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From the determinants of patent activity to the effect of regional production specialization on the use of intellectual property protection tools: a panel analysis for 18 Italian regions

Linda Mattioli
Alma Mater Studiorium, University of Bologna

Abstract

The scientific literature on the development of innovations in market economies has mainly focused on identifying the factors from which they originate. Since patents have been identified in the literature as a measure capable of approximating the production of new knowledge within an economic system, the present work aims to determine the factors underlying patent activity in eighteen Italian regions from 2012 to 2020. As demonstrated in the econometric analysis conducted, there is a positive correlation between the dependent variable - regional patent intensity index - defined as the ratio between the number of patents granted for industrial inventions in a single region and the population residing in the same region, and the following explanatory variables: i) the share of expenditure on research and development on the regional Gross Domestic Product (GDP); ii) the share of exports in regional value added. In addition, the different sectors of manufacturing activity have been reclassified using the Pavitt (1984) taxonomy, demonstrating that the transition from supplier dominated and scale intensive sectors to science-based and specialized supplier sectors implies an increase in patent activity.

JEL Classification: O1, O3

Keywords: *economic development; patents; regional production specialization.*

1. Introduction

With the aim of identifying the factors at the origin of innovative processes, a significant contribution has been made by the empirical work of Scherer (1983) who has highlighted the usefulness of patents as a measure that approximates the production of new knowledge within an economic system. Starting from this assumption, this paper aims to determine the factors at the origin of patent activity in eighteen Italian regions in the period 2012-2020. Subsequently, classifying the sectors of manufacturing activity using the Pavitt (1984) taxonomy, it will be shown that by moving towards science-based and specialized supplier sectors, the use of patents intensifies. As will be explained in detail in the fourth section, the use of patents in the regions is positively correlated with investment in Research and Development (R&D) and with export values. In the second section, a critical review of the literature is carried out, starting from the theories on innovation of Schumpeter (1912, 1942) and Schmookler (1966) according to which patents constitute an adequate proxy to investigate the evolution of innovative activity over time, as it is argued that they represent the most effective, precise, and detailed source of information on inventive activity available for a wide time horizon. Equally important are the contributions of Evenson (1993), who considers the use of patents to be an industry specified phenomenon dependent on government funding, and of Bound et al. (1984) according to whom the use of patents is determined by the size of the company, the characteristics of the industrial sector and investments in R&D. In line with the provisions of the Frascati Manual (2002) – the reference document for the collection and use of patents of data on R&D activity - research and development activities and intellectual property protection tools, including patents, trademarks, and utility models, are identified as input and output indicators of the innovation process, respectively.

The second section also presents the main theoretical contributions to the study of innovative processes, among which an important role is played by the evolutionary model due to the importance it attributes to the effect of tacit knowledge on the profitability levels of firms operating in different territories. For the study of the innovative processes of the Italian regions, the model of Cohen and Levinthal (1990) also provides a useful explanatory contribution, which demonstrates how the ability to exploit externally generated knowledge is a function of related knowledge that is already in the possession of firms, thus incorporating the absorption capacity into the determinants of the innovation process. Finally, the section offers a definition of the link between knowledge spillovers and economic growth identified by Acs et al. (2009), according to which public policies that foster spillovers through entrepreneurship can represent an innovative approach to promoting economic growth. In the analysis of regional innovation processes, it is impossible to ignore the peculiarities that characterize the economic-productive contexts of the Italian regions. Therefore, in the third section, the model of local development based on industrial districts and technological districts is initially presented, emphasizing their growing importance for the economic system.

In emphasizing the contribution of industrial districts to economic development, Fuà (1983) and Becattini (2006) highlighted their general economic importance and the specific nature of local networks of small and medium-sized enterprises specialized in the sector. In the vision of these two economists, the industrial district represents the territorial context in which positive externalities are realized and created as connections between the economic-productive dimension and the socio-cultural dimension. In recent times, under the pressure of globalization and the growing pressure due to international competition, there has been a transformation of industrial districts with respect to their original characteristics with the consequent affirmation of the reality of technological districts whose origins have been investigated by the "triple helix" model of Etzkowitz (1998), which demonstrates how the process of birth and development of a technological cluster requires collaboration through aligned objectives of the "three propellers", i.e. universities, public institutions and companies.

The same section also describes the technological districts that have developed since the 2000s in the Italian regions with the aim of having a reference framework for empirical analysis. As will be illustrated in the fourth section, dedicated to methodology, in this study the statistical units are represented by eighteen Italian regions observed annually from 2012 to 2020. For each, the dependent variable is constructed by relating the number of patents issued for industrial inventions to the population residing in the region each year. The dependent variable then defines the regional patent intensity index and is a proxy that captures the intensity of innovation processes in each region.

The explanatory variables introduced in the model are instead the following: 1) share of expenditure on research and development at regional level on total GDP; 2) share of exports on the added value produced by each region, which represents an indicator of international competitiveness capable of quantifying the role of foreign trade dynamics in stimulating domestic innovation. Subsequently, the activities of the manufacturing industry - classified according to the Ateco 2007 criterion - were placed in the four categories identified by the Pavitt taxonomy (1984) with the aim of identifying which of these there is a greater use of intellectual property protection tools. After calculating the values of the Balassa index (1965) for each region in the four Pavitt categories, it was possible to identify the pattern of production specialization at the regional level. Subsequently, it was shown that the transition from regions specialized in the supplier dominated and intensive scale sectors to those specialized in the specialized supplier and science-based sectors implies an increase in the patent intensity index, and therefore in the propensity to innovate. Finally, starting from the results obtained in the methodological section, the fifth section focuses entirely on the role played by public policies in the formulation of interventions aimed at promoting innovations. As far as the formulation of innovation policies is concerned, the literature has widely expressed its therapeutic role, starting from the identification of the weaknesses of innovative processes.

Hall and Soskice (2001), studying the relationship between political institutions and a country's economic performance, believe that at the origin of a country's comparative advantage in each sector there is an efficient collaboration between industry and public institutions. In addition, Florida (2004) and ACS (2007) underline the importance of creating a culture for innovation aimed at promoting economic growth and competitiveness: the creation of a culture for innovation concerns and encompasses all levels of society and is a process that is carried out through the promotion of public policies in favor of education, vocational training and research and development. In this process, the intervention of the public operator is crucial in encouraging entrepreneurship and in the creation of new businesses, especially those with a high knowledge intensity (ACS, 2007). In the formulation of political interventions, since the eighties of the last century, the concept of production system and industrial district has influenced the planning of territorial policies, leading to the definition of intervention frameworks aimed at supporting innovative processes rooted at the local level. The main policy interventions for innovation that have characterized the Italian economic scenario both at national and regional level are reviewed below, shedding light on its strengths and weaknesses.

The work is structured as follows: the second section consists of a critical review of academic contributions on the theme of innovation in economic systems; the third section describes local development models in Italy such as industrial districts; in the fourth section, econometric analysis is conducted for panel data; the fifth section is dedicated to the presentation of the main economic policy interventions aimed at strengthening entrepreneurship and innovation; The sixth section presents the results and conclusions of the present study.

2. Innovation in the economic system: a critical review of the literature

In the literature there are numerous empirical works that have investigated the phenomenon of patenting as a measure of the propensity to innovate.

First, it is worth mentioning the work of Schmookler (1966) which represents a significant contribution to the study of the relationships between market demand and inventions, in which patents constitute the proxy used to investigate the evolution over time of innovative processes, as it is argued that they represent the most effective and detailed sources of information on inventive activity available for a wide time horizon. Subsequently, many studies - (Taylor, 1973) (Wyatt, 1985) (Manfield, 1986) (Levin, 1987) - have investigated the effects of the patent system on the innovative behavior of the company, classifying the different instruments for the protection of intellectual property in order of importance. These works used microeconomic data at firm level collected through questionnaires and surveys carried out by government organizations, especially in studies examining the phenomenon of patenting in the United States.

Taylor (1973) demonstrated the influence of the patent system in promoting innovation by finding that about 5% of the innovations promoted by 27 British firms would not have been implemented if there had not been adequate protection of intellectual property. In line with the theses of Taylor (1973) and Mansfield (1986), the empirical work of Sirilli (1986) reaches the same conclusions starting from a questionnaire submitted to 555 Italian inventors. Among the works that are directly interested in the study of the determinants of the patent phenomenon, the contributions offered by Scherer (1983), Evenson (1984) and Bound et al. (1984) deserve particular attention. Exactly in accordance with the conclusions of the following paper, Scherer (1983) identifies the determinants of the propensity to patent such as the degree of production diversification, the degree of openness to the international market and government spending on research and development; Evenson (1984) argues that patenting is industry specific and depends on government funding, while for Bound et al. (1984) patent use is determined by the size of the firm, the characteristics of the industrial sector and investment in R&D, exactly as will be demonstrated in the fourth section. Scherer (1983) also uses enterprise-level microeconomic data from two archives that collect information on the income statement of some enterprises and on patents granted. The empirical effort of Evenson (1993) attempts to quantify to what extent the lower propensity to patent is to be attributed to a decline in the productivity of research activity, considering the relationship between patents granted and R&D expenditure not only as a simple indicator that measures the propensity to patent but as a measure of technological performance. Compared to the above-mentioned literature works, the renewed interest in the nature of the relationship between the propensity to innovate and the productivity of research and development is partly due to the spread of endogenous growth models that identify technological progress as the key determinant in the development of countries' productivity and the achievement of international comparative advantages.

2.1. Tools for empirical analysis: Pavitt's taxonomy and absorption capacity

In the methods for the empirical verification of the determinants of the innovation process, a very useful tool is represented by the taxonomy of Pavitt (1984) which will also be taken up in the following section (table 2.1). It represents the main tool for analyzing technological flows, through which a classification of companies into four groups has been constructed, distinguished since the main source of innovation for the companies operating there. Technological flows denote the exchanges, formal and informal, of technologies and innovations between sectors. Pavitt then classifies the product sectors since technological opportunities, the intensity of research and development and the type of knowledge flows that take place between sectors, identifying four groupings:

• Supplier dominated: includes companies that produce traditional consumer goods operating in the textile, footwear, food and beverage, paper and printing and timber sectors. This category is distinguished by the small-medium size of the production scale, by innovation objectives that are often cost-reducing, by the learning by doing and by using mode of learning and by a low degree of appropriability.

• intensive scales: groups together companies that produce durable goods such as base metals, motor vehicles and related engines. The characteristics of this grouping are expressed in the large size of the production scale, in the objectives of cost-reducing and quality improving, in the main external source of innovation represented by relations with suppliers, while the main source is constituted by investments in research and development and in the average degree of appropriability that manifests itself in the use of patents and industrial secrets.

• specialized suppliers which include manufacturers of agricultural and industrial machinery, office machinery and optical, precision, and medical instruments. The innovation objectives in this case focus on product innovation, the main external source of innovation comes from relationships with buyers while the main internal source of innovation is learning economies. In this sector, the high degree of appropriability is due to the tacit character of knowledge.

• science-based which includes companies in the chemical, pharmaceutical and electronics sectors. The production scale in this case can be variable, the objectives of innovation concern radical product innovation and process innovation, the main external and internal sources of innovation derive respectively from relations with university and research centers and internal investments in research and development. As in the previous case, the degree of appropriability and propensity to patent are high.

