a knowledge-based economy is very lively. It is widely recognised that technology is the driving force for national and regional economic development (Sun, 2000). It is critical to understand the inputs of technological innovation and the role they play. A pioneering strand of literature has focused on the relationship between innovation activities—proxied by the number of patents registered—and R&D expenditure. Pakes and Griliches (1984) and Hausman et al. (1984) conducted longitudinal analyses based on samples of US firms, finding a high elasticity of patents with respect to R&D expenditure. Bound et al. (1982) investigated the relationship in a size-based analysis by dividing the sample of firms into two subgroups based on R&D expenditure. They found a constant relationship in small firms, while for larger firms, the relationship decreases as R&D expenditure increases. The literature has quickly overcome the concept of a linear model with R&D as the starting point for developing innovation, moving towards a systemic model in which innovation arises from complex interactions between individuals, organisations and their operating environment.

The innovation system is characterised by the 'knowledge networks' in which innovative firms, research organisations, suppliers and schooling systems cooperate. Innovation results from collective actions of different actors linked by informal and formal network relationships. On this basis, the concept of the *geography of innovation* arose. One of the first attempts to introduce spillover effects into innovation analysis was made by Jaffe (1986), who related firms' patent applications to firms' R&D, to R&D of other firms nearby in the technological space and dummy variables for technological clusters. The results showed the importance of creating an innovative system in which knowledge-related mechanisms, including knowledge search (Katila & Ahuja, 2002), knowledge transfer (Mowery et al., 1996) and knowledge integration (Wang et al., 2018), play a fundamental role (Carayannis et al., 2014, 2018; Chen et al., 2020; Fernandez et al., 2018). Other economic geographers have focused on the spatial distribution of innovation creation centres, and an important finding was that innovation activities are not equally distributed in space (Acs et al., 2002; Anselin et al., 2000; Feldman, 1994; Gumbau-Albert & Maudos, 2009; Krugman, 1991; Moreno et al., 2005). Since cooperation between economic agents is widely regarded as a primary driver of innovation (Freire & Gonçalves, 2021), spatial proximity could be the instrument to facilitate knowledge flows (Acs et al., 2002). In other words, the spatial distribution of innovation centres can lead to different models of the local economic system and agglomeration economies, i.e. specialisation or diversification, which influence the ability to transfer technological knowledge between economic operators. The Marshall-Arrow-Romer (MAR) specialisation and the Jacobs diversification are the leading agglomeration economies. However, scholars have not reached a consensus on their economic impact. Some claim that MAR specialisation drives growth and innovation (Khoirunurrofik, 2018; Widodo et al., 2015; Drivas et al., 2014; Ejermo, 2005; Greunz, 2004), while others suggest that Jacobs diversification increases the likelihood of innovation and economic performance (Kalash, 2022; Aritenang, 2021; Lazzeretti et al., 2017; van Oort, 2002; Ouwersloot & Rietveld, 2000). Since the MAR-Jacobs dualism remains a somewhat unsolved question in the literature (Beaudry & Schiffauerova, 2009), we formulate the following research hypothesis (*RH1*): which economic system (MAR vs. Jacobs) improves innovation?

The development of innovations is strongly related to knowledge, which depends on human capital development (Castillo et al., 2020). The workforce's skills composition represents the main source of human capital (Jibir & Abdu, 2021). However, the role played by human capital depends on the relatedness of workers' competencies (i.e. workers' skills complementarity) with knowledge-generation activities and their interaction with the local economic system. Based on Cappelli et al. (2019), in the workers' skills complementarity framework, we identify three categories: (*i*) overlapped skills (workers with same skills); (*ii*) connected skills (skills are related but not the same); (*iii*) unlinked skills (skills are very different). While we expect the positive (negative) relationship between connected (overlapped/unlinked) skills and performance (Cappelli et al., 2019), there is no clear evidence of the effect of the interaction between skills and agglomeration economies on innovation (Fitjar & Timmermans, 2017; Ikari et al., 2022; Tubiana et al., 2022). To shed new insights on this topic, we establish the following research hypothesis (*RH2*): the innovation propensity is strongly influenced by the interaction between skills complementarity and specialisation/diversification.

Beyond the interaction between skills and agglomeration economies, the workers' territorial mobility affects integrating new skills (Boschma et al., 2009; Ejermo et al., 2022; Perret, 2021). On the one side, hiring workers from other innovative firms or territories is one of the most important vehicles of the tacit knowledge flow. On the other side, the positive (negative) impact of skills complementarity components (i.e. overlapped, unlinked, and connected skills) could be significantly influenced by workers' mobility, particularly their intra-regional or inter-regional nature. Therefore, we propose the following hypotheses: *RH3*, the inter-regional mobility of workers with overlapped skills does not reduce the propensity for regional innovation; *RH4*, the positive effect of mobility on workers with connected skills is stronger in intra-regional flows than in inter-regional flows. Unlinked skills are less harmful in the case of intra-regional mobility.

Based on the above, this study aims to test the four research hypotheses mentioned above to provide policymakers and practitioners with the appropriate information to promote (and possibly improve) innovation outcomes. This paper contributes to the debate on fostering innovation development by considering the main drivers of the innovation process within a comprehensive framework. While previous works considered a limited number of drivers, we test their simultaneous impact on innovation performance and how they interact with each other from both an intra- and inter-territorial perspective.

Italy is used as a case study to test research hypotheses. First, Italy is characterised by a historical economic divide between the northern and southern parts of the country (Ciccarelli & Fenoaltea, 2013), which, according to the Italian Chamber of Commerce,[1] converges in significant differences in innovation outcomes. This allows us to discriminate between specialised areas and diversified areas. The determinants of the North–South divide remain unanswered, even if debated for a long time (Felice, 2012). Second, the differences in human capital accumulation are considered a crucial determinant of the economic divide between the country's macro-areas (Cappelli, 2016). This aspect fits particularly well with our research questions as they aim to test the connection between skills complementarity (as a form of human capital), geographical patterns and innovative outcomes. Third, based on (i) and (ii), the case of Italy could bring a high value to the scientific debate. Fourth, the number of studies dealing with externalities, skills composition, workers' mobility and regional patterns of inventive activities in Italy is relatively scarce (Nuvolari & Vasta, 2017).

From an empirical point of view, the Spatial Durbin Model (SDM) is used. This method is particularly suitable for testing *RH1* and *RH2* because it simultaneously controls specialisation (diversification), skills complementarity and workers' mobility. To verify *RH3* and *RH4*, the SDM is estimated for each macro-area, i.e. the North and the South, which are internally characterised by homogenous socio-economics characteristics to compare the effects of intra- and inter-regional workers' mobility on innovation outcomes. As a strength, the analysis is conducted using the provincial-level information, representing the finest territorial level for which patent data is available. This high level of territorial detail allows us to capture patterns of spatial heterogeneity that would remain hidden at a more aggregate level (e.g. the regional level).

The article is organised as follows. The 'Literature Review and Research Hypotheses' section presents the literature debate on which the research hypotheses are developed. The 'Research Design' section deals with the case study ('Case Study: Italy' section), the methodological details ('Method' section), and the data used ('Data' section). The 'Results and Discussion' section discusses results and policy implications. The 'Conclusions' section concludes.

[1] For further details, see the following document: https://www.milomb.camcom.it/upload/file/1700/850209/FILENAME/Lombardia_brevetti.pdf (Accessed on 10 Mar 2022).

Literature Review and Research Hypotheses

Innovative systems depend on creating a network in which agents interact and share knowledge. The literature has pointed out the existence of three layers of determinants of innovation systems: (*i*) agglomeration externalities (economic systems); (*ii*) human capital composition and its interaction with agglomeration externalities; (*iii*) workers' territorial mobility.

