Pathways of Innovation: The I-District Effect Revisited

Rafael Boix, Vittorio Galletto, and Fabio Sforzi

Abstract The I-district effect establishes the existence of dynamic efficiency in Marshallian industrial districts in the form of a positive innovative differential comparing to the average of the economy. The hypothesis has been empirically validated for the case of technological innovation using patent indicators. Empirical research has assumed that all types of patentable figures (utility models, national patents, EPO, WIPO) have the same weight regardless of its actual or expected market value, which may be questionable given the differences in coverage, protection and cost of each figure. In this article, we question the existence of the I-district effect when each patent is weighted by its expected potential value. As the I-district effect theory predicts, the relative differential effect is maintained even in the presence of the weighting, rejecting that the industrial district specializes only in low-quality patents. However, in this case, the primacy of industrial district as the most innovative local production system can be outpaced by other local production systems.

Keywords Industrial districts · I-district effect · Technological innovation · Patents

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1 Introduction

In 2001 tiles and mosaic tiles reproducing photos or designs made by computer began to appear at fairs in the ceramic industry. Their origin was due to an innovation that had appeared in the industrial district (ID) of Castellón: InkJet technology applied to tile decoration. This innovation is currently having a groundbreaking effect on the ceramic districts by replacing embossing roller technology, which was slow, relatively expensive and with limited graphical capabilities, by a cheaper, fast and flexible system (Albors and Hervas 2012), capable of printing any design in real time without interrupting the print chain. Despite its specialization in traditional sectors and small firms, the generation of technological innovation, even disruptive innovation, is not unusual in Marshallian industrial districts (IDs). Boix and Galletto (2009) coined the term "I-district effect" to describe the existence of dynamic efficiency in IDs in the form of a positive innovation differential with respect to the economy average, attributing this differential to the existence of Marshallian external economies (economies of localization). The studies that have measured the I-district effect at country level (Boix and Galletto 2009; Boix and Trullén 2010) have found favourable evidence of a strong innovative differential effect in IDs. This evidence is obtained using indicators based on patent information, which are the most commonly used indicator of technological innovation in the specialized literature (OECD 2009, p. 26). However, these papers assume that all types of patentable figures (innovation models, national patents, EPO, WIPO) have the same importance irrespective of their effective, or expected, market value, which can be arguable given the differences in coverage, protection and cost of each figure.

In this article, we question the existence of the I-district effect when each patent is assigned its expected potential value. *Would a significant I-district effect continue to exist after weighting patents based on their expected potential value?* The acceptance of a dynamic efficiency in the district (Becattini 1991; Bellandi 1992; Boix and Galletto 2009; Boix and Trullén 2010; López Estornell 2010) implies that the I-district effect should be positive and significant whether we account for the patents in homogenous way or discriminating them by value. However, even if this were true, we do not know how much the intensity of the effect will change by. The objective of the article is, therefore, to empirically contrast the presence of the I-district effect by weighting the patents by their potential value and to measure the variation of the effect. For this, an indicator has been developed that approximates the different expected commercial values of the patents.

The article is divided into six sections. After the introduction, the second section is a review of the district effect and innovation literature. Section 3 develops two models of analytical and synthetic knowledge that will serve to contrast and explain the I-district effect. Section 4 explains in detail the types of local production systems (LPSs) and the elaboration of the indicators that serve as the basis for the econometric estimation of Sect. 5. Finally, Sect. 6 offers a discussion of the results and conclusions.

2 District Effect and Technological Innovation

2.1 Industrial Districts

The ID is a new approach to economic change (Becattini 2000), starting from the fact that it cannot be understood outside a given place where the community of people and the population of firm are mutually embedded and the economic and social forces co-operate (Sforzi and Boix 2015). In this way, the relevant unit of analysis moves from the firm or sector to the place, which can empirically be approximated by a local labour market area (Sforzi 2012) also definable as a local production system (LPS).