Table 2.1. *Pavitt's Taxonomy (1984).*

	supplier dominated	***scale intensive***	***specialised supplier***	***science based***
Production scale size	*small/medium*	*big*	*small*	*small/large*
Objectives of the innovations	*cost-reducing*	*cost-reducing; quality improving*	*Product innovations*	*Radical product and process innovation*
External sources of innovation	*innovations embedded in inputs*	*Supplier Relations*	*Buyer Relations*	*Relations with universities and research centers*
Internal sources of innovation	*learning by doing learning by using*	*investimenti in R&S*	*Learning Economies*	*investimenti in R&S*
Approprinability	*Low*	*Average*	*High*	*High*

Barriers to entry	*Low*	*Medium*	*Medium*	*very high*
ATECO Sectors 2007	*food, beverages, tobacco (AC); textiles, clothing, leathers, accessories (CB); wood and wood products, paper and printing (CC).*	*base metals and metal products, except machinery and equipment (CH); means of transport (CL).*	*machinery and equipment (CK)*	*chemical substances and products (EC); pharmaceutical, chemical-medicinal and botanical (CF) items; computers, electronic and optical equipment (IC).*

The methods for empirical verification also include the study of absorption capacity (Cohen and Levinthal, 1990). Cohen and Levinthal demonstrate that the ability to exploit externally generated knowledge, a crucial determinant within the innovation process, is a function of related knowledge that is already in the possession of the company.

This type of knowledge therefore includes basic skills, the sharing of a common language and knowledge of the most recent scientific and technological developments in each field. The combination of these skills outlines the absorption capacity of a company which can be strengthened in various ways:

- through investments in research and development.
- through the execution of manufacturing activities since the production experience provides companies with the necessary background to recognize value and acquire the ability to implement production processes.
- through the training of its employees.

In the Cohen and Levinthal model, the authors hypothesize that research and development perform both the function of generating new, somewhat idiosyncratic - firm specific - knowledge and the function of increasing absorption capacity. Below, the authors considered the reaction of R&D to learning incentives within a static model that captures: i) the effects of absorption capacity: as the absorption capacity of a firm decreases, the dependence of learning processes on internal R&D increases, which will therefore increase; (ii) technological opportunities: an increase in externally available knowledge will stimulate an increase in internal research and development, especially in highly competitive sectors; iii) appropriability: in a context characterized by strong spillovers, the interaction with absorption capacity represents a positive incentive to invest in research and development, counterbalancing the negative incentive that typically emerges in contexts characterized by low appropriability. The main results of Cohen and Levinthal's work suggest firstly that, in areas where applied science is more important than basic science, the increase in the intensity of research and development implies an increase in appropriability and a consequent decrease in spillovers; secondly, the effect of the interaction between the concentration of industry and the level of appropriability is positive; and finally, the effect of the interaction between the elasticity of the demand at price and level of appropriability is negative.

2.2. R&D, innovation, and knowledge spillovers

Anticipating what will be demonstrated in the methodological section, academic research and development, which represents a small share of total expenditure, is generally basic research therefore it has no economic value, although there are two particular exceptions represented by the knowledge spillovers of new graduates entering the world of work and by research considered of economic value by the universities themselves that transfer it to third parties, allowing them to exploit intellectual property through licenses and spin-offs (Acs Z. J., 2009). Conversely, industrial research and development is mainly applied research and experimental development and has economic value. The authors then introduce the so-called economic value filter, which includes only knowledge that has economic value and becomes intellectual property that can be marketed both directly (through the production of new goods, services, spin-offs, licenses) and indirectly to increase absorption capacity. In defining the link between intellectual property tools and knowledge spillovers, the literature offers conflicting views. Some authors believe that the strengthening of intellectual property rights allows firms to internalize part of the spillovers arising from research and development, which translates into an incentive for firms to invest additional resources in research (Arrow, 1962). In this perspective, it is also believed that the impact of stronger intellectual property rights (IPR) on firms' R&D investments increases as they approach the technological frontier (Acemoglu, 2006). On the other hand, there are authors who dispute the existence of a direct relationship between the strength of IPRs and innovation, demonstrating that only above a certain minimum threshold does the protection of IPRs lead to an increase in innovative activity and long-term economic growth (Bessen, 2009) and that the relationship between innovative activity and the strength of IPRs is characterized by a U-shape (Murray, 2007). The contribution of Lorenczik and Newiak (2012) is also part of this line of research, according to which a strengthening of IPRs is not followed by an increase in innovative activity where the protection of IPRs is already strong. In particular, the authors demonstrate the existence of an optimal level of protection of IPRs that maximizes the innovative activity of companies and promotes the acceleration of economic growth. Above and below this threshold, the incentive to promote innovation is reduced. The study of the determinants of economic growth includes the work of Acs et al. (2012) which identifies and studies the link between knowledge spillovers originating from research and development activities and the development of entrepreneurship. In the total factor productivity (TFP) model, the authors include a measure of entrepreneurship among the determinants of aggregate output growth, denoted by E:

$$Q = F(C, L, K, E) \quad (2.1)$$

where C is the physical capital, L is the labor factor, K is the human capital while E captures the entrepreneurial factor. The inclusion of the entrepreneurial factor in the total factor productivity model is justified by the fact that the growth of total factor productivity depends both on the learning processes within the firm and on the knowledge spillovers originating from research and development activities. In addition, areas that present differences in terms of level of education and experience can give rise to differences in the expected value of a new project that would be even more marked if the innovation processes were not aligned with the core competences and technological trajectories of the companies in which they emerge. In determining the effects of knowledge spillovers on the development of entrepreneurship, it is necessary to consider the concept of knowledge filter (Audretsch, 2004) which can therefore be defined as the gap between knowledge of potential commercial value that is produced and its fraction that is commercialized. Of course, various factors are identified that contribute to widening this gap such as risk aversion, bureaucratic formalities that hinder the creation of new businesses and the inadequacy of financial markets. Moreover, thanks to the contribution of Audretsch et al. (2004) it is possible to identify the limits of the theory of endogenous growth (Barro, 1989) which, by not explaining the mechanism of conversion of knowledge of potential commercial value into economically relevant knowledge, neglects the motivations underlying the existence of spillovers. In fact, since investments in new knowledge (university research, industrial research, education, and human capital) do not generate automatic spillovers, public policies that foster spillovers through entrepreneurship can represent an innovative approach to promoting economic growth. Consequently, the fact that there are business opportunities originating from knowledge filters could be a necessary condition to encourage knowledge spillovers, but not sufficient to promote them on a large scale due to the obstructive factors listed above. Therefore, an adequate endowment of entrepreneurial capital is necessary that reflects a combination of legal, institutional, and cultural factors and that manifests itself in the creation of new businesses. Since entrepreneurial capital is not an observable quantity, the following proxies are typically used in studies: (i) the rate of new business formation (flow measure); ii) the share of business owners in the total workforce. In the model proposed by Audretsch et al. (2004) the degree to which economic agents identify entrepreneurial opportunities starting from knowledge spillovers and decide to commercialize them through the creation of a new business is represented in the equation of employment choice (2.2):

$$E = \gamma\ (\pi * - w)\ (2.2)$$

where E is the parameter in which the decision (expressed in terms of probability) to become an entrepreneur is reflected, $\pi *$ denotes the expected profit, w is the salary that a person would receive if he or she preferred to work as an employee and γ represents all the other factors that could influence the entrepreneurial decision (Parker, 2004). Since the expected profits from carrying out a business activity are the result of knowledge created but not marketed by incumbent firms, entrepreneurial opportunities will be a direct function of the breadth of new knowledge and will be constrained by the marketing capabilities of incumbent firms themselves. Therefore, the authors define the following relationship for knowledge opportunities (2.3) where K represents the aggregate stock of knowledge and $\boldsymbol{\Theta}$ represents the fraction of new knowledge not commercially exploited by the incumbent firms:

$$E = g\ (p*(K\Theta) - w)\ (2.3)$$

The equation implicitly excludes the presence of institutional, individual, and financial barriers to entrepreneurship. However, given that these barriers are widely studied in the literature (Parker, 2004), the previous equation of entrepreneurial choice needs to be modified as follows:

$$E = g(p*(K\Theta) - w)\ \beta\ (2.4)$$

where β is the coefficient that incorporates both the presence of financial, legal, bureaucratic constraints and factors related to risk aversion, the rigidity of the labor market, and the low social acceptance of entrepreneurial activity. The existence of such barriers associated with high β values explain why some individuals prefer not to become entrepreneurs even when there are entrepreneurial opportunities generated by knowledge filters.

The model proposed by Audretsch et al. (2004) therefore detects the entrepreneurial factor as a function of the following factors:

$$E = f\ (K, \theta, \beta, w)\ (2.5)$$

where K represents the stock of new knowledge, θ represents the efficiency of the incumbents in exploiting this stock, β denotes the barriers to entry while w denotes the level of wages. The authors show that:

- An increase in the stock of knowledge has a positive effect on the rate of entrepreneurship, albeit limited, of the efficiency of incumbents in exploiting new knowledge.
  In fact, the more efficient the incumbents are, the smaller the value of θ and, consequently, the effect of new knowledge on the rate of entrepreneurship itself.
- as regulation, bureaucratic constraints and state intervention in the economy increase, the rate of entrepreneurship decreases.
- A higher wage level should result in a monotonic reduction in entrepreneurship.

3. The Italian economic scenario

The interest of this study in the innovative process of the Italian regions stems from the observation of a varied economic scenario. In the description of the latter, we certainly cannot ignore the local development model based in Italy on industrial districts and their growing importance for the economic system. In fact, it is precisely the industrial districts in which small and medium-sized enterprises operate that are the engines of innovative capacity in the industrial development model based on manufacturing specializations, innovation and internationalization. To better understand the determinants of the innovation process at the regional level, it is necessary to accurately describe the characteristics of the local development model based in Italy on industrial districts and technological districts and their importance for the economic system, the evolutionary aspects, and the metamorphosis of the districts themselves. In the 70s of the last century, Italy experienced a process of strong industrialization that also characterized the regions that did not belong to the so-called "industrial triangle", thus becoming an economic system with considerable structural and territorial diversity and "characterized by the presence of multiple localized specializations" (Schilirò, 2008). In underlining the contribution of industrial districts to economic development, Fuà (1983) and Becattini (2007) expressed themselves in opposition to the traditional vision of industrial development that radiates from the "center" to the "peripheries" and thus limits the economic importance of industrial districts understood as local networks of small and medium-sized enterprises specialized in the sector, identifying in industrial districts the places where connections between the size of the industrial sector take place. economic-productive and the socio-cultural dimension (Schilirò, 2008). In agreement with this theory, Fortis and Curzio (2006) also underline the importance of the Italian model of development based on small and medium-sized enterprises and on the most structured companies operating in industrial districts and based on manufacturing specialization, innovation and internationalization that manages to maintain a prominent role in Europe and worldwide through the export of productions in which each area has a comparative advantage. Although this model has constituted a paradigm of competitiveness over time, the weight of bureaucracy, excessive taxation, and poor infrastructures have led to the emergence of some fragilities of the Italian system which, to face future economic and technological challenges, also needs large industrial companies that must interact positively with the district realities. Finally, it should also be clarified that any reflection on the theme of districts cannot disregard the analysis of the socio-cultural contexts of the territory in which they develop. In this context, it is certainly appropriate to recall the studies of Marshall (Becattini, 1989) which show how the presence of multiple companies operating in the same sector and in the same geographical area creates an "industrial atmosphere" that favors the strengthening of local industry. Marshall himself identified the importance of the local dimension for the organization of industries and economic development. Subsequently, these intuitions were widely studied in the literature and applied to the analysis of districts in Italy by Becattini (1989) who defined the industrial district as "a socio-territorial entity characterized by the active coexistence, in a circumscribed territorial area, of a community of people and a population of industrial enterprises", seeing in the link between communities and companies operating in a district the key factor of the innovation process.