Differences in local economic systems are based on the dichotomy of agglomeration externalities, i.e. MAR vs. Jacobs externalities. As stated by Dicken and Malmberg (2001), agglomeration externalities can be the result of a geographic specialisation concentration of similar industrial activities (i.e. MAR externality) or the result of a diversified productive structure (i.e. Jacobs externality). MAR externality (Arrow, 1962; Marshall, 1890; Romer, 1986) is based on the concept that the economic development of a location is typically related to the degree of industrial specialisation of the area because specialisation enables economic agents (e.g. firms) to develop a network that allows them to access a highly educated and skilled workforce or a dedicated supplier. Regarding the knowledge externalities and the innovation-related context, MAR externality facilitates the dissemination and exchange of information, knowledge, ideas and the circulation of skilled workers and triggers the imitation process that could lead to the growth in innovation capability of an area. Labour market pooling is another important advantage of geographic specialisation because it allows workers to have more job opportunities (especially for lay-offs), thus increasing the knowledge spillover due to the transition of workers from one firm to another (Galliano et al., 2015). The MAR theory argues that it is complicated for knowledge spillover to occur in areas characterised by high production heterogeneity (Beaudry & Schiffauerova, 2009).

Jacobs' externality (Jacobs, 1969) argues that knowledge spillovers occur when people with different working experiences and skills meet. Since this diversity is greater in areas with heterogeneous socio-economic backgrounds and productive structures, this theory stresses the importance of diversification. In other words, the productive variety of a geographic location promotes knowledge externalities and, ultimately, innovative activities and economic growth. The basic idea is that the interaction between diverse agents fosters the opportunity to imitate, share and recombine ideas to generate new ones. A location characterised by diversification conducts complementary knowledge flows and the exchange of skills necessary for experimentation and innovation (Koster et al., 2020). A firm's invention could be incorporated into the production of another firm (Combes, 2000). Moreover, Jacobs' externality leads to a more competitive environment, which is a strong incentive for firms to innovate and adopt new technologies.

MAR and Jacobs' externalities agree on geographic effects on innovation propensity but disagree on its effects. MAR externality considers that knowledge spillovers occur in a specialised scenario with a less competitive environment. Jacobs' externality advocates that diversification and a high degree of the local competition are crucial for economic growth and the propensity for innovation.

Which of the two theories could better explain the innovation activities remains an unresolved question.

Many scholars have shown that specialisation and diversification could increase the likelihood of achieving innovative output without converging on a univocal conclusion. Duranton and Puga (2000) suggested that a diversified environment is more challenging than a more specialised one. Beaudry et al. (2001) and Massard and Riou (2002) found no evidence of a positive relationship between diversified environment and innovation. Similar findings come from the studies by Van der Panne (2004) and Van der Panne and van Beers (2006), who highlighted the weak influence of diversification on innovative capability. Ejermo (2005) used patent data to capture technological diversity in Swedish regions, stressing that the number of patent applications is positively dependent on regional technological specialisation. The effects of spatial concentration of innovation activity on local US patent production were studied by Drivas et al. (2014). As one of the main results, the research shows the leading role of technological specialisation. Widodo et al. (2015) examined the effects of agglomeration economies on firm performance, indicating that specialisation is more conducive than diversity to drive high outcomes. Khoirunurrofik (2018) focused on the local economic structure, explaining that although MAR and Jacobs' externalities are important for growth, the former appears stronger than the latter. Goya (2022) explored the role of MAR and Jacobs' externalities in a common framework, finding significant evidence of the Marshallian but not of Jacobian effects.

On the contrary, Ouwersloot and Rietveld (2000) and van Oort (2002) argued that innovation is more stimulated by diversification rather than specialisation. This finding is in line with previous studies such as Feldman and Audretsch (1999) and Paci and Usai (1999, 2000). To analyse the growth of creative employment, Lazzeretti et al. (2017) applied the variety-based approach in Italy, revealing an important effect of variety on the growth of creative industries. Aritenang (2021) conducted an empirical analysis based on a specialisation-diversification comprehensive framework, concluding that the areas with less specialisation would have a higher economic growth; the higher the industrial spatial dispersion, the faster the economic growth.

Although the debate has dated roots, what keeps it alive are the structural differences among the studies. In particular, the level of analysis (i.e. at the firm or regional level) is an important choice because it could influence the empirical results (Ejermo, 2005; Goya, 2022). According to Beaudry and Schiffauerova (2009), studies conducted at the firm level are more likely to support the MAR thesis, while the regional level supports Jacobs' externality. In this divergence, many authors have seen the evidence that MAR may have a deeper impact on small firms (Mukkala, 2004; Van der Panne, 2004) while Jacobs may benefit large agents (Henderson, 2003).

Based on the above, we define a specialised territory with a high concentration of innovation-oriented activities (proxied by the number of patents filed with the European Patent Office); otherwise, they are defined as diversified. Therefore, the following hypothesis is tested:

RH1: Which economic system (MAR vs. Jacobs) improves innovation?

Beyond the dichotomy between specialisation and diversification, economic geographers have stressed that the workers' interaction plays a pivotal role in promoting knowledge transmission. Since people are the primary vector of knowledge, employees moving from one firm (territory) to another could activate its generating process. However, creating new knowledge depends on the propensity to recombine individual skills and the macro-context in which the skills interact (Tubiana et al., 2022). In the literature, several studies conclude that human capital (measured primarily through education and skills) has an overall positive effect in driving innovation activities (Jibir & Abdu, 2021; Martinidis et al., 2021), but little evidence exists on the ability of economic agents (i.e. firms or local economic system) to absorb the heterogeneity of new skills and knowledge. In other words, how workers' skills interact with each other and whether agglomeration externalities affect the assimilation of new knowledge deserve a closer look.

According to Cappelli et al. (2019), firms can only absorb the new skills acquired through workers' flows if they are close to and linked to the knowledge and skills. Moreover, they should not be too close to avoid the lock-in effect (i.e. closing upon themselves, becoming isolated and impermeable, and preventing knowledge and fresh, innovative ideas from outside to flowing in). This introduces the 'skills complementarity' scheme. It allows the definition of the following three scenarios: (*i*) *overlapped skills*: whether the skills acquired are the same (i.e. the new employees have working experience in the same sector the firm is already specialised in), they are absorbed, but they do not contribute to improving performance because they do not add anything new to the existing skillset; (*ii*) *unlinked skills*: whether the new skills are not related (i.e. the new employees have working experience in very different sectors from the sector the firm is specialised in), it is difficult to learn from them and generate new knowledge because the new skills cannot be absorbed; (*iii*) *connected skills*: whether new skills are related (but not the same) to the existing ones, there are real learning opportunities and the new knowledge generated have a positive impact on local growth. Several works have supported this thesis. Duranton and Puga (2004) claimed that efficient skills matching between related industries in a region leads to production complementarities that generate new knowledge.

Similarly, Nooteboom (2000) showed the importance of the right degree of cognitive proximity to enable communication that triggers the learning process. Ellison et al. (2010), Boschma et al. (2014), and Fitjar and Timmermans (2017) demonstrated how the presence of a local labour market characterised by high skills complementarity implies regional growth.) stressed the importance of a high degree of skills connection in explaining the local industry growth. Other authors stressed the positive relationship between local skill-related industries and regional economic outcomes (see, for example, Luengo-Valderrey & Moso-Díez, 2019; Diodato et al., 2018; Neffke et al., 2018; Eriksson & Hane-Weijman, 2017; Holm et al., 2017; Diodato & Weterings, 2015).