Patterns of IDs have been identified as a generalized phenomenon in industrialized countries (Becattini et al. 2009; Boix and Trullén 2011), with them being especially significant in Italy and Spain (Sforzi 1990; Boix and Galletto 2005). In these two countries, the 2001 measurement using similar methodologies resulted in 156 and 205 IDs, respectively, accounting for 25% and 21% of total employment and 39% and 35% of manufacturing employment (ISTAT 2006; Boix and Galletto 2008).

2.2 District Effect and I-District Effect

The term "district effect" was coined by Signorini (1994) to explain the high efficiency rates of firms located in IDs. Dei Ottati (2006, p. 74) defines the district effect as the "set of competitive advantages derived from a strongly related collection of economies external to individual firms but internal to the district".

The empirical research of the district effect has been especially intense on the static effects (cost-productivity and export-comparative advantages). The main line of research seeks to quantify the differential outcome of IDs in productivity and efficiency and includes Signorini (1994), Camisón and Molina (1998), Fabiani et al. (2000), Soler (2000), Hernández and Soler (2003), Brasili and Ricci (2003), Cainelli and De Liso (2005), Becchetti et al. (2009) and Botelho and Hernández (2007). Results vary by country, sector, and type of measurement, although, in general, they provide evidence of the district effect in the form of increased productivity and increased efficiency. The district effect on competitiveness is addressed directly in Costa and Viladecans (1999), Becchetti and Rossi (2000), Gola and Mori (2000), Bronzini (2000) and Belso (2006). The aggregate results for the industry suggest the existence of a positive and significant district effect in terms of export quota, a positive but lesser effect on the likelihood of export and the existence of revealed comparative advantages. The data disaggregated by sector are not conclusive, although they suggest the existence of a district effect in more than half of the sectors.

Research on the changing component of the dynamic effect, linked to the ID's ability to innovate, has taken longer to develop. Cainelli and De Liso (2005, p. 254) argue that this fact is partly explained by the literature on IDs that considers external economies affecting the firm performance associated with low levels of innovation and partly by the difficulty of having detailed data on innovation available. The first assertion would be debatable, since members of the Florence school (Becattini 1991, 2001; Bellandi 1989, 1992) and Modena (Brusco 1975; Russo 1986) expressly emphasize the innovative capacity of the district, although it is true that other authors have continued to draw a marked bias against the district's innovative capacity as a small firm environment.

Leoncini and Lotti (2004), by means of survey data from an Italian region with a high density of IDs (Emilia-Romagna), show that ID firms have a higher probability of patenting, although the probability of carrying out research and development (R&D) activities is lower than that of firms located outside the district. Muscio (2006) also obtains evidence that the probability that the firm introduces innovation is superior for the firms located in IDs. Santarelli (2004), using data from European patents, obtains inconclusive evidence on the existence of a district effect. On the other hand, Cainelli and De Liso (2005) show that ID firms that introduce product innovations perform better than non-ID firms and that district-based product innovation firms perform better than those that innovate in processes.

Boix and Galletto (2009) investigate the differential innovative capacity of Spanish IDs with respect to the rest of the country using the number of patents per million employees. Their results prove that the IDs show a higher innovative intensity than the national average, the district innovative effect or the "I-district effect" as Boix and Galletto termed it. This behaviour is associated with the Marshallian external economies (special skilled labour, subsidiary industries, shared knowledge between firms specialized in different stages and branches of the same production process). Afterwards, Boix and Trullén (2010) disaggregated the territorial and sectoral part of the effect, concluding that the effect is more robust in the territorial dimension than in the sectorial, and therefore due to the socioeconomic organization of the district rather than its sectoral specialization. Finally, mention should be made of the work of López Estornell (2010), which asks whether the behaviour of the innovative firm is different, depending on its location in an ID of the Valencia's region, finding that the IDs specialize in a lighter and more local type of innovation with no formal protection (e.g. utility models) against a more formalized type of innovation (e.g. patents) of non-district LPS.

2.3 Innovation in IDs and the Sources of the District Effect

In the literature related to ID, it has been emphasized that the district model contributes in sustaining the innovative capacity of the firms and favours the adoption of innovations. From the theoretical point of view, there would be two explanations that could complement each other to explain the I-district effect.