Becattini himself has identified the key determinants of the birth of the districts:

- the presence of a dominant activity of an industrial nature that configures a specialization in a specific production of goods.
- a local community made up of people and a plurality of institutions.
- a population of companies, each of which is specialized in a phase (or a few phases) of the production process typical of the district.
- the specialization of the district that involves companies that belong mainly to the same industrial sector, defined in such a way as to also include what Marshall defines as "auxiliary industries" or companies located along the production chain.

The studies of Trigilia (2005) also move in the same direction, considering the territorial context as a key factor for the interpretation of industrial development, thus managing to explain the reasons why economic growth occurs in certain areas while the development processes of other areas are slower. In addition, the author underlined the centrality of territorial policies as tools for the development of innovative processes, explaining the "fertility" of some regions as the product not only of local production traditions but also as the result of efficient cooperation between local authorities, institutions and companies capable of producing and intensifying external tangible and intangible economies. From this point of view, production becomes an intrinsically localized process in which each territory contributes with its own history, culture and social organization (Schilirò, 2008). In his analysis of local development, Becattini (2000) recalls the concept of "circular production", defining the production system as a system inevitably linked to social changes in terms of values, knowledge and institutions. In any case, the interpretative analyses of Becattini and other scholars from a theoretical point of view have been widely successful, while empirical applications have proved difficult to implement, both because many variables that come into play in the theory of industrial districts are not directly observable, such as, for example, the quality of information flows, and because of the lack of census data referring to a correct classification of the territory suitable for capturing the reality of industrial districts.

3.1 Strengths and weaknesses of Italian industrial districts

In the description of the Italian production system, the reality of industrial districts certainly represents the most appropriate configuration that differs from the production systems of European countries with an advanced level of development (Schilirò, 2008). So, the features of Italian industrial districts are:

- the dynamism of the small and medium-sized enterprises that constitute them, an expression of lively and widespread entrepreneurship. Small-medium businesses are characterized by a widespread presence on the Italian territory, from the North-East to the Center but also in some areas of Southern Italy such as Abruzzo, Puglia, and Basilicata.

- the production specialization in traditional sectors such as textile-clothing, the leather and footwear sector, the timber processing sector and light mechanics that makes the industrial districts in the Italian territory strongly linked to Made in Italy.

In this regard, Fortis (1998) has identified as the main categories of Made in Italy the goods of the home furnishings complex, food products, mechanical appliances and specialized machines or capital goods from manufacturing specializations. To confirm this, in 2005 ISTAT surveyed 156 specialized manufacturing systems that are mainly concentrated in the "4 A's" of Made in Italy: clothing-fashion, furniture-home, automation-mechanics, food-beverages that mainly involve small and medium-sized enterprises which, taken together, account for 77.6% of national exports and on which 90.7% of employment depends.[1] Undoubtedly, the factors of advantage of the Made in Italy industrial districts are based on flexibility in the organization of work, on the ability to acquire and adapt to new technologies and on the quality of products, on marketing and after-sales services (Schilirò, 2008). Investments aimed at the purchase of automated machinery that have reduced production costs, the computerization of many activities and the constant re-organization of processes have also represented factors of competitive advantage for the Italian districts that have led to the consequent realization of economies of scale and an efficient division of labor among the companies operating in the district (Onida, 1992). In addition, the development of industrial districts has proved to be a phenomenon closely linked to the sharing of knowledge, which in turn depends on research, the quality of human capital, the existence and quality of networks defined as "an indivisible structure of interdependencies that influence the performance of the subjects operating there" (Schilirò, 2008).

Although these factors represent the winning determinants of the development of Italian districts, many scholars believe that they have hindered in some way the evolution of the production structure of the Peninsula, attributing to the industrial districts an attitude of excessive closure towards foreign markets and a low propensity to change in response to the sudden evolution of the markets. In this perspective we find that Grandinetti (1999) thinks that if on the one hand the reality of industrial districts has been a determining factor in the achievement of a competitive advantage, it can also be considered a limit to the evolution in the current economic context of the globalization of processes and the speed of technological change. In this scenario, the importance of the challenge that Italian districts have faced is recognized, which consists in finding the balance point in the trade-off between closing and opening borders. In particular, the closed attitude of the district realities towards foreign markets has proved necessary to avoid the dissemination of district specific knowledge while an attitude of openness is essential to be able to have access to knowledge that would be unthinkable to produce in-house given the rising costs of research and the short life cycles of technologies. Innovation is increasingly linked to internationalization processes, a thesis confirmed by numerous studies that have highlighted the importance of sectoral specificities, the variety of innovation processes and the role of internationalization (Schilirò, 2008). In this regard, empirical studies have confirmed that: i) innovation is the strategic factor through which companies compete in the market; ii) innovation develops on specific and differentiated paths that depend on the sector in which it develops; iii) the innovative process is possible thanks to the dissemination of knowledge and through learning mechanisms (Bonaccorsi, 2008).

4. Econometric analysis of the determinants of the patent phenomenon

The methodological approach of this paper starts from the definition of the variables under study and from the specification of the sources of the data used for their construction: the share of industrial patents issued in each of the 18 Italian regions examined on the total population of the regions themselves is the dependent variable of the analysis (qbrevind_popreg), while the explanatory variables considered are the share of intra-muros R&D expenditure compared to regional GDP (qspesars_pilreg) and the share of exports in each region on the total value added (qexp_vareg). Subsequently, an evaluation and interpretation of the descriptive statistics of the reference variables was carried out, highlighting the salient characteristics of the regions of the panel. Subsequently, a preliminary exploratory survey was conducted aimed at identifying the most appropriate estimation method given the panel structure of the dataset, first applying the estimation by pooled OLS, fixed effects, and random effects. Starting from these estimates, the results provided by the Hausman test, used to verify the presence of endogenous regressors in the model, suggested the specification of the GLS random effects model, whose diagnostic tests showed the presence of cross-sectional dependence, stationarity, heteroskedasticity and serial correlation. For the correction of cross-sectional dependency and serial correlation, the techniques of correcting standard errors by means of the White method have been applied. Subsequently, the GLS random effects model chosen previously was compared with a GLS feasible model whose use is justified by the violation of the hypothesis of homoskedasticity and/or independence of the model's errors.
Repeating the Hausman test again, the results obtained direct the specification of the econometric model towards the feasible GLS model with fixed effects. Below are the sections of manufacturing activity - classified according to the Ateco 2007 criterion - have been placed in the four categories identified by the Pavitt taxonomy with the aim of identifying which of these there is a greater use of intellectual property instruments. After calculating the values of the Balassa index (Sapir, 2005) for each region in the four Pavitt categories, it was possible to understand the pattern of production specialization at the regional level. Furthermore, by inserting into the model a polytomic variable that takes as its modality one of the four categories depending on the specialization of the region, it has been shown that the transition from regions specialized in dominant supplier sectors/intensive scale to those specialized in specialized supplier/science-based sectors implies an increase in the patent intensity index, and therefore in the propensity to innovate.

4.1. Data and choice of variables

This statistical analysis identifies and studies the relationship between the dependent variable - regional patent intensity index - defined as the ratio between the number of patents granted for industrial inventions in a single region and the population residing in the region itself and the following explanatory variables[1]: i) the share of intra-muros research and development expenditure on regional GDP; ii) the share of exports

[1] Data regarding the number of patents issued in each region were provided by the UIBM (Italian Patent and Trademark Office) database. It should be specified that the absolute values regarding the number of patents granted are not appropriate to establish comparisons between the units of investigation since each region of the panel differs from the others in terms of size. For this reason, it was necessary to standardise the data on the number of patents granted. In this case, the choice fell on the number of residents in each region despite the fact that there were other possible alternatives such as, for example, the number of active companies in the region. The latter possibility is inappropriate since it can provide a distorted estimate for those areas characterized by the presence of many medium-small enterprises with the following underestimation of the size in the areas characterized by the presence of a few large enterprises. For this reason, the denominator of the dependent variable measures the resident population on 1 January in each Italian region in the 2012-2020 time interval. It was therefore necessary to consult the ISTAT database "Resident population as of 1 January" which provides data on the resident population by sex, year of birth and marital status as of 31 December of each year.

in regional value added.[2] Since for each of the 18 observed regions there are 9 annual observations (2012-2020) for the observed variables, it is correct to say that the dataset has a panel structure, in particular it is a balanced panel. The choice of the share of patents filed in the 18 Italian regions for industrial inventions on the total regional population as a dependent variable is justified by the fact that the number of patents granted is a suitable measure to assess the capacity for innovation in each geographical area. On the other hand, the use of this variable as a proxy for innovation capacity has the following limitations (Usai, 1996):

• there are innovations that are not patentable, such as scientific theories and mathematical methods, methods for surgical, therapeutic, or diagnostic treatment of the human or animal body, methods for intellectual activity, for play or for commercial activities.

• patents are not the only tool for protecting intellectual property, there are in fact alternative solutions such as trademarks, copyrights, trade secrets, protection of designs and models.

• the propensity to patent varies over time also according to the costs to be incurred, which are proportional to the number of claims submitted. In addition, to extend the validity of the patent abroad, it is necessary to pay the grant fees in each country in which you wish to extend the validity of the patent.

• The propensity to patent more accurately describes the innovation capacity of large companies as they can spread R&D costs over a higher sales base. In addition, by exploiting size and diversification, they have a greater probability of incurring unexpected discoveries from which they can benefit.

Despite the presence of these limitations, previous studies have highlighted the usefulness of patents as a measure that approximates the production of new knowledge, especially in the realization of economic surveys at the regional level. The data necessary for the construction of the explanatory variables have also been extrapolated from the I. STAT bank. In particular, the explanatory variable qspesars pilreg, included in the model as a measure of the level of technology, was obtained for each region by relating intra-mural R&D expenditure to the GDP of the region itself. In the measurement of this variable, intra-muros research and development expenditure refers to the expenses incurred for research and development activities carried out by companies with their own personnel and equipment; therefore, expenses incurred to finance external projects, i.e., the so-called extra-muros research and development expenses, are excluded. For each region, the share of expenditure on research and development recorded refers to the total economy, including companies, public institutions, universities, private non-profit institutions.[3]
In addition, the model also includes the share of exports in the total value added at regional level among the explanatory variables. For the construction of this variable, it was necessary to make use of data from the Survey System relating to statistics on the trade of goods between the Member States of the European Union. In a similar way to the construction of the previous variables, the data relating to exports have also been normalized with respect to the regional added value, where the added value given by the value of production minus the value of intermediate costs is a measure of the growth of the economic system in terms of new goods and services available for final uses. This explanatory variable is to be considered an indicator of international competitiveness included in the model to verify the presence of a link with the patent intensity index and to quantify the role of foreign trade dynamics in stimulating domestic