Some studies have also considered the economic context. For instance, Ikari et al. (2022) investigated the relationship between industrial specialisation, skilled labour and technological growth by dividing the industrial specialisation patterns into four types, i.e. autarky, relative specialisation, absolute specialisation and moderate specialisation. Their results show that the relationship between skilled workers and technological growth differs vastly among industrial specialisation patterns. Focusing on innovation in European metropolitan areas, Tubiana et al. (2022) studied the collaboration between co-workers and geographically co-located firms. They show that the greater the complexity of the ideas and knowledge required, the greater the importance of geographic proximity and network knowledge. The same does not occur for less complex ideas, as the network knowledge is less relevant. Although these studies have explored the effect of workers' interaction on regional economic growth and its relationship with externalities, what emerges is that a clear picture does not yet exist and much remains to be investigated. This is mainly because most previous studies considered one innovation driver at a time or a partial interaction between them (e.g. considering how skills interact in the specialised context without considering the role of diversification). To reach new evidence, our contribution is to consider the simultaneous relationship between innovation, different types of externalities and workers' skills complementarity. For this purpose, we derive the following research hypothesis:

> RH2: The innovation propensity is strongly affected by the interaction between skills complementarity and specialisation/diversification

Naturally, workers' flows are not limited to regional boundaries but can occur across regions. Thus, a stream of literature has explored the relationship between intra- (i.e. within regional boundaries) and inter-regional flows (i.e. between regions), skills complementarity and economic performance. The basic assumption is that the skills' complementarity scheme is influenced by the mobility of intra- and inter-regional workers. In the case of *overlapped skills*, while intra-regional recruitment could reinforce the risk of running into lock-in problems, inter-regional recruitment could reduce it. In other words, in the case of inter-regional flows, the overlapped skills may be less damaging to economic performance because extra-regional employees may represent valuable resources acquired in distant locations (Asheim & Isaksen, 2002). Ejermo et al. (2022) analysed the effect of easier workers' inter-regional mobility on inventive activity, showing that attracting human capital (albeit overlapping) across regional borders could better match skills generating greater innovation outcomes. Similarly, Perret (2021) highlighted that reducing the barriers of inventors' mobility across regions increases the diffusion of knowledge. Essletzbichler and Rigby (2005) and Rigby and Essletzbichler (2006) argued that intra-regional mobility has less chance of bringing in new knowledge because firms of the same local productive system tend to look more alike. Since this is less true for firms belonging to the same sectors but in different local productive systems, the new knowledge generation could be fostered by hiring people from firms located in other regions. The relationship can be different in the case of *connected skills* and *unlinked skills*. According to Boschma et al. (2009), intra-region flows are more likely to create new knowledge for both types of competencies. For connected skills, geographical proximity improves the capability to absorb new skills. In the case of unlinked skills, the greater the unrelatedness, the greater the geographical proximity needed to solve potential communication and coordination problems. In sum, intra- and inter-regional mobility do not necessarily contribute to economic performance because it depends on the types of skills flows (and to what extent these match the existing skill portfolio) and the types of economic activities considered. Cappelli et al. (2019) proved this ambiguous relationship by evaluating the impact of inter-regional workers' mobility on the survival rates of firms belonging to industries in different development stages. The authors split their sample into young and mature industries finding that intra-regional flows and connected skills improve the survival chances of firms in young industries. In mature industries, inter-regional mobility reduces the negative effect of overlapped skills on firms' survival. To the best of our knowledge, no similar schemes have been proposed in innovation-based studies. In this field, we wonder what type of relationship characterises the innovation-related sector and workers' mobility across regions:

RH3: Inter-regional mobility of workers featuring overlapped skills does not reduce the regional innovation propensity.
RH4: The positive effect of mobility on workers with connected skills is stronger in intra-regional flows than in inter-regional flows. Unlinked skills are less damaging in the case of intra-regional mobility.

Research Design

Case Study: Italy

The four research hypotheses detailed in the previous section were tested on the Italian provinces, which can be considered differentiated territories characterised by productive specialisations and human capital endowments that distinguish them from each other. Ciccarelli and Fenoaltea (2013) stated that Italy has historically been characterised by a huge economic gap between North and South (Fig. 1a). The persistence of territorial inequalities remains partially unanswered despite being debated for a long time and is still the subject of ever-expanding international literature (Felice, 2012). This gap was inevitably reflected in human capital accumulation and the geography of innovation outcomes (Ballarino et al., 2014).

First, the differences in human capital accumulation are often linked to the economic gap between the two Italian macro-areas (Cappelli, 2016), which leads to differences in the respective productive structures. This aspect fits well with our research questions that aim to test the connection between skills complementarity (as a form of human capital), geographical patterns and innovative outcomes. The idea is that if the level of technical progress differs among firms, industries and nations, it differs among regions due to their different productive structures. To discriminate whether an area is specialised or diversified, we resort to local spatial association indexes (Anselin, 1988) on data referred to innovation (i.e. patents). Figure 1b shows local spatial dependence through the local Moran's *I* statistics (LISA). LISAs indicate whether one or more local areas exhibit significant spatial clusters of similar values (Anselin, 1988). This local measure identifies 'hot' and 'cold' spots where

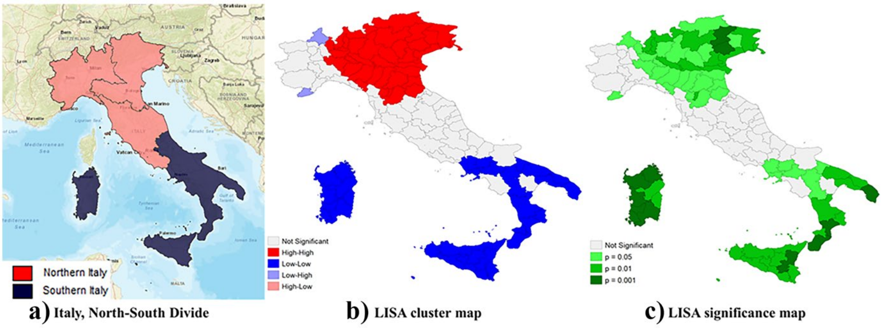

Fig. 1 North–South Italy divide (**a**), local innovation indicator (**b**), and local indicator significance (**c**). *Source*: Authors' elaborations on EPO (European Patent Office) data

provinces with high or low patent intensity are adjacent. Local Moran's *I* statistic also identifies areas where neighbouring provinces have significantly different data values. Our results show significant clusters of patent-intensive provinces in the northern area (the red provinces in Fig. 1b), suggesting the presence of a local knowledge network. Thus, we can classify this area as specialised. Southern Italy presents low patent intensity provinces (the blue provinces in Fig. 1b). This suggests that the local knowledge network is not active across the provinces, highlighting the presence of productive diversification. Figure 1c shows the associated significance map.

Second, although the number of registered patents has increased in recent years,[2] Italy is classified by Giovannini et al. (2015) as a 'moderate innovator', showing a patent intensity below the EU-27 average. In general, Italy is mainly characterised by more traditional low-tech sectors with less patent activity (i.e. textiles, clothing, leather goods, footwear, wood products) compared to patent-intensive ICT sectors and those more prone to innovation (i.e. chemistry, medical and precision equipment, office machines, computers). However, according to the Italian Chamber of Commerce,[3] over 60% of all Italian patents in 2018 were due to three regions in Northern Italy (i.e. Lombardy, Emilia Romagna, Veneto). Indeed, technology-intensive activities in machinery manufacturing and the automotive and aerospace sectors prevail in Lombardy (one of the most innovative regions in Europe), Emilia-Romagna (the number of patents per million inhabitants is one and half times higher than the national average) and Veneto, as well as metal processing. All southern regions are below the national average; in particular, Basilicata, Calabria, Sicily and Sardinia have fewer than ten patent applications per million inhabitants. Latium shows more creative, innovative or high-tech employees. Based on the above, the focus on Italy allows us to apply our research framework in a context characterised by a marked territorial polarisation both in terms of innovation activities and socio-economic and productive structures.

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

[3] For further details, see the following document: https://www.milomb.camcom.it/upload/file/1700/850209/FILENAME/Lombardia_brevetti.pdf (Accessed on 10 Sept 2020).

Method

The empirical strategy relies on the Spatial Durbin Model (SDM). Belonging to the framework of spatial econometric models, the SDM represents an extension of the spatial autoregressive model (SAR) because it considers the spatial lags of the explanatory variables and the spatial lag of the dependent variable (Abreu et al., 2004; LeSage, 2008). Following Elhorst (2014), the SDM is formally expressed as follows:

$$Y = \rho WY + \alpha \iota_N + X\beta + \gamma WX + \varepsilon \ with \ \varepsilon \sim N\left(0_{nx1}, \sigma^2 I_n\right) \tag{1}$$

where Y is the vector of the dependent variable (in this work, the patents intensity of all Italian provinces); ι_N is a vector of ones associated with the constant term parameter α to be estimated; X is the matrix of the explanatory variables, and β is the vector of associated parameters. W is the spatial weight matrix;ρ is the spatial autoregressive parameter for the endogenous interaction effects (WY) and captures the spatial interaction associated with the dependent variable; γ is the vector of the spatial parameters for the exogenous interaction effects (WX); ε is the stochastic term, that is, a vector of independently and identically distributed error terms with zero mean and constant variance.