First, the I-district effect would be explained by the existence of "decentralized (or diffused) industrial creativity" (Becattini 1991, 2001; Bellandi 1989). The basis of this idea is like that of the flexible integration process: if innovation can be performed in big companies and in a planned way, the innovative process could also be divisible into multiple interlinked small firms in an unplanned way, hence their denotation as "decentralized" or "diffused". Decentralized industrial creativity is reinforced by a decentralized model of absorption of new knowledge, which in turn circulates as a self-regulating output of interactions between local agents. This is a result more of search strategies and multiple interfirm co-operative interactions than of planned and deliberate efforts to carry out R&D activities as proposed in the linear model.

These interactions with their corresponding feedback take place throughout the supply chain and in all the different interfirm networks in a district, in which the firms co-operate in the manufacture of the different products, product components or stages of production. When existing knowledge is combined within a firm, new knowledge is generated which can be translated into either a simple imitation or a variant of the original innovation. Thus, marginal modifications take place through different sources: design activities, learning processes in manufacturing, interactions with customers and suppliers and reuse and re-elaboration of pre-existing external knowledge. This decentralized model of knowledge absorption conceives the innovative process as a circular process with feedback and information connections between the needs of the market and the processes of design, manufacture and search for new solutions, that is, in a cognitive spiral form in the district (Becattini 2001).

Secondly, the I-district effect can also be explained by theories of knowledge bases and differentiated modes of innovation. Rosenberg (1982) and more elaborately Jensen et al. (2007), Parrilli (2010) and Asheim and Parrilli (2012) differentiate between three types of knowledge bases, analytical, synthetic and symbolic, which are intertwined with two innovation models: STI and DUI.

The STI (science, technology and innovation) model is associated with the production of analytical knowledge that is generated in deductive and formal models of science and technology and is codified (explicit). An example is the linear model of innovation, based on science, R&D and the generation of disruptive innovations (although in practice, the bulk of the innovation generated by the model is incremental). The pharmaceutical industry is a good example of this model.

The DUI (doing, using and interacting) model, more associated with synthetic knowledge, is based on the generation of innovation through learning and problem-solving that the daily development of work raises, especially when workers face continuous changes and interact with customers, which forces them to face new problems and solve them. The search for solutions to these problems strengthens workers' skills and know-how and makes extensive use of tacit and often localized knowledge. The model of innovation DUI is oriented to the client or to the market and produces mainly incremental innovations, although in practice it is also capable of producing radical innovations. Examples of this model abound in the mechanical, ceramic or furniture industry.

The innovative process in IDs presents clear similarities to the DUI model. Thus, it entails knowledge that can be largely tacit and specialized in its context of development and application. This model recovers the importance of the experience raised in the "learning by doing" and "learning by using" models formulated by Arrow (1962) and Rosenberg (1982).

Both arguments, decentralized creativity and synthetic knowledge, are intertwined (Bellandi 1989) to such an extent that marginal modifications serve to increase demand. The existence of a broader market increases the return resulting from a greater division of labour between firms, as this specialization increases economies of scale and scope. During this process of growth, some ID firms generate new knowledge, introducing radical innovations of Schumpeterian type, that when spread around the district makes the whole district more competitive. In other words, a process is initiated that makes the district maintain its competitiveness over time. However, there are IDs that have been characterized by a growth in which continuous learning has resulted in a process of intense product differentiation, which ensures the competitiveness of their firms (Belussi 2009, p. 470). The operation of these processes causes IDs to show a positive innovative differential over other types of LPS (I-district effect) and that a priori IDs do not have to focus solely on minor technological innovation.