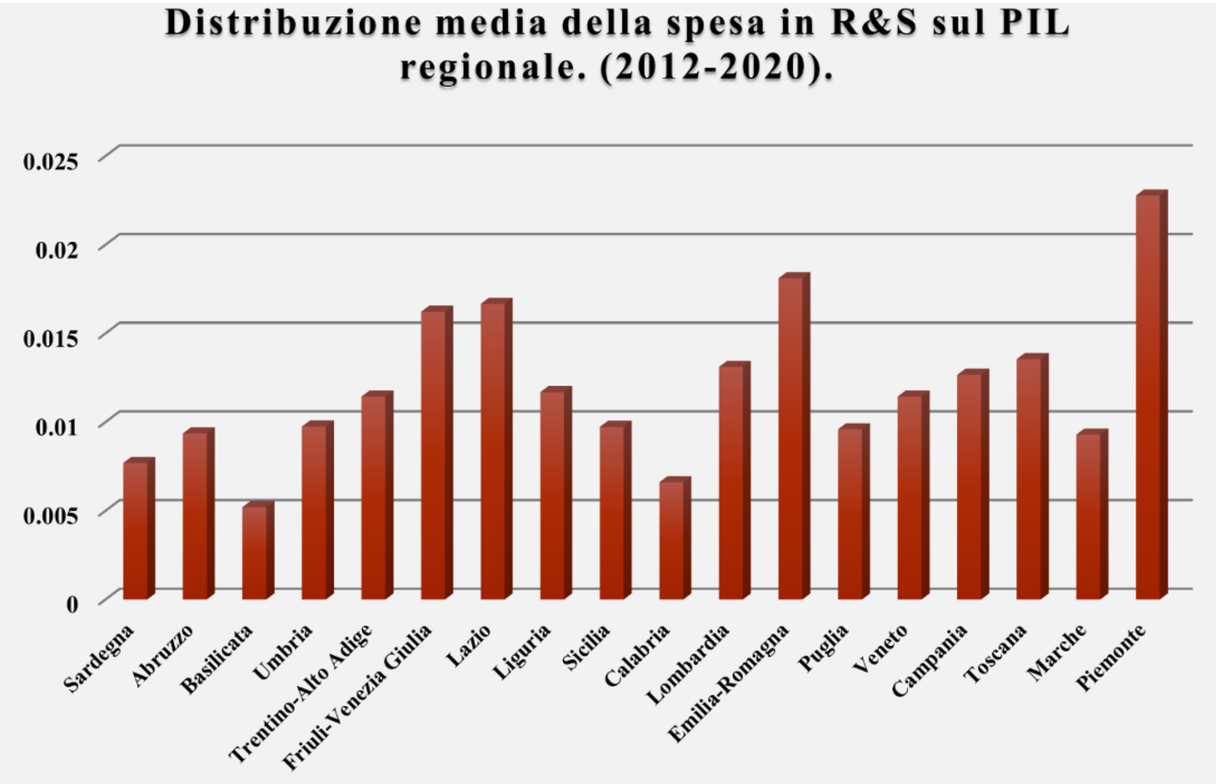
[2] The dataset from which the analysis was conducted can be consulted in the appendix.
[3] Just as it was previously necessary to normalize the number of patents issued for industrial inventions compared to the regional population, also in this case the figure regarding research and development expenditure has been normalized with respect to the amount of regional GDP to avoid distortions deriving from systematic differences between regions.

innovation.[4] The average values assumed by this variable in the time dimension considered attribute the leading positions to the regions of the North East, followed by the regions of Central Italy while the regions of Southern Italy show fairly homogeneous and low values.

4.2. Descriptive statistics

Figure 4.1 represents a further confirmation of what was stated during the analysis: from the average distribution of the dependent variable, it can be deduced that the propensity to innovate is mainly concentrated in the regions of Northern Italy, which play a leading role in technological development. Conversely, the regions of Southern Italy are assigned the lowest shares of patents per capita.

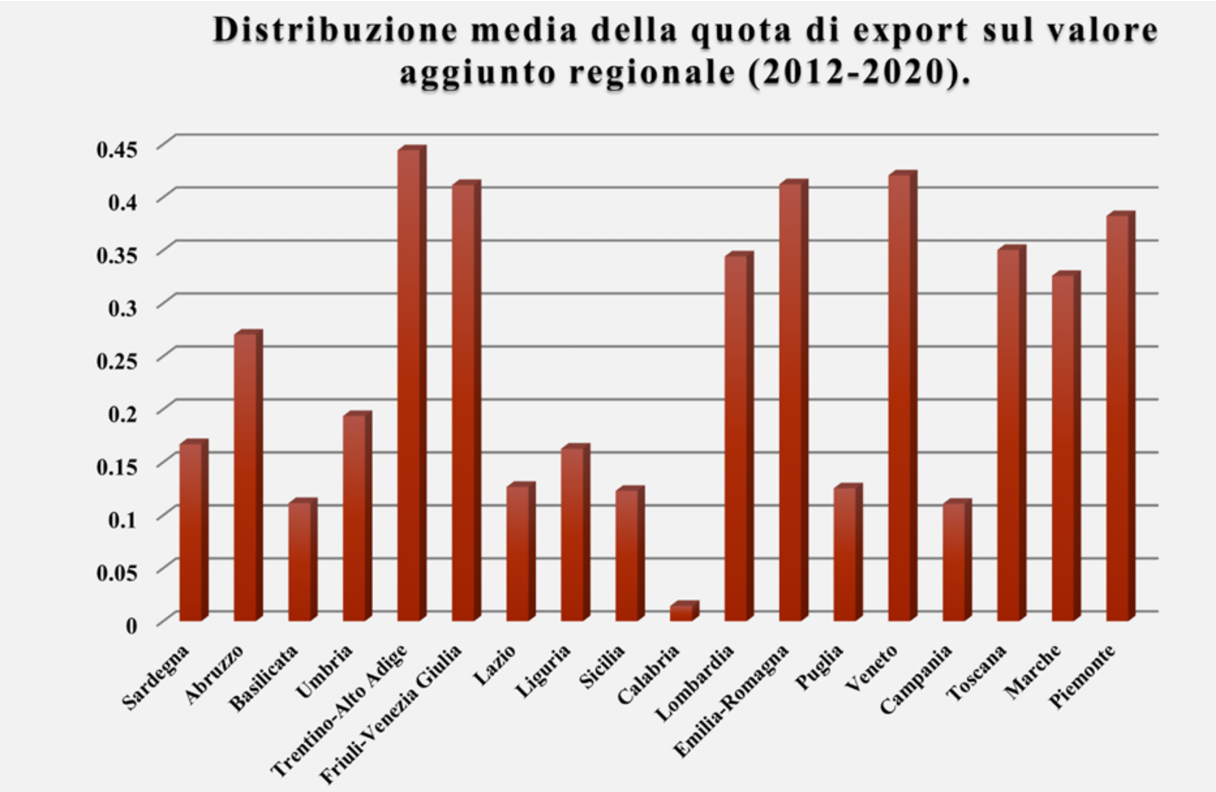
Figure 4.2. *Average Distribution of R&D expenditure on regional GDP*



Source: *author's elaboration on ISTAT data*

[4] This indicator of international competitiveness proposed by Evenson (1983) is imperfect because it neglects intra-industrial trade that can exert a significant influence.

Figure 4.3. *Average Distribution of the share of exports in regional value added*



The main export sectors refer to the production of machinery and mechanical equipment, among the exported products there are mainly machinery and equipment for the food industry, machine tools and machinery for the wood industry. The other export sectors concern products of the agri-food industry, textiles, and chemical products.

With reference to the latter, Trentino-Alto Adige is home to numerous companies active in the chemical-pharmaceutical sector and, more generally, to companies active in highly specialized technological sectors.

In Veneto, the contribution to exports comes mainly from the machinery and mechanical equipment sector, the metal products sector, textiles and clothing, leather products and footwear. Just like Trentino-Alto Adige, Veneto exports high quality products thanks to the presence of companies active in sectors with high technological specialization and traditional production of excellence.

The sectors just mentioned contribute largely to the value of exports also in Emilia-Romagna which, in addition to what has been said so far, is home to numerous companies operating in the pharmaceutical industry with excellent productions in various fields and companies operating in the rubber and plastic production sector that export rubber products for the automotive industry.

In general, the average distributions of the variables under study intuitively show a strong polarization that characterizes the Italian territory: the regions of Northern Italy record much better performance regarding the indicators examined, while the data relating to the regions of Southern Italy outline the great fragility of this geographical area to innovate and invest in research. The data for the regions of Central Italy describe a hybrid scenario compared to the previous ones, except for Umbria, which in the values of the dependent variable is like a region of Southern Italy.

In the values assumed by the share of exports on added value, Tuscany and the Marche reach positions worthy of consideration: Tuscany stands out for the exports of food products, textile products such as clothing and furnishing fabrics while the Marche is known for the exports of footwear, textile products, machinery for the leather processing industry.

4.3. Econometric analysis

Starting from the dataset containing the values of the variables for each of the 18 regions observed annually from 2012 to 2020, a preliminary exploratory analysis was carried out aimed at identifying the most appropriate estimation method by verifying the robustness of the same methods implemented. The results of the regression coefficients are commented on below based on the estimation method adopted. (Table 4.2).

Table 4.2. ***Pooled OLS estimates (1), fixed effects (2) and random effects (3)***

	dependent variable log(Y[5])		
	(1)	**(2)**	**(3)**
log(X1[6])	2.116***	0.958***	1.013***
	0.303	0.197	0.191
log(X2[7])	0.440***	0.566**	0.614***
	0.137	0.249	0.205
Constant	1,357		-3.317
	1,258		0.955
Observations	162	162	162
R^2	0.427	0.166	0.195
Adjusted R^2	0.420	0.055	0.185
F Statistic	59.234****	14.145***	0.185***
Note:	*p<0.1;	**p<0.05;	***p<0.01.

Source: ***author's elaboration on ISTAT data***

In the pooled OLS estimate (column 1 table 4.2), which does not take into account the differences between the units of observation and changes in the temporal dimension, a variation of 1% in the share of intra-muros research and development expenditure on the total regional GDP determines, with the same exports on value added, a variation equal to 2,116% in the patent intensity index since in the logarithmic scale model the regression coefficient represents the elasticity of the dependent variable with respect to the explanatory variable. Similarly, it is correct to say that a unit percentage change in the international competitiveness index produces a positive change of 0.440% in the patent intensity index for constant values of the first explanatory variable. It is also observed that intra-muros R&D spending on regional GDP explains 39% of the total variability of the dependent variable.

Furthermore, the value of the corrected coefficient of determination suggests that the two regressors can explain 42% of the overall variance of the dependent variable and the F test is statistically significant with

[5] Y represents the dependent variable of the analysis - regional patent intensity index - i.e. the ratio between the number of patents granted for industrial inventions in a single region and the population residing in the region itself.

[6] X1 represents the explanatory variable share of intra-muros research and development expenditure on regional GDP.

[7] X2 represents the explanatory variable share of exports on regional value added.

a significance level of less than 1%. However, the disadvantage of the OLS method is that, by not considering individual variations between units of observation, it can lead to inaccurate or ineffective estimates of model parameters. Therefore, alternative methods such as fixed-effect and random-effect estimates have been implemented. In the estimates obtained with the fixed effects model (column 2 table 4.2) which takes into account the differences between the Italian regions but does not assume that these differences change over time, the regression coefficients assume different values: a variation of 1% in the share of expenditure on research and development in the regional GDP, with the same values assumed by the international competitiveness index, determines a variation of 0.958% in the regional patent intensity index.

This coefficient is statistically significant with a significance level of less than 1%.

Similarly, a unit percentage change in the share of exports on the total regional value added causes a variation equal to 0.566% of the dependent variable, with the same expenditure on intra-muros research and development on the total regional GDP. The value of the coefficient of determination for the fixed effects model of 0.166 is lower than the coefficient of determination calculated with the pooled regression model. As an alternative to the OLS model and the fixed effects model, estimation using the random effects model is also proposed. The latter considers both variability between regions and variability within regions. In terms of estimation, the random effects model estimates the coefficients by considering the differences both within and between units.

Observing the values of the coefficients of the random effects model (column 3 table 4.2) we conclude that a variation of 1% in the share of expenditure on research and development on the total regional GDP, with the same values assumed by the international competitiveness index, determines a variation equal to 1.013% of the variable dependent on time and by region as well as a unit percentage variation in the share of exports on value added determines a variation equal to 0.614% of the dependent variable. Even in the random effects model, the regression coefficients are statistically significant with a significance level of less than 1%. In this case, the value of the coefficient of determination increases to 0.185 compared to the fixed effects model.