In the SDM, therefore, the structure spatial effects enter both *endogenously* through the spatial autoregressive term to reflect the impact of innovation propensity in neighbours and *exogenously* reflect the consequence for each province of the change in an exogenous variable (LeSage, 2008). As the spatial lagged dependent variable is usually correlated with the disturbance term, the SDM suffers from endogeneity, which can be addressed by using a set of instruments (Anselin, 1988), i.e. variables that are correlated with the spatially lagged variable (instrument relevance) and independent of the errors (instrument exogeneity) (see the 'Conclusions' section). The SDM does not impose prior restrictions on the magnitude of spatial spillover effects, which can be global or local and be different for different covariates; moreover, the SDM provides unbiased coefficient estimates even in the presence of spatial error dependence (Elhorst, 2014).

In the presence of the spatial autoregressive term ρ, the change in a covariate in a given province *directly* affects the dependent variable in that province and *indirectly* affects the dependent variable (spillover effects) in neighbouring provinces (Elhorst, 2014; LeSage, 2008). Both direct (2) and indirect (3) effects of a particular covariate also depend on the coefficient γ_k of the spatially lagged value of that variable (Elhorst, 2014). Formally:

$$\text{Diagonal elements of } (I - \rho W)^{-1}[\beta_k + W\theta_k] \tag{2}$$

$$\text{Off} - \text{diagonal elements of } (I - \rho W)^{-1}[\beta_k + W\theta_k] \tag{3}$$

As there is no well-established rule in the literature for choosing spatial weights (Elhorst, 2014), which may change according to the research needs, in this work, we use the spatial weight matrix obtained through the k-nearest neighbours method, which allows identifying a cohort of k nearest provinces and controlling for the dependence between these provinces (Anselin, 1988; LeSage, 2008). We obtain the binary contiguity matrix in which 1 denotes two neighbouring provinces and 0 otherwise. To better explain, setting k equal to 10 neighbours, the value is 1 for province A with respect to the first 10 surrounding provinces (e.g. province A and province B, provinces A and C, provinces A and D, and so on). To select the number of k-neighbours, we use the cross-validation scheme through Moran's I value (LeSage, 2008). We build different spatial matrices (i.e. $k=5$, $k=10$, $k=15$, and so on), and for each of them, we compute the Moran index. We choose the matrix that returns the highest index value, $k=10$. This result is well suited to our objectives because it allows us to control for inter-regional effects.

Data

The analysis is based on a dataset obtained by assembling the information gathered from official sources, namely EPO (European Patent Office) and ISTAT (National Institute of Statistics). The data covers 110 Italian provinces—corresponding to the NUTS-3 level of the Eurostat classification—allowing us to use the finest territorial level, which presents a large amount of information on patents and covariates. Due to constraints on data availability, the analysis refers to 2012, which represents the date with the most up-to-date information on both the dependent variable and the covariates.

This study explores the determinants of innovative activities in the Italian provinces. Since measuring innovation activities is difficult, we resort to its reliable proxy measure, i.e. the patents intensity variable. Patent intensity is measured as the ratio between the number of patents and inhabitants. There is much evidence in the literature that patents provide a fairly reliable measure of innovative activities at the firm level (Acs & Audretsch, 1989) and the territorial level (Acs et al., 1992). The reliability of this variable has also been proved at high territorial details to study the nature of knowledge flows that could be locally bounded. Anselin et al. (1997) carried out a study at the US metropolitan statistical areas (MSAs) level, providing the first evidence of an explicit account for the effects of localised knowledge flows on innovation. Acs et al. (2002) tested the accuracy of patents as a measure of innovative activity at the regional level, the lowest possible levels of geographical aggregation they could analyse. Other empirical evidence on the reliability of patents as a proxy for innovation comes from Baghdadi and Aouadi (2018), who linked the technological performance of Mediterranean countries with their patenting activities. Caliari and Chiarini (2021) used patent application data to proxy knowledge production to evaluate the relationship between economic development and the domestic capacity to produce new knowledge. Furthermore, patents still play a central role in innovation studies in the recent empirical literature (see, for example, Cuellar et al., 2021; Sun and Ghosal, 2020; Braunerhjelm et al., 2020; Innocenti et al., 2020; Burhan et al., 2017; Dressler, 2012). For completeness, the patent variable has some limitations (Ganau & Grandinetti, 2021, for details).

Explanatory variables include *R&D expenditure*. It is expressed as the share of GPD dedicated to developing technological innovations and new products. To allow comparability between provinces, this variable is relativised by the number of employees in R&D. It has been commonly used in the literature in patent production models because R&D is an input to the generation of patents. Meliciani (2000) demonstrated the importance of investment activities in contributing to innovation and technical change through longitudinal and multi-country analysis. Many other authors have shown that patents are highly correlated with the overall level of R&D expenditure (Buerger et al., 2012; Gumbau-Albert & Maudos, 2009; Piergiovanni & Santarelli, 2001; Sun et al., 2020). *Population density* is another control variable of our empirical analysis. It is obtained as the ratio of people per square kilometre. As argued by Moreno et al. (2005), the rationale behind introducing this variable in the model is to capture the urbanisation rate of the Italian provinces. The idea is that innovative activities are higher in large metropolitan areas than in less urbanised ones. Ciccone (2002) highlighted how population density is a good proxy for urbanisation and agglomeration. Beyond these due control variables, we resort to skill-based variables to test the research hypotheses to capture information related to the *skills complementarity*, i.e. *overlapped skills*, *connected skills*, and *unlinked skills*. Measuring the complementarity of skills is a complex task as it would require a comprehensive description of human capital needs across industries or occupations. In light of the difficulties in collecting this information accurately and exhaustively for all industries in the Italian economy, we follow the approach proposed by Neffke and Henning (2013). They developed a skill relatedness index to study the Sweden labour market in 2004–2007. Their index is based on the labour flows among industries because individuals changing jobs are likely to stay in industries that value the skills associated with their previous job. From a methodological point of view, the index is formulated as follows: $SR_{ij} = ^{F_{ij}} / _{\widehat{F_{ij}}}$ where F_{ij} represents the labour flows from the industry of origin i to the destination industry j while $\widehat{F_{ij}}$ is the predicted labour flows from industry i to industry j. The predicted labour flows are estimated through the zero-inflated negative binomial model in which the dependent variable is the observed labour flows (F_{ij}), and the covariates are industry characteristics-based variables (e.g. size, employment growth, wage levels, and so on). When $SR_{ij} = 1$, the skills are unlinked; values greater than 1 indicate overlapped skills while less than 1 indicate connected skills. Based on the above, Neffke and Henning (2013) developed a skills relatedness matrix that we used on the data referring to the provincial component of the workforce in Italy to define the three variables of skills complementarity (i.e. *overlapped skills*, *connected skills*, and *unlinked skills*).