3 Parametric Modelling of the I-District Effect

3.1 The Analytical Knowledge Model

To model the creation of economically valuable knowledge, quantified by means of innovation indicators based on patents, the most usual way is to use a function of knowledge creation in the style of Griliches-Jaffe's functions (Griliches 1979, 1992; Jaffe 1986, 1989). In the empirical literature that employs these functions, there are explanatory variables that reflect the creation of knowledge of typically analytical type (such as an effort in R&D activities), which reflect specific characteristics of each territorial unit and indicators of the geographical proximity between agents. Regarding these indicators of proximity, let us remember that our territorial units of analysis are the LPS, which have been identified from the daily journey-to-work relationships, so that, implicitly, the geographical proximity indicator is already included. In addition, this proximity involves also an organizational proximity, answering the criticism raised about the estimates of the production function of knowledge used by administrative units as units of analysis.

The knowledge production function for a LPS j can be expressed as

$$K_j = f\left(R_j, Z_j\right) \tag{1}$$

where K_j represents the creation of knowledge in the LPS j, R_j is an indicator of the research effort carried out in the LPS j and Z_j is a vector of specific characteristics to j, which can be replaced by a combination of local indicators.

The specification of the knowledge production function is

$$K_j = \gamma R_j^{\beta} Z_j^{\delta} \varepsilon \tag{2}$$

where γ, β, and δ are parameters and ε is an error term. In the specifications of this function following Jaffe (1989), the variables are quantified in absolute terms so that a variable is included that reflects the scale (e.g. population) and, thus, considers the fact that the number of innovations may be directly related to the size of the territorial unit under study. However, for capturing the differential innovation capacity of the ID, what is relevant is to measure the relative differences, not the absolute ones, so that the input and output variables are divided by the number of employees in each territorial unit, that is, of each LPS. So, the function is

$$k_j = \gamma r_j^{\beta} Z_j^{\delta} \varepsilon \tag{3}$$

where k_j is the average innovation per worker in the LPS j, r_j is the average R&D effort per worker in the LPS j and the variables in the vector Z can also be relativized if necessary. Using logarithms, we obtain a knowledge production function transformed into a log-linear expression:

$$\log k_j = \gamma + \beta \log r_j + \delta \log Z_j + \varepsilon_j \tag{4}$$

To estimate the expression (4) for the case of the 806 LPSs identified in Spain, we consider that the innovative capacity of the LPS depends on the R&D efforts (Griliches 1979) and on factors that are specific to each LPS type, so that $\delta^* = f(Z_j)$. In this case, we will obtain estimators of the parameters β and of the specific parameters for each type of LPS. These parameters are considered as the measure of the differential effect on the dependent variable of each LPS type with respect to the mean of the set of observations. This interpretation is consistent with the estimation of a model of fixed effects or model of effects not observed, collecting in the δ^* the "individual effects" or "individual heterogeneity" of each group.

$$\log k_j = \gamma + \beta \log r_j + \delta^* + \varepsilon_j \tag{5}$$

3.2 *The Analytic-Synthetic Knowledge Model*

Secondly, we will approach the modelling of these fixed effects, that is, we will introduce in the model the variables related to synthetic knowledge and that in accordance with the theory also influence the local innovation capacity. This modelling will be done by introducing the vector that collects the indicators of external economies (economies of localization and urbanization) in Eq. (5), obtaining Eq. (6):

$$\log k_j = \gamma + \beta \log r_j + \delta Z_j + \delta^* + \varepsilon_j \tag{6}$$

Note that if, as the district effect hypothesis implies, δ and δ^* are correlated, the value of the coefficients and the statistical significance of δ^* will be markedly reduced, or will disappear, upon introduction of the vector of regressors Z_j.

4 Measuring Innovation in Industrial Districts

4.1 A Typology of Local Production Systems

The relevant territorial units for measuring innovation in IDs are the 806 LPS identified in Spain (Boix and Galletto 2009) through the methodology developed by Sforzi-ISTAT (ISTAT 2006; Sforzi 2009). The types of LPS are those used by Boix and Galletto (2009) and Boix and Trullén (2010), while the identification of the dominant specialization comes from the third stage of the above-mentioned methodology. Based on this methodology, seven types of LPS have been identified (Fig. 1).