Subsequently, the Breusch-Pagan Lagrange (LM) (table 4.3)[8] and Hausman (table 4.4) tests were conducted to understand which model specification to prefer, where the first allows a choice between a random effects model and OLS regression and the second aims to detect endogenous regressors in a regression model. In particular, the LM test presents the null hypothesis that the variance between regions is zero. Given the value of the p-value (table 4.3), the null hypothesis is rejected, and the random effects model is chosen. In the analysis of panel data, the Hausman test tests the null hypothesis that there is no correlation between the regressors and the error terms, allowing to understand whether the fixed effects model or the random effects model is preferable. Observing the value of the p-value (table 4.4) we accept the null hypothesis and exclude the presence of endogeneity between the regressors and the error term, thus preferring the random effects model.

Table 4.3. ***Breusch-Pagan Lagrange test.***

Lagrange Multiplier Test Breusch-Pagan		
data: y ~ log(X1) + log(X2)		
chisq= 556.95	*df=1,*	*p-value< 2.2e-16*

8 Starting from Table 4.3 to Table 4.21, Y, X1 and X2 are indicated respectively by the dependent variable index of patent intensity, the explanatory variable share of intra-muros research and development expenditure on regional GDP, the explanatory variable share of exports on regional added value.

alternative hypothesis: significant effects

Source: ***author's elaboration on ISTAT data.***

Table 4.4. ***Hausman test.***

Test at Hausman		
data: **log(Y) ~ X1 + X2**		
chisq=1.7003	df=2,	p-value=0.4274
alternative hypothesis: one model is inconsistent		

Source: ***author's elaboration on ISTAT data.***

Subsequently, the results provided by the diagnostic tests testify to the presence of:

- cross-sectional dependence verified with the Breusch-Pagan test (table 4.5) which derives from the correlation between the observed units, i.e., the Italian regions, in a specific time wave.

Table 4.5. ***Breusch-Pagan LM test.***

Breusch-Pagan LM test for cross sectional dependence in panels		
data: log(Y) ~ X1 + X2		
chisq = 451.83,	df=153,	p-value < 2.2e-16
alternative hypothesis: cross sectional dependence.		

Source: ***author's elaboration on ISTAT data.***

- stationarity verified by the Dickey-Fuller test. The output of the Dickey Fuller test returns a p-value of 0.01, so the null assumption that the series has a unit root is rejected and the series can be concluded to be stationary (Table 4.6).

Table 4.6. ***Dickey Fuller test.***

Dickey-Fuller Test		
data: Panel.set$qbrevind_popreg		
Dickey-Fuller = -4.3481	Lag order=2	p- value = 0.01
alternative hypothesis: stationary		

Source: ***author's elaboration on ISTAT data.***

- heteroskedasticity by means of the Breusch-Pagan test which verifies the heteroskedasticity of residues in a regression model. Since the p-value of the test is below the set significance level, it can be concluded that there is evidence of heteroskedasticity in the residues (Table 4.7).

Table 4.7. ***Breusch-Pagan test.***

Breusch-Pagan Test		
data: log(Y) ~ log(X1) +log(X3) + factor (ID_REGIONE)		
BP = 56.863,	df=19,	p-value=1.2e-05

Source: ***author's elaboration on ISTAT data.***

- serial correlation verified with the Breusch-Godfrey/Woolridge test (table 4.8).

Table 4.8. Test di di Breusch-Godfrey/Woolridge

Breusch-Godfrey/Wooldridge test for serial correlation in panel models		
data: log(Y) ~ X1 + X2		
chisq = 64.365	df = 9,	p-value = 2.9e-10.

Source***: author's elaboration on ISTAT data.***

Returning to the estimates of the random effects model, the standard errors (table 4.9) and the correlations between the logarithms of the regressors (table 4.10) show the following values:

Table 4.9. ***Standard error in the random effects model.***

Standard Error		
Intercept	**log(X1)**	**log(X3)**
0.9548744	0.1914811	0.2053116

Applying White's corrections to standard errors (Table 4.11),

Table 4.10. ***Correction of standard errors using the White method.***

	Intercept	**log(X1)**	**log(X3)**
HC0	0.9548744	0.1914811	0.2053116
HC1	0.9548744	0.1914811	0.2053116
HC2	0.9548744	0.1914811	0.2053116
HC3	0.9548744	0.1914811	0.2053116
HC4	0.9548744	0.1914811	0.2053116

there are no changes in terms of standard errors compared to the GLS random effect model previously. Subsequently, the correction of standard errors was carried out through clustering techniques that are appropriate when serial correlation and cross-sectional dependency occur. For the correction of serial correlation, clustering by groups is applied (table 4.12) which determines an increase in standard errors for both explanatory variables and an increase in the correlation between regressors. (Table 4.13)

Table 4.11. ***Correction of standard errors by clustering by groups.***

	Intercept	**log(X1)**	**log(X3)**
HC0	1.439752	0.2590164	0.2996306

HC1	1.453271	0.2614485	0.3024441
HC2	1.460527	0.2635398	0.3050429
HC3	1.481838	0.2682103	0.3106409
HC4	1.484163	0.2708779	0.3148268

Table 4.12. *Correlations between the logarithms of variables.*

	Intercept	**log(X1)**	**log(X3)**
Intercept	1	0.8810514	0.5914466
log(X1)	0.8810514	1	0.1759492
log(X3)	0.5914466	0.1759492	1

Subsequently, clustering was implemented in time, indicated to correct the cross-sectional dependency. From the results of Table 4.14 the standard error for the first regressor increases while it decreases for the second regressor.
As regards the correlation between the logarithms of the regressors, a reduction is observed compared to the previous case:

Table 4.13. *Correction of standard errors through clustering in time.*

	Intercept	**log(X1)**	**log(X3)**
HC0	1.874858	0.273702	0.1886004
HC1	1.892462	0.276272	0.1903714
HC2	1.902982	0.2797364	0.1924587
HC3	1.931335	0.2859876	0.1964415
HC4	1.942209	0.2921091	0.1997093

Table 4.14. *Correlation between the logarithms of regressors.*

	Intercept	**log(X1)**	**log(X3)**
Intercept	1	0.9623895	-0.0888225
log(X1)	0.9623895	1	-0.3083282
log(X3)	-0.0888225	-0.3083282	1

When violations of the hypotheses of homoskedasticity and/or independence of errors occur in the linear model, the GLS feasible estimation can be useful and allows the model to be estimated using an error covariance matrix that considers these correlations, thus improving the efficiency of the estimates. In particular, the implementation of this procedure is divided into two phases:

- A first estimate is made using a fixed effect model.
- The residuals of the within estimator are used to estimate an error covariance matrix for use in a feasible GLS analysis.

Looking at the results of the FGLS model (Table 4.16), it can be observed that the coefficients remain statistically significant, in particular: a unit percentage change in the share of R&D expenditure on regional GDP causes a variation of 0.436% in the patent intensity index by region, if the regional share of exports on value added remains constant. In a similar way, there is also a positive and statistically significant relationship for the national competitiveness indicator: a unit percentage change in the latter contributes positively to the diffusion of innovations in the territory. Also in this case, the procedure for choosing the panel model is given by the Hausman test, whose p-value suggests that the FGLS model with fixed effects is to be preferred over the previous model with random effects.

Table 4.15. *Estimates of the coefficients with FGLS model.*

FGLS	Estimate	Std.Error	z-value	
log(X1)	0.43610	0.13221	32,985	0.000972***
log(X3)	0.21481	0.09063	23,702	0.017780*
Significant codes:	0 '***'	0.001 '**'	0.01 '*'	
Total Sum of Squares	405.12			
Residual Sum of Squares	12,812			
Multiple R-Squared	0.96838			

Source: *author's elaboration on ISTAT data.*

Table 4.16. *Test at Hausman.*

Hausman Test		
data: log(Y) ~ log (X1) + log (X2)		
chisq= 24.294	df=2,	p-value=8.743e-06
alternative hypothesis: one model is inconsistent.		

Source: *author's elaboration on ISTAT data.*

4.4. Effects of production specialization on the patent phenomenon

With the aim of verifying which manufacturing sectors most of the patents issued come from and therefore to assess which sectors contribute most to the spread of innovations, data on foreign trade were collected through the information system COEWEB2 completely dedicated to foreign trade statistics that provide information about Italy's trade flows with the rest of the world. Therefore, the collection of this type of data is justified by the need to build regional specialization indices. The territorial data offer a view of the annual flow of exports in the manufacturing sector whose economic activities have been classified according to the Ateco 2007 criterion. Subsequently, the sections belonging to the macro-sector "manufacturing activity C" have been reclassified according to the Pavitt (1984) taxonomy. This strategy has made it possible to place each economic activity in the manufacturing sector in the respective category to which Pavitt belongs:

• the supplier dominated category includes food, beverage, tobacco (CA), textile, clothing, leather, and accessories (CB) and wood, paper and printing (CC) productions.

• the intensive scale category includes the production of basic metallurgy, excluding machinery and equipment (CH) and the production of means of transport such as motor vehicles, trailers and semi-trailers and other means of transport (CL).

• the specialized supplier category which includes the production of machinery and equipment (CK).

• the science-based category which includes the production of chemical substances and products (CE), pharmaceutical, chemical-medicinal and botanical (CF) production, the production of plastics and the processing of non-metallic materials (CG), the production of computers, electronic and optical equipment (CI).

Subsequently, in each year, for each region and for each of the four Pavitt groupings, the Balassa indices (Revealed Comparative Advantage Index or RCA), a measure of export specialization widely used in international economics studies, were calculated. In our case, the Balassa index is used to verify whether a region has a comparative advantage revealed, compared to the country, in the export of products attributable to each category of the Pavitt taxonomy (equation 4.1).

$$\frac{\frac{x_{iJ}}{\sum_i x_{iJ}}}{\frac{\sum_J x_{iJ}}{\sum_i \sum_J x_{iJ}}} \qquad (4.1)$$

with i = 1, ..., 18 and J = 1, ..., 4.

In (4.1):
x_{iJ} it represents the exports of products belonging to the j-th category of Pavitt by region i.
$\sum_i x_{iJ}$ it represents the national exports of products belonging to the j-th category of Pavitt.
$\sum_J x_{iJ}$ represents the total exports of region i.
$\sum_i \sum_J x_{iJ}$ represents total national exports.

For RCA values above unity, region i has a comparative advantage in exporting products from sectors belonging to a given category of the Pavitt taxonomy. Table 4.18 shows the average values of the Balassa index in the period (2012-2020) for each region. Looking at the values reported, we first note that:

- over time, the regions tend to maintain their comparative advantage in the same production category, as proof of a certain stability in the specialization pattern.
- there are Italian regions that on average have a comparative advantage in several sectors (all the regions of Northern Italy except Emilia-Romagna, Marche, Umbria, Campania, Puglia and Sardinia).
- the regions that have comparative advantages in the science-based sectors tend to be the regions of the Northwest (Piedmont, Lombardy, Liguria) characterized by a strong industrial and technological tradition, with a wide range of companies active in the chemical and pharmaceutical sector, including some of the largest and most important companies in the sector worldwide. In addition to these, the contributions deriving from the regions of Lazio, Marche and Sicily in this sector also deserve particular attention. It should be specified that it is not easy to interpret the value assumed by the Balassa index in the Lazio region since the main companies operating in the science-based sectors

have their administrative headquarters in this region. The Marche region, located in central Italy, is an area that is developing rapidly in the science-based sector, particularly in the areas of biotechnology, life sciences and biomedical engineering, boasting productions that are based on advanced and innovative technologies.