The variables are expressed in terms of percentage share of the total workforce. SR has been used in other works. For example, Cappelli et al. (2019) used it to study the Dutch labour market in 2001–2009;) focused on Germany in 1975–2014. As stated in the 'Literature Review and Research Hypotheses' section, the skills endowments of hired workers may impact the innovation propensity. When new skills can be easily integrated and absorbed into existing knowledge, the probability of generating innovations increases (Cappelli et al., 2019). To determine the effects of specialisation (diversification) and inter-regional workers' mobility, we resort to the SDM, which considers both dependent and independent spatially lagged variables. The spatial lag of patents intensity captures the peer effect exerted by neighbouring provinces, highlighting whether an innovative network is activated locally, leading

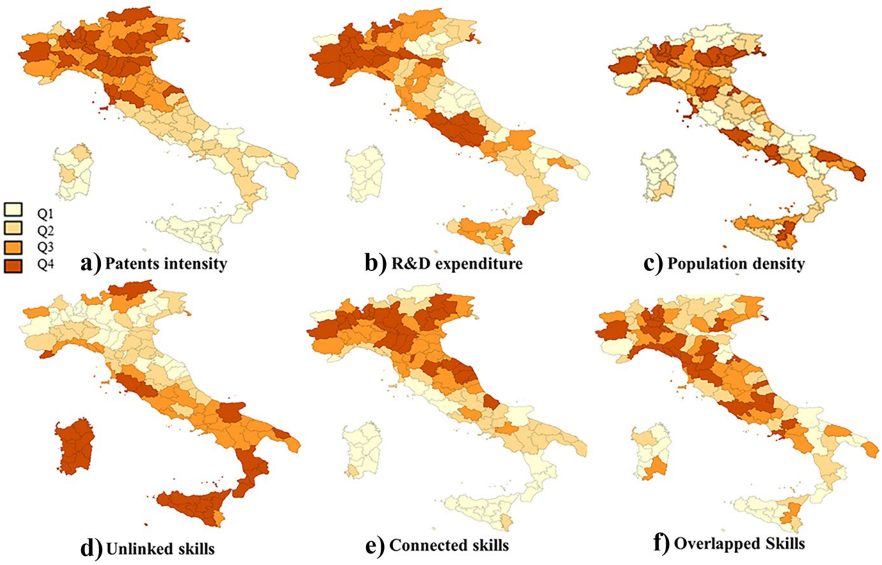

Fig. 2 Territorial distribution (provincial level) of variables by quantiles. *Source*: Authors' elaborations on ISTAT and EPO data

to the specialisation of an area in innovative activities. In other words, it is a measure of the productive specialisation (diversification) of the areas. The spatial lag of the covariates allows us to control for their indirect effects, i.e. the impact of a covariate on the neighbouring provinces. Figure 2 presents the territorial distribution by quantile of the main variables we used in the analysis to characterise the Italian context.

Results and Discussion

Table 1 shows the SDM estimates that allow us to test the research hypotheses detailed in the 'Literature Review and Research Hypotheses' section. As previously stated, the SDMs were estimated both globally on all the Italian provinces (first column) and separately on the two macro-areas of northern provinces (second column) and southern provinces (third column). The log–log specification allowed for the interpretation of coefficients as the elasticity of the dependent variable with respect to covariates, i.e. the percentage change in patent intensity for a percent change in a given covariate. The maximum likelihood estimator was used to cope with the endogeneity issue due to the inclusion of spatially lagged dependent variable (Anselin, 1988). For robustness, the SDMs were also estimated using the two-stage least squares approach, which uses the spatially lagged covariates as instruments to solve endogeneity. Convergence between the two sets of estimates was found.

Regarding the SDM estimates for all Italian provinces, the elasticity of patent intensity with respect to R&D expenditure (0.514) is statistically significant. This result is perfectly in line with other studies showing an elasticity range of

Table 1 SDM estimates on Italian provinces and by macro-area

	Pooled (Italy)	Northern Italy	Southern Italy
W*Patents intensity	0.499***	0.778***	0.131***
	(0.154)	(0.204)	(0.036)
Direct effects			
Population density	0.205	0.166	0.164
	(0.246)	(0.147)	(0.357)
R&D	0.514***	0.865***	0.199***
	(0.043)	(0.279)	(0.041)
Overlapped skills	0.240**	0.127	0.297*
	(0.118)	(0.871)	(0.204)
Connected skills	1.792***	1.822***	0.994***
	(0.666)	(0.445)	(0.229)
Unlinked skills	0.539	0.913**	0.279
	(0.458)	(0.405)	(0.472)
Indirect effects			
Population density	0.131	0.324	0.069
	(0.141)	(0.258)	(0.747)
R&D	0.098***	0.148***	0.017**
	(0.039)	(0.635)	(0.011)
Overlapped skills	0.448***	0.158***	0.391**
	(0.135)	(0.396)	(0.211)
Connected skills	1.724***	1.176***	0.678***
	(0.623)	(0.453)	(0.226)
Unlinked skills	0.073	0.197*	0.064
	(0.202)	(0.138)	(0.374)
Constant	1.612**	2.471	1.768
	(0.779)	(5.095)	(1.688)

0.2–0.9 in the USA (Acs et al., 1994; Anselin et al., 1997) and 0.2–0.8 in Europe (Bottazzi & Peri, 2003; Moreno et al., 2005). Even within the two macro-areas (northern and southern Italy), the elasticities of patent intensity with respect to R&D expenditure are pretty consistent with the range established by the literature. However, a significant difference emerges, as Northern Italy appears more skilled than the South at transforming R&D input into innovation output.

The spatially lagged patent intensity variable can help explain the role played by agglomeration externalities on innovative activities and investigate which type of externalities (i.e. specialisation or diversification) is most incisive in stimulating them. The coefficient of this variable provides a measure of the influence of neighbours on a given province by highlighting whether the knowledge network is active in that area. In this case, the area shows a high concentration of innovation activities and can be considered specialised with MAR externalities; in the absence of knowledge networks, the area is characterised by a low patent production, such as being classified as a diversified area with Jacobs externality. Regarding the global SDM, the spatially lagged patent intensity variable's coefficient highlights the significant role of interprovincial spillovers in innovative outputs. However, only SDMs by macro-area allowed us to verify any differences in the levels of innovation due to the two different types of externalities, specialisation and diversification. The results show a higher advantage of the specialised areas (northern Italy) than the diversified areas (southern Italy). The different magnitude of the coefficients between the two models allowed us to answer the *RH1* that specialised areas (MAR externalities) have a deeper impact on innovation activities by stimulating innovation propensity.

From a policy perspective, the question is how to promote agglomeration externalities in the South, where the presence of activities with a high propensity for innovation is relatively scarce. One way could be to promote innovative small and medium-sized enterprises (SMEs) and highly technological start-ups through two possible actions: incentives and business networks.

As regards incentives, the Italian Government has introduced financial instruments, such as 'Smart & Start Italy' and 'Patents plus', aimed at 'promoting, throughout the national territory, the conditions for the diffusion of new entrepreneurship and supporting the policies of technology transfer and economic enhancement of the results of the public and private research system'.[4] However, such initiatives are targeted to the entire national territory, and only a small percentage is destined exclusively for firms in southern Italy. Moreover, these measures must be adequately managed to promote innovation over time. In this field, increasing the role played by local governments in terms of funding and monitoring could be a proper solution to narrow the North–South divide.

As regards business networks, one strategy could be represented by network contracts, that is, contracts signed by several entrepreneurs to increase, individually and collectively, the innovative capacity and competitiveness on the market. To this end, entrepreneurs undertake to collaborate on a common program, exchanging information or services of an industrial, commercial, technical or technological nature and jointly carrying out one or more activities. Theoretically, network contracts are a powerful tool for activating knowledge networks; in practice, these collaborations risk being underused, becoming only a vehicle for reaching funding rather than sharing knowledge, skills and competencies. Also in this case, monitoring activities of national and local administrations can play a crucial role in favouring the development of the territory.

Regarding the skills complementarity variables, i.e. unlinked skills, connected skills and overlapped skills, direct effect estimates allow us to explore *RH2*. The global SDM show the heterogeneous impact of workers' skills on innovation. As expected, workers with unlinked skills have no impact on patent intensity, confirming the theory that this type of human capital does not generate new knowledge (Cappelli et al., 2019). The results also show the positive relationship between innovation and connected/overlapped skills, and that connected skills are the most important type of human capital because cognitive proximity allows the generation of new knowledge (Neffke et al., 2017a, b). More precisely, in a highly specialised

[4] For further details: https://www.mise.gov.it/index.php/it/incentivi/impresa/smart-start; https://www.invitalia.it/cosa-facciamo/rafforziamo-le-imprese/brevetti

context in northern Italy, the role of workers with connected skills keeps its importance, while overlapped skills become insignificant. However, in such contexts, workers with unlinked skills can contribute to innovation activities, probably thanks to their scarce diffusion within the macro-area (compared to the rest of the country, see Fig. 2). This does not apply to diversified southern Italy, where the role of workers with unlinked skills appears to be insignificant. Similar considerations concern workers with overlapped skills whose coefficient is weakly significant.