First, there are three categories of manufacturing LPS totalling 332 LPSs: 205 are IDs, which account for 20.9% of total Spanish employment; 66 are LPSs of large firms (10.9% of employment); and 61 are LPSs classified neither as IDs nor as LPSs of large firms (0.8% of employment).

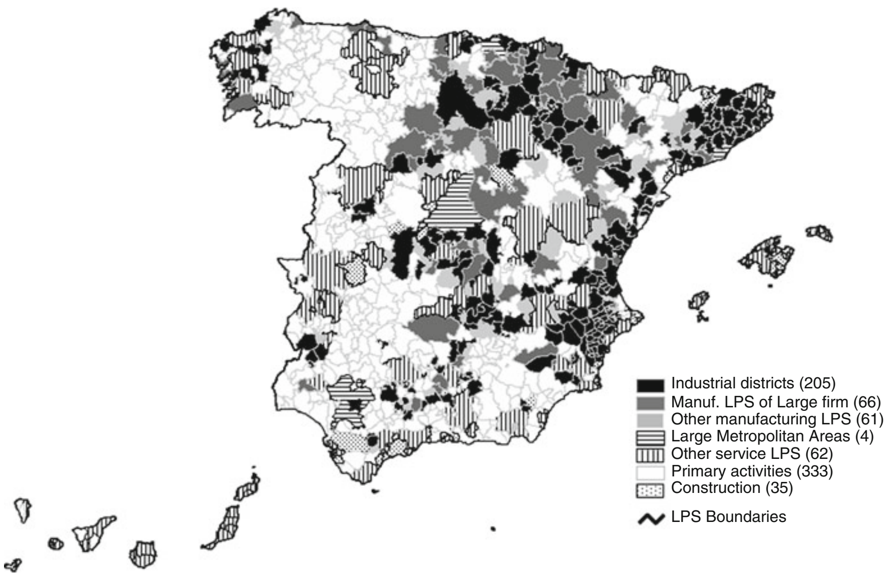

Fig. 1 Types of LPS in Spain. Source: Boix and Galletto (2009) and Boix and Trullén (2010)

Secondly, there are two categories of LPS specialized in service activities totalling 106 LPSs: 4 LPSs are specialized in business services and correspond to the central LPS of 4 (of the 5) largest Spanish metropolitan areas (28% of total employment),[1] while 102 LPSs are specialized in other services (25% of employment).

Finally, there are two remaining categories which include 333 LPSs specialized in primary agricultural and extractive activities (12.2% of total employment) and 35 LPSs specialized in construction activities (2.2% of total employment).

4.2 Measurement of Technological Innovation in LPS: The Unweighted Indicator of Innovation

The unweighted innovation indicator is elaborated following the methodology proposed by Boix and Galletto (2009). To measure local technological innovation in a comprehensive way, patent registers (national, European or world patents) and utility models (a figure of intellectual property protection that offers lower guarantees and lower application and registration costs than patents) are added to a single indicator. When a single innovation has been registered with several figures, it has been counted only once. After that the criteria to account for each type of patents have been established, we can order them according to the municipality that appears in the patent document—using the inventor address and fraction in case of more than one inventor—and elaborate the simple aggregate indicator of technological innovation by LPS.

For comparability with Boix and Galletto (2009), the technological innovation of the years 2001 to 2005 is summed. The grouping by periods is usual in innovation literature to avoid bias if only 1 year is used (Griliches 1990, 1992). However, the coverage of our patent database for the same period is almost 20% (3957 patents) higher than that of Boix and Galletto (2009). This is due to the very late appearance of records that were hidden either by administrative delays in the publication or by having exercised the right to confidentiality granted by the intellectual property law.

Table 1 shows the distribution of the unweighted local innovation indicator for the different types of LPS identified in Boix and Galletto (2009). This table also includes the distribution of employment, so that the innovative intensity can be calculated for the period 2001–2005. The most intensive innovative type of LPS is the IDs, with 446 innovations per million employees; the metropolitan areas with 427 innovations per million employees come second, followed by the manufacturing LPSs of large firms with 366 innovations per million employees.