- as regards the possession of comparative advantages in the specialized suppliers' sectors, the Italian regions specialized in the production of machinery and equipment are Emilia-Romagna and Friuli-Venezia Giulia, regions historically active in the production of machinery and industrial equipment.
- This experience has led to the creation of a highly developed industrial ecosystem, with a wide range of suppliers and companies specialized in the production of machine parts and components.
- The average values of the Balassa indices calculated in the intensive scale sectors underline the comparative advantage of the southern regions: in particular, Puglia, Basilicata, Abruzzo, and Sardinia are areas of strong specialization about the intensive scale sector. For example, in Puglia there is a significant presence of metalworking companies, especially in the precision mechanics sector, which supply components and parts to large companies in the transport sector.
- Unlike what happens for these three categories, the comparative advantages in the production of the textile, food, wood, and paper industries are not concentrated in a specific geographical area but are common to several regions (Veneto, Trentino-Alto Adige, Marche, Umbria, Tuscany, Campania, Calabria, and Sardinia). Veneto, for example, boasts a strong tradition in the textile sector, with important textile and clothing production centers such as Venice, Padua, Verona, and Vicenza. In addition, the region is known to produce high-quality footwear as well as the Marche is active in the textile sector, with the production of high-quality footwear, clothing, and accessories. Trentino-Alto Adige, on the other hand, is a region very active in the food sector (as is the Umbria region), in the production of wooden furniture and furnishings, thanks to the numerous carpentry shops in the area.

In Tuscany, the textile sector is of great importance, with the production of high-quality clothing, accessories, and fabrics. The region is also known to produce quality wines and food products.

Table 4.18. ***Average values of the Balassa index in the period (2012-2020) for the sectors considered***

	supplier dominated	***scale intensive***	***specialized supplier***	***science based***
Piedmont	0.9876	1.4199	0.8931	**1.7769**
Lombardy	0.8291	1.0847	0.9715	**1.6757**
Liguria	0.4766	1.2794	0.9739	**1.3948**
Friuli-Venezia Giulia	0.5612	1.6233	**1.7227**	0.6406
Veneto	**1.5234**	0.8344	1.1126	0.6529
Emilia-romagna	0.9428	0.8587	**1.3954**	0.8272
Trentino-Alto Adige	**1.3829**	1.0855	1.0761	0.6409
Marche	1.2437	0.7723	0.8730	**1.2927**
Tuscany	**1.8289**	0.8174	0.7201	0.7095
Umbria	**1.4570**	1.2524	0.7893	0.6256
Latium	0.3892	0.7956	0.1905	**2.6584**
Campania	**1.5996**	1.2001	0.2471	0.8623
Apulia	0.9808	**1.3469**	0.5363	1.0578
Calabria	**1.5497**	0.9220	0.9220	0.4220
Abruzzo	0.5359	**2.4325**	0.4367	0.7208

Basilicata	0.1697	**4.4596**	0.0590	0.4860
Sicily	0.8534	0.4851	0.1898	**1.0736**
Sardinia	1.2173	**1.2696**	0.2387	0.4023

Source: ***author's elaboration on COEWEB data: https://www.coeweb.istat.it/***

Since the values assumed by the Balassa index, dummy variables have been constructed that take a value of 1 in case the region has a comparative advantage in that category, 0 otherwise. The polytomic variable has therefore been introduced in the model, which takes the following forms:

- science based if the region has a comparative advantage in science-based sectors each year.
- specialized supplier if the region each year has a comparative advantage in the specialized supplier sector.
- supplier dominated; if the region has a comparative advantage in the supplier dominated sectors each year.
- intensive scale if the region has a comparative advantage in the intensive scale sectors each year.

There are three dummy variables constructed, using the scale intensive category as a reference category. Below, looking at the regression outputs in Table 4.19, we can make the following considerations:

- In the OLS estimate, the statistically significant dummies are given by the specialized, supplier and science-based groupings. Moving from the regions in which there is a comparative advantage in the intensive scale sectors to those with a comparative advantage in the science-based sectors, the patent propensity index increases by 1,343% (with the same expenditure on research and development on regional GDP and exports on regional added value). Similarly, the transition from regions with comparative advantage in intensive scales to specialized supplier sectors determines an increase in the patent propensity index of 1,229%. Both coefficients are statistically significant with a significance level of less than 1%.
- In the random effects model, the significant dummy is the science-based category whose significance level is less than 10%. In particular, the transition over time from regions with a comparative advantage in intensive scale production to those specialized in science-based sectors produces an increase in the propensity to patent equal to 1.43%. Also in this case, the transition takes place with the same values assumed by the variables: share of expenditure on research and development on regional GDP and share of exports on regional added value. Therefore, the possession of a comparative advantage in science-based production sectors determines an increase in the use of patents.

Table 4.19. ***Pooled OLS estimates (1), fixed effects (2) and random effects (3).***

	Dependent	**Variable**	
	log (Y)		
	1	2	3
log (X1)	1.171***	0.958***	0.961***
	0.353	0.197	0.193

log(X2)	0.483***	0.566**	0.553***
	0.129	0.249	0.21
sciencebased	1.343***		1.430*
	0.293		0.839
specialisedsupplier	1.229***		1.328
	0.405		1.142
supplierdominated	0.222		0.286
	0.263		0.833
Constant	-4.477		-4.368
Observations	162	162	162
R^2	0.523	0.166	0.215
Adjusted R^2	0.508	0.055	0.19
F Statistic	34.204***	14.145***	42.668***
Note:	*p<0.1;	**p<0.05	p<0.01

Source: *author's elaboration on ISTAT data.*

What emerged is fully consistent with the considerations made regarding the Pavitt taxonomy according to which it is precisely the science-based and specialized suppliers' sectors that are characterized by a high degree of appropriability or by a high use of intellectual property protection tools such as patents and trade secrets.
The p-value of the LM test, which allows you to choose adequately between the model estimated with OLS and the random effects model, directs the choice towards the latter. (Table 4.20).
In the regression results (Table 4.21) we observe that the fixed-effects model has no coefficients for the dummies since the categories do not change considering the same region, so it would be superfluous to implement the Hausman test for the choice between the fixed-effects model and the random-effects model. In any case, the assumed p-value directs the choice towards random effects estimation.

Table 4.20. *Lagrange Multiplier Test.*

Lagrange Multiplier Test - Breusch Pagan for balanced panels
data: log (y) ~ log (x1) + log (x3) + x4
chisq = 559.41; df= 1; p-value < 2.2e-16
alternative hypothesis. Significant effects

Table 4.21. *Hausman test.*

Hausman Test
data: log (y) ~ log (x1) + log (x3) + x4
chisq = 0.032497, df = 2, p-value = 0.9839

alternative hypothesis: one model is inconsistent

Having demonstrated that companies operating in the science-based sector are those in which the patent phenomenon is most established, it is reasonable to deduce that the birth and development of innovations that are most relevant to the production system are concentrated in this sector. Consequently, in the formulation of public interventions aimed at promoting innovation, it is crucial to concentrate efforts and resources on this sector, as we will see in the next section.

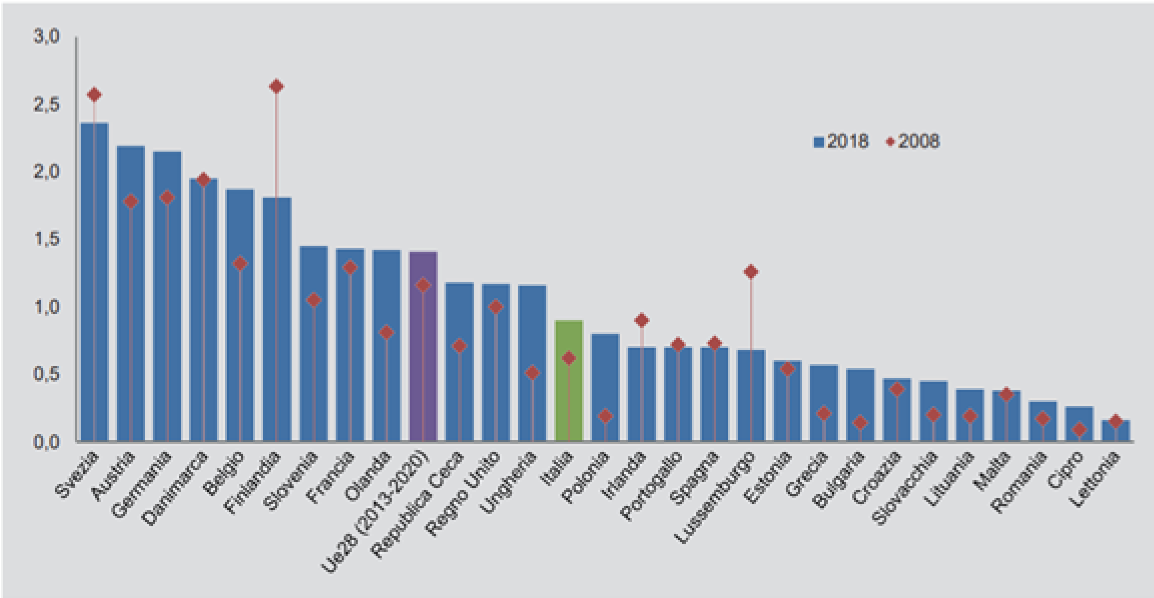
5. Politics as a remedy for the weaknesses of the innovation process

As far as the formulation of policies for innovation is concerned, the literature has profoundly emphasized its therapeutic function starting from the identification of the weaknesses of innovative processes. Hall and Soskice (2001), studying the relationship between political institutions and a country's economic performance, believe that the origin of a country's comparative advantage in each sector is an efficient collaboration between industry and public institutions. Specifically, the authors distinguish liberal market economies (LME's) from coordinated market economies (CME's), where the former are characterized by greater competition between firms and less government regulation of the labor market, while the latter emphasize the role played by public institutions in the regulation of the labor market.
By studying the complementarity of skills training systems and inter-company collaborations in research and development, the authors demonstrate the superiority of LME's in producing radical innovations compared to CME's. It is also worth mentioning the contribution of Dosi, Freeman and Soete (1988) who, in determining the relationship between national policies and technological innovation, argue that the structure and composition of a country's production system can influence its ability to innovate.
Countries with a highly fragmented production system and specialized in sectors with low research and development intensity tend to have a lower capacity for innovation than those with a more integrated and diversified production system. In line with this study and with the results obtained in the previous section, Nelson, and Winter (1982) argued that the sectoral composition of the production system influences the ability of an industry to innovate: R&D-intensive industries such as pharmaceuticals or information tend to have a greater capacity to innovate than labor-intensive industries such as clothing and woodworking. Applying these considerations to the Italian economic context, it is logical to deduce that the Italian territory, if it has a sectoral structure and size like that of the other large industrial countries, would witness a doubling of the intensity of spending on research and development by private operators. Starting from these assumptions, the intervention of the public operator is necessary in strengthening the innovative capacity through the formulation of appropriate policies for the promotion of entrepreneurship and innovation.

a. **Towards the taxonomy of policies for entrepreneurship and innovation**

In 2018, the total R&D expenditure carried out by companies, public institutions, private non-profit institutions amounted to 25.2 billion euros, representing 1.43% of the national GDP. Certainly, the main component of R&D spending is carried out by companies (64.1% of total spending in 2018) at both national and European level (ISTAT, 2021). However, it should be emphasized that business investments in research and development are still far from the European average levels: in 2018, Italy in the EU ranking is in an intermediate position and is surpassed not only by historically important private investors such as Northern European countries but also by Slovenia, the Czech Republic and Hungary. (Figure 5.1).