While the relationship between complementarity skills and innovation is confirmed in the global model (i.e. workers with connected/overlapped skills improve the innovation propensity), significant differences emerge when considering productive specialisation (diversification). The specialised areas valorise the contribution of workers with connected skills, while the overlapping of skills seems to be the victim of the lock-in effect. However, specialised contexts also valorise unlinked skills. In diversified contexts, only workers with connected skills play a significant role.

The results show the difficulty of southern Italy in retaining within its border workers with skills strongly linked to the knowledge sectors. Most of the workers with connected and overlapped skills are in northern Italy, and most of the southern workforce is composed of unlinked workers who contribute in a limited way to the creation of innovations. Between 2002 and 2017, over two million workers moved from the South to the North of Italy, and more than a third were young people and graduated/highly skilled workers (ISTAT online dataset).[5] While this is also a relevant issue from a social perspective, the results highlight that homogenous socio-economic contexts can valorise the workers' skills by helping the integration and assimilation of new knowledge to create new ones. Therefore, it is important to support the creation of local knowledge networks through the development of new innovation-orientated enterprises in the South. In this view, policymakers should consider that the valorisation of skills (with the differences due to skills complementarity) cannot be separated from the actions required to improve the productive structure of the less innovative-oriented areas. In summary, it seems necessary to consider the socio-economic specificities when dealing with innovation policies. However, the joint action of territorial agglomeration externalities (specialisation) and the workforce skills composition plays a pivotal role in generating new knowledge and promoting innovation outcomes.

Based on the above, considering the indirect effects of overlapped skills provides us with information to explore the *RH3*. The results confirm that the mobility of workers featuring overlapped skills can contribute to innovative activities when it occurs between provinces of different macro-areas. In particular, while the direct effects showed that the overlapping of competencies was not contributing in a highly specialised context, the indirect effects highlight that extra-provincial workers might represent valuable resources. Thus, we can confirm the *RH3* of a positive relationship between innovation propensity and inter-regional mobility of workers with overlapped skills.

[5] The ISTAT online dataset can be found at the following URL: http://dati.istat.it/

Finally, comparing the magnitude of direct and indirect effects in the connected/unlinked skills coefficients allows us to answer *RH4*. In the case of connected skills, the magnitude of the direct effect appears significantly higher than that of indirect effects for both the specialised and diversified areas. This confirms the hypothesis that even in the context of innovation, geographical proximity improves the capability to absorb the related skills regardless of the productive structure of the areas. *RH4* is also confirmed in the case of unlinked skills. While in the diversified area their role is not always significant, in the specialised area their contribution is greater for intra-regional flows because the spatial proximity helps to solve potential incompatibility issues.

Conclusions

The European Commission recognised innovation as a major driver of productivity growth and a key long-term lever for economic growth and prosperity (Giovannini et al., 2015). Fostering innovation is part of the European agenda, particularly the Goal 'resilient infrastructure, promoting inclusive and sustainable industrialisation'. The United Nations, through the Addis Ababa Action Agenda, share the same opinion underlining that 'the creation, development and diffusion of innovations and technologies and associated know-how, including the transfer of technology on mutually agreed terms, are powerful drivers of economic growth and sustainable development' (Agenda, 2015).

In this context, exploring the driving forces behind the innovation generation process is a research question of great relevance. Previous studies focused on the one-to-one relationship between innovation outcomes and their drivers (such as externalities, knowledge flows, and worker mobility), highlighting a research gap about their simultaneous effect on innovation.

This study aimed to provide original empirical evidence on the innovation activity generation process by using a more comprehensive framework in which the impact of agglomeration externalities (MAR vs. Jacobs externalities), skills complementarity and intra- and inter-regional mobility of workers are assessed jointly. Furthermore, the focus on Italy allowed us to apply the research framework in a context characterised by a marked territorial polarisation in terms of innovation activities and socio-economic and productive structures. Well-performing northern Italy can represent a benchmark for the more backward South, providing the ground for identifying policy actions that could favour convergence between the two Italian macro-areas.

In general, the results obtained for all the Italian provinces align with the literature on the relationship between human capital and economic performance. However, the inclusion in the analysis of the dimension of specialisation/diversification has led to different thoughts.

First, the results highlighted that the productive specialisation (MAR externalities) plays a more decisive role in fostering innovation activities with respect to more diversified productive structures (Jacobs externality). The second point of interest regards human capital. The results showed that the contribution of workers with connected skills is more valorised in the specialised areas of northern Italy, which also valorise unlinked skills. The diversified contexts can only valorise workers with connected skills. Third, the results showed that the mobility of workers with overlapped skills could contribute to innovative activities when it occurs between provinces of different macro-areas since the inter-regional mobility of workers with overlapped skills does not reduce the regional innovation propensity. Fourth, the results showed that geographical proximity could improve the territory's ability to absorb the related skills regardless of its productive structure. However, in specialised areas, the contribution of unlinked skills is greater for intra-regional flows as spatial proximity helps to solve incompatibility issues.

Inter-country differences in the effectiveness of joint action of agglomeration externalities and skills complementarity could be investigated together with the implications of countries' specialisation patterns in influencing their ability to generate innovation activities. Another research development could consist in using data with finer territorial detail, i.e. municipal data. In this way, we would provide more detailed insights into the role played by the workforce's skills composition and agglomeration externalities. However, there is a lack of data with this territorial detail, but once available, it is research that we could carry out.

Data Availability The data that support the findings of this study are available from the corresponding author, GM, upon reasonable request.

References

Abreu, M., De Groot, H. L., & Florax, R. J. (2004). Space and growth: A survey of empirical evidence and methods. *Région Et Développement, 21*, 13–44.

Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy, 31*(7), 1069–1085.

Acs, Z. J., & Audretsch, D. B. (1989). Patents as a measure of innovative activity. *Kyklos, 42*(2), 171–180.

Acs, Z. J., Audretsch, D. B., & Feldman, M. P. (1992). Real effects of academic research: Comment. *The American Economic Review, 82*(1), 363–367.

Acs, Z. J., Audretsch, D. B., & Feldman, M. P. (1994). R&D spillovers and recipient firm size. *The Review of Economics and Statistics*, 336–340.

Agenda, A. A. A. (2015). Addis Ababa Action Agenda of the Third International Conference on Financing for Development. UN. *Development, 2*, 37.

Ahmad, M., & Zheng, J. (2022). The cyclical and nonlinear impact of R&D and innovation activities on economic growth in OECD economies: A new perspective. *Journal of the Knowledge Economy*, 1–50.

Aho, E., Cornu, J., Georghiou, L., & Subira, A. (2006). Creating an innovative Europe. *Report of the independent expert group on R&D and innovation appointed following the Hampton Court Summit, 1*, 1–25. https://ec.europa.eu/invest-in-research/pdf/download_en/aho_report.pdf

Anselin, L. (1988). Spatial econometrics: Methods and models (Vol. 4). *Studies in Operational Regional Science. Dordrecht: Springer Netherlands.*

Anselin, L., Varga, A., & Acs, Z. (1997). Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics, 42*(3), 422–448.

Anselin, L., Varga, A., & Acs, Z. J. (2000). Geographic and sectoral characteristics of academic knowledge externalities. *Papers in Regional Science, 79*(4), 435–443.

Aritenang, A. F. (2021). The importance of agglomeration economies and technological level on local economic growth: The case of Indonesia. *Journal of the Knowledge Economy, 12*(2), 544–563.