[1]These four metropolitan areas are Madrid, Barcelona, Seville and Bilbao. The metropolitan area of Valencia is classified as an ID.

Table 1 Distribution of innovation by type of LPS: simple aggregate indicator of innovation, 2001–2005

Types of LPS	LPS		Innovation 2001–2005		Employment 2001	
	Total	%	Total	%	Total	%
Agriculture and extractive activities	333	41.3	1164	4.4	1,993,921	12.2
Manufacturing	332	41.2	11,011	41.5	5,317,479	32.6
– Industrial districts	205	25.4	7627	28.8	3,419,384	20.9
– Large firms	66	8.2	3252	12.3	1,776,129	10.9
– Other manufacturing	61	7.6	132	0.5	121,966	0.8
Construction	35	4.3	272	1.0	363,865	2.2
Services	106	13.2	14,062	53.1	8,654,448	53.0
– Metropolitan areas	4	0.5	9752	36.8	4,566,857	30.0
– Other services	102	12.7	4310	16.3	4,087,591	25.0
Total	806	100.0	26,509	100.0	16,329,713	100.0

Source: Authors' elaboration on data from OEPM, WIPO, EPO and INE 2001 Census

4.3 Elaboration of the Weighted Innovation Indicator

The expected commercial value associated with each type of patentable figure may be very different, and, therefore, adding records linearly has the risk of adding innovations of very different value. In the literature, methodologies have been proposed to deal with this problem (Guellec and van Pottelsberghe 2007, pp. 107–109), but these are complex methods, which require very complete complementary qualitative information of each patent. The large number of innovation records that we are dealing with in this research makes it impossible to follow these methods, so we propose using a method that consists of weighting patents based on the estimated average cost of obtaining a patent.

The implicit hypothesis is that who can best assess the innovative quality of a patent, understood as its potential or expected commercial value, is its applicant, who is in the best position to evaluate whether the benefit of protecting an invention outweighs the costs which are incurred when patenting. However, calculating this cost is not a simple task, since there are many parameters that determine the final cost. In this case, we will follow a very simple criterion, which consists of obtaining the costs of direct application of a patent to the corresponding office of registry of the intellectual property and indexing the cost from the most expensive of the procedures. The costs of European patents are obtained from the minimum cost calculated by Guellec and Van Pottelsberghe (2007, p. 194) for a patent designating three countries and assuming at least one translation into one of the three official languages of the European Patent Office (EPO). The resulting cost is 6370 euros. In the case of world patents (applications to the World Intellectual Property Office, WIPO), since we do not have a reference to average costs, we will use the approximation between the maximum costs (4193 euros) and minimum costs (2615 euros), according to the information we have collected from the OEPM (Spanish Office of

Table 2 Cost of the direct application for a patent to the Spanish (OEPM), worldwide (WIPO) and European (EPO) offices, in euros (2005) and quality weighting for each type of application

Cost of the direct application	Spanish utility model	Spanish patents	World patent	European patent
Cost incurred between application and being granted (euros)[a]	120	972	3404	6370
Weighting	0.02	0.15	0.53	1.00

[a]We use the 1-year rate data because differences in valuation of the invention are maintained in proportion to each year
Source: Authors' elaboration on OEPM, WIPO and EPO data

Table 3 Distribution of innovation by type of LPS: weighted aggregate innovation indicator, 2001–2005

Types of LPS	LPS		Innovation 2001–2005		Employment 2001	
	Total	%	Total	%	Total	%
Agriculture and extractive activities	333	41.3	176	2.0	1,993,921	12.2
Manufacturing	332	41.2	3463	39.0	5,317,479	32.6
– Industrial districts	205	25.4	2308	26.0	3,419,384	20.9
– Large firms	66	8.2	1124	12.7	1,776,129	10.9
– Other manufacturing	61	7.6	31	0.4	121,966	0.8
Construction	35	4.3	54	0.6	363,865	2.2
Services	106	13.2	5188	58.4	8,654,448	53.0
– Metropolitan areas	4	0.5	4041	45.5	4,566,857	30.0
– Other services	102	12.7	1147	12.9	4,087,591	25.0
Total	806	100.0	8882	100.0	16,329,713	100.0

Source: Authors' elaboration on OEPM, WIPO, EPO data and INE 2001 Census

Patents and Trademarks), regarding patent applications to the WIPO (that is, the cost that does not include the national phase). This average value is 3404 euros. For the Spanish patents (submitted to the OEPM), the average value between the maximum and minimum costs has also been considered in accordance with the official rates published by the OEPM, which gives a result of 972 euros. In the case of utility models, the cost of obtaining is 120 euros. In all cases these are values that were in force in the period to which the data refer.