Figure 5.1. ***R&D spending by companies in EU countries. Years 2018 and 2008. (Percentage values on GDP).***



Source: ***Eurostat, Science, Technology and Innovation.***

Even within the Italian territory there are huge differences between the regions as emerged in the fourth section. In 2018, 75% of companies' R&D spending was concentrated in the regions of Northern Italy (Piedmont, Emilia-Romagna, Lombardy, Veneto, Tuscany), while the entire South of Italy accounted for about 10% of national business spending.
As shown in Figure 4.9 (fourth section), in terms of incidence on regional GDP, the best performance is observed in Piedmont, which also has higher values of the patent intensity index. Furthermore, as demonstrated in the previous section, the regions that have the greatest propensity to innovate tend to be in the Northwest and Northeast and are those with comparative advantages in the specialized supplier and science-based sectors. Having noted both the inferiority of the performance of the Italian economy compared to the countries of Northern Europe and the strong differentiation within the Peninsula, the planning and implementation of policy interventions aimed at intensifying the innovation process is necessary both at national and regional level.
Since a large part of R&D spending is carried out by companies, it is important to define both policies to support entrepreneurship and policies to promote innovation, since entrepreneurial activity is an economic factor that contributes not only to job creation and social cohesion, but also to the diffusion of innovative and competitive capacity when it has a high endowment of human capital. In general, policy makers fear that individuals are dissuaded from becoming entrepreneurs when promoting entrepreneurship due to over-regulation - resulting in high administrative barriers - lack of information on starting a business, unfavorable economic conditions, and a shortage of human capital.
Therefore, in the formulation of interventions, policy makers generally identify entry subsidies as the best tool to increase the rate of entrepreneurship in each geographical area. In general, however, there are two schools of thought that analyze the impact of regulation on the development of entrepreneurship:

- on the one hand, it is believed that the regulation of entry translates into the incurring of additional costs for those who intend to create new businesses and that these costs being socially undesirable translate into a reduction in the birth rate of companies (Djankov, 2009). The study by Klapper et al. (2006) is along the same lines, demonstrating that regulation represents an obstacle to the development of entrepreneurship, especially in sectors that are naturally characterized by high barriers to entry.

- on the other hand, it is believed that the main effect of regulation is the alteration of the distribution of entrepreneurship between "official activities" and "informal activities". Therefore, countries where there is a high level of regulation at entry are characterized by a greater difference between the share of "official activities" and the share of "undeclared activities" (Russell, 2008).

In fact, in the formulation of policies to support entrepreneurship it should be considered that in general the survival rates of new enterprises are very low: about 20-40% of enterprises entering an industry fail within the first two years after start-up, while only 40-50% survive beyond the seventh year (Geroski, 1995). Therefore, the process of forming new firms is characterized by a revolving door mechanism that implies that a significant share of the entrepreneurial dynamic is only business ownership and often coincides with the phenomenon of "structural turbulence" (Schumpeter, Theory of Economic Development, 1912). Moreover, the phenomenon of entry into industry characterizes a large majority of imitators and a small minority of innovators (Schumpeter, 1934); similarly, Baumol (2005) shows that entering an industry sees numerous replicative entrepreneurs who start businesses like those already existing.

Consequently, it is easily demonstrable that the provision of *erga omnes* entry subsidies is not an optimal policy but rather turns out to be a waste of public resources: public subsidies should be reserved for companies that, despite being based on a valid business idea, incur constraints on entry and growth due to market failure. As regards the interventions related to the formulation of innovation policies that will be described in detail in the following paragraph, ACS (2007) and Lee (2004) see at the basis of these interventions the creation of a culture for innovation aimed at promoting economic growth and competitiveness.

According to ACN (2007), the creation of a culture for innovation concerns and encompasses all levels of society and is a process that is carried out through the promotion of public policies in favor of education, vocational training and research and development activities. In accordance with what has been stated above, ACS believes that the public operator should encourage entrepreneurship and the creation of new businesses, especially those with a high knowledge intensity.

The culture of innovation promoted by these authors must be followed by the creation of a culture for evaluation and monitoring for the improvement of the innovative capacity of companies and the production system (Evangelista, 2007). These authors argue that companies and production systems capable of constantly evaluating and monitoring their innovation processes can improve their ability to learn and adapt to new technological and market challenges.

6. Conclusions

As pointed out in the introduction, the scientific literature on the development of innovations in market economies has mainly focused on identifying the factors from which they originate. In this regard, in the second section, particular importance has been given to the empirical work of some authors, including Scherer (1983) who has highlighted the usefulness of patents as a measure that approximates the production of new knowledge within an economic system. Also of interest for this study were the theories on innovation by Schumpeter (1912, 1942) and Schmookler (1966) according to which patents constitute an adequate proxy to investigate the evolution over time of innovative activity, as it is argued that they represent the most effective, precise, and detailed source of information on inventive activity available for a long-time horizon. Subsequently, with the aim of better understanding the determinants of innovative processes at the regional level, the local development model based in Italy on industrial and technological districts and the consequent importance for the Italian economic system was accurately described.

The studies of Trigilia (2005) have focused on this direction, considering the territorial context as a decisive factor for the interpretation of industrial development, thus managing to explain the reasons why economic growth occurs in certain areas while the development processes of other areas are slower. In addition, the author emphasized the centrality of territorial policies as tools for the development of innovative processes, explaining the "fertility" of some regions as the product not only of local production traditions but also as the result of efficient cooperation between local authorities, institutions, and companies capable of producing and intensifying external tangible and intangible economies. From this point of view, production becomes an intrinsically localized process in which each territory contributes with its own history, culture, and social organization (Schilirò, 2008).

In the fourth section, it was demonstrated through the analysis of panel data that the regional patent intensity index, defined as the ratio between the number of patents granted for industrial inventions in a region and the resident population, is positively correlated with the share of R&D expenditure at regional level on GDP and the share of exports on regional added value. In particular, from the values of the coefficients of the random effects model, we conclude that a unit percentage change in the share of expenditure on research and development on the total regional GDP, with the same values assumed by the international competitiveness index, determines a variation equal to 1.013% of the variable dependent over time and by region, just as a unit percentage change in the share of exports on added value determines a variation equal to 0.614% of the dependent variable. Subsequently, the sections belonging to the macro-sector "manufacturing activity C" have been reclassified according to the Pavitt taxonomy, making it possible to place each economic activity in the manufacturing sector in the respective category to which Pavitt belongs. Subsequently, in each year, for each region and for each of the four categories identified by Pavitt, the Balassa indices were calculated to identify the pattern of specialization in each region. From the values assumed by the Balassa index, it was possible to make several considerations:

• over time, the regions tend to maintain their comparative advantage in the same production category, as evidence of a certain stability in the pattern of specialization.

• the regions that have comparative advantages in *the science-based* sectors tend to be the regions of the Northwest (Piedmont, Lombardy, Liguria) characterized by a strong industrial and technological tradition, with a wide range of companies active in the chemical and pharmaceutical sectors.

• as regards the possession of comparative advantages in the *specialized suppliers'* sectors, the Italian regions specialized in the production of machinery and equipment are Emilia-Romagna and Friuli-Venezia Giulia, regions historically active in the production of machinery and industrial equipment.

• values of the Balassa indices calculated in the *intensive scale* sectors underline the contribution made by the southern regions: in particular, Puglia, Basilicata, Abruzzo, and Sardinia are areas of strong specialization about the intensive scale sector.

• unlike what happens for these three categories, the comparative advantages in the production of the textile, food, wood, and paper industries are not concentrated in a specific geographical area but are widespread in the Italian territory (Veneto, Trentino-Alto Adige, Marche, Umbria, Tuscany, Campania, Calabria, and Sardinia).

Subsequently, it has been shown that the transition from regions specialized in dominant suppliers/intensive scales to *science-based* ones implies an increase in the patent intensity index, and therefore in the propensity to innovate. In particular, the transition over time from regions with a comparative advantage in intensive scale production to those specialized in *science-based* sectors produces an increase in the propensity to patent equal to 1.43% with the same values assumed by the variables share of expenditure on research and development on regional GDP and share of exports on regional added value. Therefore, *science-based* production sectors are those characterized by greater appropriability in accordance with the thesis of Nelson and Winter (1982) according to which the sectoral composition of the production system influences the ability of an industry to innovate: industries with a high intensity of research and development such as pharmaceuticals or information tend to have a greater innovative capacity than labor-intensive industries such as clothing and woodworking. Furthermore, the subsequent comparison with the countries of the European Union revealed the backwardness of the innovative processes of the Peninsula and the consequent need for intervention by the public operator through policies for entrepreneurship and innovation: in 2018 Italy was in an intermediate position in the EU ranking in terms of spending on research and development on total GDP, surpassed by Slovenia, Czech Republic, and Hungary. Even within the Italian territory, there are huge differences between regions: in 2018, 75% of business R&D spending was concentrated in the regions of Northern Italy (Piedmont, Emilia-Romagna, Lombardy, Veneto, Tuscany) while the entire South accounted for about 10% of national business spending (ISTAT, 2021). These results have therefore highlighted the importance played by public institutions in the formulation of appropriate policies according to the "triple helix" model which sees the interaction and strategic collaboration of universities, industry, and public institutions as the key factor of economic growth. For this reason, the fifth section of the paper presents the so-called "Smart Specialization Strategy" (S3) aimed at identifying investment priorities in research and development that integrate the resources of a territory with the aim of building competitive advantages and sustainable growth paths in the long term. Currently, twenty-one regional specialization strategies and one smart specialization strategy are active in Italy. The objective of these strategies, regardless of the context in which they are implemented, is identified in the creation of new value chains which, starting from R&D, arrive at the generation of innovative products and services aimed at increasing the wealth of a territory. Furthermore, in line with what has been demonstrated in the fourth section, smart specialization strategies are aimed at the development of knowledge-intensive sectors such as biotechnology, bioinformatics and pharmaceuticals, the latter being the sectors characterized by the greatest use of intellectual property protection tools.

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Annex

Values assumed in the period 2012-2020 by the variables:

- **qbrevind_popreg** (share of patents issued for industrial inventions on the regional population);[9]
- **qspesars_pilreg** (share of expenditure on research and development in regional GDP);[10]
- **qexp_vareg** (value of exports on regional added value);[11]
- **categorypavitt** or the category of the Pavitt taxonomy in which the region has a comparative advantage;
- **RCA** (value assumed in the region by the Balassa index in the production sectors in which the region has a comparative advantage)[12]

ID_REGIONE	*qbrevind_popreg*	*qspesars_pilreg*	*qexp_vareg*	*categoriapavitt*	*RCA*
Piedmont	0.0018	0.02	0.36	sciencebased	1.846026
Piedmont	0.0018	0.022	0.38	sciencebased	1.764384
Piedmont	0.0014	0.022	0.38	sciencebased	1.756532
Piedmont	0.0014	0.022	0.401	sciencebased	1.847760
Piedmont	0.0014	0.022	0.39	sciencebased	1.777582
Piedmont	0.0015	0.022	0.398	sciencebased	1.706447
Piedmont	0.0019	0.026	0.392	sciencebased	1.788756

[9] Data on the number of patents issued for industrial inventions are available on the database of the Italian Patent and Trademark Office (UIBM) https://www.uibm.gov.it/bancadati/ while data on regional populations have been extrapolated from the I.Stat database of ISTAT https://esploradati.istat.it/databrowser/#/ .

[10] Data on regional R&D spending and regional GDP are also available on the https://esploradati.istat.it/databrowser/#/ portal, as are regional export values and value added.

[12] For the construction of the Balassa Index, data from the Coeweb information system dedicated to foreign trade statistics were used https://www.coeweb.istat.it/.