Arrow, K. J. (1962). The Economic Implications of Learning by Doing/Arrow KJ. *Review of Economic Studies, 29*, 29–32.
Asheim, B. T., & Isaksen, A. (2002). Regional innovation systems: The integration of local 'sticky'and global "ubiquitous" knowledge. *The Journal of Technology Transfer, 27*(1), 77–86.
Baghdadi, H. B., & Aouadi, S. (2018). Does Patent Performance Promote Relative Technological Performance in Countries Bordering the Mediterranean? *Journal of the Knowledge Economy, 9*(4), 1246–1269.
Ballarino, G., Braga, M., Bratti, D. C., Filippin, A., Fiorio, C., Leonardi, M., Meschi, E., & Scervini, F. (2014). chapter 16 ITALY: HOW LABOUR MARKET POLICIES CAN FOSTER EARNINGS INEQUALITY. *Changing Inequalities and Societal Impacts in Rich Countries: Thirty Countries' Experiences*, 369.
Beaudry, C., Breschi, S., & Swann, G. (2001). Clusters, innovation and growth: A comparative study of European countries. In J. Dunning & J. L. Mucchielli (Eds.), *Multinational Firms: The Global and Local Dilemma* (pp. 190–213). Routledge.
Beaudry, C., & Schiffauerova, A. (2009). Who's right, Marshall or Jacobs? The localisation versus urbanisation debate. *Research Policy, 38*(2), 318–337.
Boschma, R., Eriksson, R. H., & Lindgren, U. (2014). Labour market externalities and regional growth in Sweden: The importance of labour mobility between skill-related industries. *Regional Studies, 48*(10), 1669–1690.
Boschma, R., Eriksson, R., & Lindgren, U. (2009). How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity. *Journal of Economic Geography, 9*(2), 169–190.
Bottazzi, L., & Peri, G. (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review, 47*(4), 687–710.
Bound, J., Cummins, C., Griliches, Z., Hall, B. H., & Jaffe, A. B. (1982). *Who does R&D and who patents?*. National Bureau of Economic Research.
Braunerhjelm, P., Ding, D., & Thulin, P. (2020). Labour market mobility, knowledge diffusion and innovation. *European Economic Review, 123*, 103386.
Buerger, M., Broekel, T., & Coad, A. (2012). Regional dynamics of innovation: Investigating the co-evolution of patents, research and development (R&D), and employment. *Regional Studies, 46*(5), 565–582.
Burhan, M., Singh, A. K., & Jain, S. K. (2017). Patents as proxy for measuring innovations: A case of changing patent filing behavior in Indian public funded research organisations. *Technological Forecasting and Social Change, 123*, 181–190.
Caliari, T., & Chiarini, T. (2021). Knowledge production and economic development: Empirical evidences. *Journal of the Knowledge Economy, 12*(2), 1–22.
Cappelli, G. (2016). One size that didn't fit all? Electoral franchise, fiscal capacity and the rise of mass schooling across Italy's provinces, 1870–1911. *Cliometrica, 10*(3), 311–343.
Cappelli, R., Boschma, R., & Weterings, A. (2019). Labour mobility, skill-relatedness and new plant survival across different development stages of an industry. *Environment and Planning a: Economy and Space, 51*(4), 869–890.
Carayannis, E. G., Depeige, A., & Sindakis, S. (2014). Dynamics of ultra-organisational co-opetition and circuits of knowledge: A knowledge-based view of value ecology. *Journal of Knowledge Management*.
Carayannis, E. G., Grigoroudis, E., Campbell, D. F., Meissner, D., & Stamati, D. (2018). The ecosystem as helix: An exploratory theory-building study of regional co-opetitive entrepreneurial ecosystems as quadruple/quintuple helix innovation models. *R&d Management, 48*(1), 148–162.
Castillo, V., Figal Garone, L., Maffioli, A., Rojo, S., & Stucchi, R. (2020). Knowledge spillovers through labour mobility: An employer–employee analysis. *The Journal of Development Studies, 56*(3), 469–488.
Chen, H., Yao, Y., Zan, A., & Carayannis, E. G. (2020). How does coopetition affect radical innovation? The roles of internal knowledge structure and external knowledge integration. *Journal of Business & Industrial Marketing, 36*(11), 1975–1987.
Ciccarelli, C., & Fenoaltea, S. (2013). Through the magnifying glass: Provincial aspects of industrial growth in post-Unification Italy 1. *The Economic History Review, 66*(1), 57–85.
Ciccone, A. (2002). Agglomeration effects in Europe. *European Economic Review, 46*(2), 213–227.
Combes, P. P. (2000). Economic structure and local growth: France, 1984–1993. *Journal of Urban Economics, 47*(3), 329–355.

Commission of the European Communities. (2009). Communication From the Commission to the Council, the European Parliament, the European Economic and Social Committee, and the Committee of the Regions: A Mid-Term Assessment of Implementing the EC Biodiversity Action Plan. *Journal of International Wildlife Law & Policy, 12*(1–2), 108–120.

Cuellar, S., Méndez-Morales, A., & Herrera, M. M. (2021). Location matters: A novel methodology for patent's national phase process. *Journal of the Knowledge Economy*, 1–26.

Dicken, P., & Malmberg, A. (2001). Firms in territories: A relational perspective. *Economic Geography, 77*(4), 345–363.

Diodato, D., Neffke, F., & O'Clery, N. (2018). Why do industries coagglomerate? How Marshallian externalities differ by industry and have evolved over time. *Journal of Urban Economics, 106*, 1–26.

Diodato, D., & Weterings, A. B. (2015). The resilience of regional labour markets to economic shocks: Exploring the role of interactions among firms and workers. *Journal of Economic Geography, 15*(4), 723–742.

Dressler, M. (2012). Assessing the economic effects of patents. *Journal of the Knowledge Economy, 3*(3), 294–301.

Drivas, K., Economidou, C., & Karkalakos, S. (2014). Spatial aspects of innovation activity in the US. *Journal of the Knowledge Economy, 5*(3), 464–480.

Duranton, G., & Puga, D. (2000). Diversity and specialisation in cities: Why, where and when does it matter? *Urban Studies, 37*(3), 533–555.

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In *Handbook of Regional and Urban Economics* (Vol. 4, pp. 2063–2117). Elsevier.

Ejermo, O. (2005). Technological diversity and Jacobs' externality hypothesis revisited. *Growth and Change, 36*(2), 167–195.

Ejermo, O., Hussinger, K., Kalash, B., & Schubert, T. (2022). Innovation in Malmö after the Öresund bridge. *Journal of Regional Science, 62*(1), 5–20.

Elhorst, J. P. (2014). *Spatial econometrics: from cross-sectional data to spatial panels* (Vol. 479, p. 480). Heidelberg: Springer.

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review, 100*(3), 1195–1213.

Eriksson, R. H., & Hane-Weijman, E. (2017). How do regional economies respond to crises? The geography of job creation and destruction in Sweden (1990–2010). *European Urban and Regional Studies, 24*(1), 87–103.

Essletzbichler, J., & Rigby, D. (2005). Competition, variety and the geography of technology evolution. *Tijdschrift Voor Economische En Sociale Geografie, 96*(1), 48–62.

Feldman, M. P. (1994). *The geography of innovation* (Vol. 2). Springer Science & Business Media.

Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities: Science-based diversity, specialisation and localised competition. *European Economic Review, 43*(2), 409–429.

Felice, E. (2012). Regional convergence in Italy, 1891–2001: Testing human and social capital. *Cliometrica, 6*(3), 267–306.

Fernandez, A. S., Le Roy, F., & Chiambaretto, P. (2018). Implementing the right project structure to achieve coopetitive innovation projects. *Long Range Planning, 51*(2), 384–405.

Fitjar, R. D., & Timmermans, B. (2017). Regional skill relatedness: Towards a new measure of regional related diversification. *European Planning Studies, 25*(3), 516–538.

Freire, J. A. F., & Gonçalves, E. (2021). Cooperation in innovative efforts: A systematic literature review. *Journal of the Knowledge Economy*, 1–37.

Galliano, D., Magrini, M. B., & Triboulet, P. (2015). Marshall's versus Jacobs' externalities in firm innovation performance: The case of French industry. *Regional Studies, 49*(11), 1840–1858.

Ganau, R., & Grandinetti, R. (2021). Disentangling regional innovation capability: What really matters? *Industry and Innovation, 28*(6), 749–772.

Giovannini, E., Niestroy, I., Nilsson, M., Roure, F., & Spanos, M. (2015). *The Role of Science, Technology and Innovation Policies to Foster the Implementation of the Sustainable Development Goals (SDGs): Report of the Expert Group Follow-up to Rio+ 20, notably the SDGs*. European Commission.

Goya, D. (2022). Marshallian and Jacobian Externalities in Creative Industries. https://publications.iadb.org/publications/english/document/Marshallian-and-Jacobian-Externalities-in-Creative-Industries.pdf

Greunz, L. (2004). Industrial structure and innovation-evidence from European regions. *Journal of Evolutionary Economics, 14*(5), 563–592.
Gumbau-Albert, M., & Maudos, J. (2009). Patents, technological inputs and spillovers among regions. *Applied Economics, 41*(12), 1473–1486.
Hausman, J. A., Hall, B. H., Griliches, Z. (1984). *Econometric models for count data with an application to the patents-R&D relationship* (No. t0017). National Bureau of Economic Research.
Henderson, J. V. (2003). Marshall's scale economies. *Journal of Urban Economics, 53*(1), 1–28.
Holm, J. R., Østergaard, C. R., & Olesen, T. R. (2017). Destruction and reallocation of skills following large company closures. *Journal of Regional Science, 57*(2), 245–265.
Ikari, H., Kono, T., & Zhou, Y. (2022). Industrial specialisation patterns across cities, agglomeration of skilled labour and technological growth. *Spatial Economic Analysis*, 1–21.
Innocenti, N., Capone, F., & Lazzeretti, L. (2020). Knowledge networks and industrial structure for regional innovation: An analysis of patents collaborations in Italy. *Papers in Regional Science, 99*(1), 55–72.
Jacobs, J. (1969). The economics of cities random house. *New York, NY*.
Jaffe, A. B. (1986). *Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value* (No. w1815). National Bureau of Economic Research.
Jibir, A., & Abdu, M. (2021). Human capital and propensity to protect intellectual properties as innovation output: The case of Nigerian manufacturing and service firms. *Journal of the Knowledge Economy, 12*(2), 595–619.
Kalash, B. (2022). *Agglomeration and Technological Specialization* (No. 2022–04). Groupe de REcherche en Droit, Economie, Gestion (GREDEG CNRS), Université Côte d'Azur, France. http://www.gredeg.cnrs.fr/working-papers/GREDEG-WP-2022-04.pdf
Katila, R., & Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal, 45*(6), 1183–1194.
Khoirunurrofik, K. (2018). Local economic structure, productivity growth, and industry life cycle: Evidence from Indonesia. *Asia-Pacific Journal of Regional Science, 2*(2), 453–475.
Koster, S., Brouwer, A. E., & van Leeuwen, E. S. (2020). Diversity as the key to success? Urban and rural employment dynamics in the Netherlands. *Regional Studies*, 1–13.
Krugman, P. R. (1991). *Geography and Trade*. MIT press.
Lazzeretti, L., Innocenti, N., & Capone, F. (2017). The impact of related variety on the creative employment growth. *The Annals of Regional Science, 58*(3), 491–512.
Lerner, J. (2010). Innovation, entrepreneurship and financial market cycles. https://www.oecd-ilibrary.org/science-and-technology/innovation-entrepreneurship-and-financial-market-cycles_5kmjp6nt8rr8-en
LeSage, J. P. (2008). An introduction to spatial econometrics. *Revue D'économie Industrielle, 123*, 19–44.
Luengo-Valderrey, M. J., & Moso-Díez, M. (2019). Interaction between knowledge management activities, innovation barriers and innovation performance: Spanish high and medium technology firms. *Journal of the Knowledge Economy, 10*(1), 298–317.
Marshall, A. (1890). Principles of economics Macmillan. *London (8th ed. Published in 1920)*.
Martinidis, G., Komninos, N., & Carayannis, E. (2021). Taking into account the human factor in regional innovation systems and policies. *Journal of the Knowledge Economy*, 1–31. https://doi.org/10.1007/s13132-021-00722-z
Massard, N., & Riou, S. (2002). L'impact des structures locales sur l'innovation en France: Spécialisation ou diversité. *Région Et Développement, 16*(2), 111–136.
Meliciani, V. (2000). The relationship between R&D, investment and patents: A panel data analysis. *Applied Economics, 32*(11), 1429–1437.
Moreno, R., Paci, R., & Usai, S. (2005). Spatial spillovers and innovation activity in European regions. *Environment and Planning A, 37*(10), 1793–1812.
Mowery, D. C., Oxley, J. E., & Silverman, B. S. (1996). Strategic alliances and interfirm knowledge transfer. *Strategic Management Journal, 17*(S2), 77–91.
Mukkala, K. (2004). Agglomeration economies in the Finnish manufacturing sector. *Applied Economics, 36*(21), 2419–2427.
Neffke, F. M., Otto, A., & Hidalgo, C. (2018). The mobility of displaced workers: How the local industry mix affects job search. *Journal of Urban Economics, 108*, 124–140.
Neffke, F. M., Otto, A., & Weyh, A. (2017a). Inter-industry labor flows. *Journal of Economic Behavior & Organization, 142*, 275–292.

Neffke, F., & Henning, M. (2013). Skill relatedness and firm diversification. *Strategic Management Journal, 34*(3), 297–316.
Neffke, F., Otto, A., & Weyh, A. (2017b). *Skill-relatedness matrices for Germany: Data method and access* (No. 2017b04_en). Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg [Institute for Employment Research, Nuremberg, Germany].
Nooteboom, B. (2000). *Learning and innovation in organisations and economies*. OUP Oxford.
Nuvolari, A., & Vasta, M. (2017). The geography of innovation in Italy, 1861–1913: Evidence from patent data. *European Review of Economic History, 21*(3), 326–356.
Ouwersloot, H., & Rietveld, P. (2000). The geography of R&D: Tobit analysis and a Bayesian approach to mapping R&D activities in the Netherlands. *Environment and Planning A, 32*(9), 1673–1688.
Paci, R., & Usai, S. (1999). Externalities, knowledge spillovers and the spatial distribution of innovation. *GeoJournal, 49*(4), 381–390.
Paci, R., & Usai, S. (2000). The role of specialisation and diversity externalities in the agglomeration of innovative activities. *Rivista Italiana Degli Economisti, 2*, 237–268.
Pakes, A., & Griliches, Z. (1984). Patents and R&D at the Firm Level: A first look. *R&D, patents and Productivity, University of Chicago: Chicago*, 55–70.
Perret, J. K. (2021). Interregional Inventor Mobility in the Russian Federation as Evidenced by European Patent Data. *Journal of the Knowledge Economy*, 1–33.
Piergiovanni, R., & Santarelli, E. (2001). Patents and the geographic localisation of R&D spillovers in French manufacturing. *Regional Studies, 35*(8), 697–702.
Rigby, D. L., & Essletzbichler, J. (2006). Technological variety, technological change and a geography of production techniques. *Journal of Economic Geography, 6*(1), 45–70.
Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy, 94*(5), 1002–1037.
Sun, X., Li, H., & Ghosal, V. (2020). Firm-level human capital and innovation: Evidence from China. *China Economic Review, 59*, 101388.
Sun, Y. (2000). Spatial distribution of patents in China. *Regional Studies, 34*(5), 441–454.
Tubiana, M., Miguelez, E., & Moreno, R. (2022). In knowledge we trust: Learning-by-interacting and the productivity of inventors. *Research Policy, 51*(1), 104388.
Van der Panne, G. (2004). Agglomeration externalities: Marshall versus jacobs. *Journal of Evolutionary Economics, 14*(5), 593–604.
Van der Panne, G., & van Beers, C. (2006). On the Marshall-Jacobs controversy: It takes two to tango. *Industrial and Corporate Change, 15*(5), 877–890.
Van Oort, F. (2002). Innovation and agglomeration economies in the Netherlands. *Tijdschrift Voor Economische En Sociale Geografie, 93*(3), 344–360.
Wang, M. C., Chen, P. C., & Fang, S. C. (2018). A critical view of knowledge networks and innovation performance: The mediation role of firms' knowledge integration capability. *Journal of Business Research, 88*, 222–233.
Widodo, W., Salim, R., & Bloch, H. (2015). The effects of agglomeration economies on technical efficiency of manufacturing firms: Evidence from Indonesia. *Applied Economics, 47*(31), 3258–3275.

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