Piedmont	0.0025	0.026	0.382	sciencebased	1.779710
Piedmont	0.0027	0.023	0.358	sciencebased	1.725114
Marche	0.0002	0.008	0.29	sciencebased	1.269959
Marche	0.00024	0.0084	0.358	sciencebased	1.343147
Marche	0.00016	0.0088	0.36	sciencebased	1.631054
Marche	0.00016	0.0089	0.319	sciencebased	1.268268
Marche	0.00016	0.0088	0.357	sciencebased	1.347260
Marche	0.00016	0.0088	0.317	sciencebased	1.132874
Marche	0.00018	0.011	0.31	sciencebased	1.165743
Marche	0.00024	0.011	0.318	sciencebased	1.314776
Marche	0.00028	0.01	0.303	sciencebased	1.161486
Tuscany	0.00018	0.012	0.335	supplierdominated	2.099800
Tuscany	0.00015	0.012	0.325	supplierdominated	1.870730
Tuscany	0.00015	0.013	0.327	supplierdominated	1.923080
Tuscany	0.00015	0.013	0.334	supplierdominated	1.499259
Tuscany	0.00015	0.013	0.331	supplierdominated	1.767474
Tuscany	0.00015	0.013	0.338	supplierdominated	1.976492
Tuscany	0.00017	0.015	0.35	supplierdominated	1.784222
Tuscany	0.00021	0.015	0.395	supplierdominated	1.715277
Tuscany	0.00025	0.016	0.418	supplierdominated	1.824076
Campania	0.000013	0.012	0.102	supplierdominated	1.123140
Campania	0.000015	0.013	0.106	supplierdominated	1.775778
Campania	0.000021	0.012	0.104	supplierdominated	1.924422
Campania	0.000023	0.013	0.104	supplierdominated	1.633795
Campania	0.000025	0.012	0.106	supplierdominated	1.800397
Campania	0.000027	0.012	0.109	supplierdominated	1.684008
Campania	0.000028	0.013	0.115	supplierdominated	1.049568
Campania	0.000035	0.013	0.124	supplierdominated	1.521376
Campania	0.000046	0.014	0.127	supplierdominated	1.883985
Veneto	0.00037	0.01	0.391	supplierdominated	1.805166
Veneto	0.00036	0.011	0.402	supplierdominated	1.517493
Veneto	0.00036	0.011	0.412	supplierdominated	1.520187
Veneto	0.00036	0.011	0.424	supplierdominated	1.313488
Veneto	0.00036	0.011	0.417	supplierdominated	1.520507

Veneto	0.00036	0.011	0.429	supplierdominated	1.554662
Veneto	0.00045	0.012	0.435	supplierdominated	1.519868
Veneto	0.00054	0.012	0.439	supplierdominated	1.435553
Veneto	0.00058	0.014	0.437	supplierdominated	1.526351
Apulia	0.000029	0.0081	0.137	scaleintensive	1.296305
Apulia	0.000037	0.0084	0.125	scaleintensive	1.377520
Apulia	0.000034	0.0092	0.128	scaleintensive	1.389505
Apulia	0.000034	0.0094	0.124	scaleintensive	1.348186
Apulia	0.000045	0.0097	0.12	scaleintensive	1.203217
Apulia	0.000054	0.0098	0.123	scaleintensive	1.334031
Apulia	0.000094	0.0099	0.118	scaleintensive	1.341108
Apulia	0.000097	0.0099	0.129	scaleintensive	1.568842
Apulia	0.000098	0.012	0.125	scaleintensive	1.263550
Emilia-romagna	0.00035	0.016	0.388	specialisedsupplier	1.486096
Emilia-romagna	0.00035	0.017	0.394	specialisedsupplier	1.381844
Emilia-romagna	0.00033	0.017	0.404	specialisedsupplier	1.363478
Emilia-romagna	0.00033	0.018	0.414	specialisedsupplier	1.230272
Emilia-romagna	0.00033	0.017	0.408	specialisedsupplier	1.352688
Emilia-romagna	0.00033	0.017	0.424	specialisedsupplier	1.472905
Emilia-romagna	0.00037	0.02	0.441	specialisedsupplier	1.374267
Emilia-romagna	0.00049	0.02	0.456	specialisedsupplier	1.344943
Emilia-romagna	0.00057	0.021	0.451	specialisedsupplier	1.552285
Lombardy	0.0015	0.013	0.343	sciencebased	1.635799
Lombardy	0.0015	0.013	0.345	sciencebased	1.675882
Lombardy	0.0011	0.013	0.343	sciencebased	1.668990
Lombardy	0.0011	0.013	0.342	sciencebased	1.650570
Lombardy	0.0011	0.013	0.334	sciencebased	1.634693
Lombardy	0.0011	0.013	0.352	sciencebased	1.720706
Lombardy	0.0018	0.013	0.36	sciencebased	1.720892
Lombardy	0.0022	0.013	0.357	sciencebased	1.690128
Lombardy	0.0024	0.014	0.338	sciencebased	1.683582
Calabria	0.000016	0.005	0.012	supplierdominated	1.235797
Calabria	0.000016	0.0055	0.012	supplierdominated	1.413259
Calabria	0.000027	0.008	0.011	supplierdominated	1.677189

Calabria	0.000027	0.0081	0.013	supplierdominated	1.948043
Calabria	0.000027	0.008	0.014	supplierdominated	1.487642
Calabria	0.000027	0.008	0.016	supplierdominated	1.531018
Calabria	0.000031	0.0054	0.018	supplierdominated	1.728398
Calabria	0.000039	0.0054	0.016	supplierdominated	1.478375
Calabria	0.000044	0.0061	0.015	supplierdominated	1.447170
Sicily	0.000012	0.008	0.166	sciencebased	1.082423
Sicily	0.000014	0.009	0.144	sciencebased	1.078493
Sicily	0.000018	0.011	0.127	sciencebased	1.072900
Sicily	0.000019	0.012	0.11	sciencebased	1.072207
Sicily	0.000019	0.011	0.091	sciencebased	1.074381
Sicily	0.00002	0.011	0.117	sciencebased	1.073349
Sicily	0.000022	0.0083	0.135	sciencebased	1.071963
Sicily	0.000023	0.0083	0.118	sciencebased	1.074004
Sicily	0.000025	0.009	0.099	sciencebased	1.074303
Liguria	0.00017	0.013	0.164	sciencebased	1.696734
Liguria	0.00017	0.014	0.156	sciencebased	1.332769
Liguria	0.00016	0.0074	0.169	sciencebased	1.186686
Liguria	0.00016	0.014	0.16	sciencebased	1.549848
Liguria	0.00016	0.0074	0.17	sciencebased	1.279805
Liguria	0.00016	0.0074	0.182	sciencebased	1.219630
Liguria	0.00021	0.013	0.17	sciencebased	1.461004
Liguria	0.00027	0.013	0.158	sciencebased	1.693411
Liguria	0.00031	0.016	0.136	sciencebased	1.132926
Latium	0.00096	0.016	0.111	sciencebased	2.968389
Latium	0.00095	0.016	0.107	sciencebased	2.899270
Latium	0.00059	0.016	0.111	sciencebased	2.796211
Latium	0.00059	0.016	0.115	sciencebased	2.494606
Latium	0.00059	0.016	0.113	sciencebased	2.533472
Latium	0.00059	0.016	0.134	sciencebased	2.477832
Latium	0.00183	0.017	0.129	sciencebased	2.588003
Latium	0.0027	0.017	0.153	sciencebased	2.456006
Latium	0.0028	0.02	0.152	sciencebased	2.711533
Friuli-Venezia Giulia	0.00085	0.015	0.37	specialisedsupplier	2.139043

Friuli-Venezia Giulia	0.00085	0.015	0.37	specialisedsupplier	1.478867
Friuli-Venezia Giulia	0.00074	0.016	0.408	specialisedsupplier	1.566517
Friuli-Venezia Giulia	0.00074	0.016	0.42	specialisedsupplier	1.925518
Friuli-Venezia Giulia	0.00074	0.016	0.378	specialisedsupplier	1.254812
Friuli-Venezia Giulia	0.00074	0.017	0.449	specialisedsupplier	1.436424
Friuli-Venezia Giulia	0.0012	0.017	0.439	specialisedsupplier	1.573477
Friuli-Venezia Giulia	0.00126	0.017	0.439	specialisedsupplier	1.677184
Friuli-Venezia Giulia	0.00144	0.017	0.432	specialisedsupplier	1.559557
Trentino-Alto Adige	0.00014	0.01	0.409	supplierdominated	1.524140
Trentino-Alto Adige	0.00013	0.012	0.408	supplierdominated	1.356050
Trentino-Alto Adige	0.0001	0.011	0.417	supplierdominated	1.440095
Trentino-Alto Adige	0.0001	0.012	0.449	supplierdominated	1.346486
Trentino-Alto Adige	0.0001	0.011	0.443	supplierdominated	1.353824
Trentino-Alto Adige	0.0001	0.011	0.471	supplierdominated	1.346486
Trentino-Alto Adige	0.00016	0.012	0.468	supplierdominated	1.529860
Trentino-Alto Adige	0.00016	0.012	0.472	supplierdominated	1.219187
Trentino-Alto Adige	0.00019	0.012	0.463	supplierdominated	1.330416
Umbria	0.000055	0.009	0.198	supplierdominated	1.809226
Umbria	0.000055	0.0085	0.189	supplierdominated	1.307385
Umbria	0.000029	0.009	0.177	supplierdominated	1.572100
Umbria	0.000029	0.0091	0.187	supplierdominated	1.452811
Umbria	0.000029	0.0096	0.187	supplierdominated	1.451847
Umbria	0.000029	0.0098	0.194	supplierdominated	1.402724
Umbria	0.00003	0.0098	0.205	supplierdominated	1.361029
Umbria	0.000051	0.011	0.208	supplierdominated	1.343517
Umbria	0.000073	0.012	0.198	supplierdominated	1.412067
Basilicata	0.00015	0.005	0.112	scaleintensive	3.048398
Basilicata	0.00017	0.0051	0.108	scaleintensive	3.406303
Basilicata	0.00017	0.0048	0.112	scaleintensive	3.069547

Basilicata	0.00018	0.0049	0.111	Scaleintensive	3.530543
Basilicata	0.00019	0.0048	0.11	Scaleintensive	3.707746
Basilicata	0.0002	0.0048	0.114	Scaleintensive	3.725274
Basilicata	0.00022	0.0062	0.115	scaleintensive	3.651812
Basilicata	0.00023	0.0062	0.112	scaleintensive	3.499874
Basilicata	0.00036	0.0051	0.109	scaleintensive	3.497180
Abruzzo	0.000037	0.008	0.239	scaleintensive	2.188142
Abruzzo	0.000036	0.0086	0.236	scaleintensive	2.786309
Abruzzo	0.000024	0.0096	0.244	scaleintensive	2.109293
Abruzzo	0.000024	0.0097	0.26	scaleintensive	2.532801
Abruzzo	0.000024	0.0096	0.284	scaleintensive	2.434638
Abruzzo	0.000024	0.0096	0.285	scaleintensive	2.411685
Abruzzo	0.000028	0.0096	0.296	scaleintensive	2.505064
Abruzzo	0.000018	0.0096	0.293	scaleintensive	2.710973
Abruzzo	0.000035	0.01	0.297	scaleintensive	2.213275
Sardinia	0.000009	0.007	0.213	scaleintensive	1.036149
Sardinia	0.000011	0.0078	0.183	scaleintensive	1.421577
Sardinia	0.000012	0.0077	0.159	scaleintensive	1.522332
Sardinia	0.000012	0.0078	0.156	scaleintensive	1.108103
Sardinia	0.000012	0.0077	0.14	scaleintensive	1.691214
Sardinia	0.000012	0.0077	0.175	scaleintensive	1.121963
Sardinia	0.000011	0.0079	0.184	scaleintensive	1.188147
Sardinia	0.000012	0.0079	0.178	scaleintensive	1.400302
Sardinia	0.000014	0.0078	0.115	scaleintensive	1.067910