The result is that the most expensive procedure is the European patent (6370 euros), and the costs of all figures are divided by this value to obtain the weight of each type of patent (Table 2). Next, we proceed as in the simple indicator, adding the total of patents weighted for each LPS and dividing by the number of people employed (Table 3).

The results obtained with this indicator for the period 2001–2005 show that the innovative intensity of the whole of Spain is 109 innovations per million employees, resulting from dividing the total patents among the total employment. The LPS with superior innovative capacity is now the large metropolitan areas, with 178 innovations

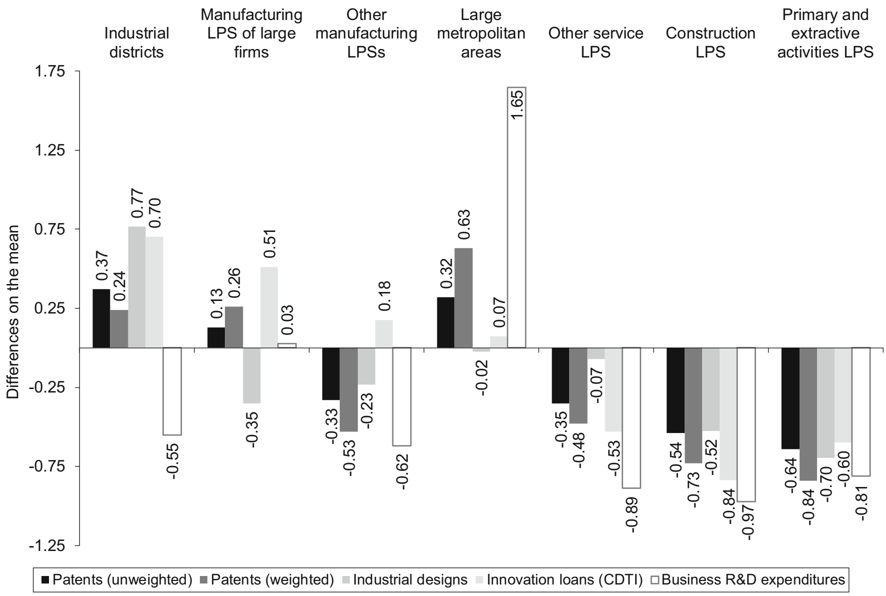

Fig. 2 Innovative capacity by type of LPS and indicator: innovations per million employees per year, with differences from the average of each indicator, 2001–2005. Source: Authors' elaboration on OEPM, EPO, WIPO, CDTI, SABI, and Census (INE) data

per million employees, ahead of the IDs that, with 135 innovations per million employees, are in second place. Third are the manufacturing LPS of large firms with 127 innovations per million employees. The other types of LPS are considerably below the mean (Table 3).

Following Boix and Galletto (2009), we compared the sensitivity of the two patent-based indicators to two other indicators whose microdata allow LPS measurement over the same time period: industrial designs from the OEPM and OHIM (now European Union Intellectual Property Office), which are indicators of innovation by output, and two input indicators: public sector grants and credits for innovation from the Centre for the Development of Industrial Technology (CDTI) and business R&D expenditures. Except for the weighted indicator and business R&D expenditures, the IDs show the most significant positive differential effect in relation to the Spanish average, and in the case of the weighted indicator, they are only surpassed by the large metropolitan areas. The results show that patent indicators are adequate for the measurement of output technological innovation in ID environments, being a more conservative option than industrial designs or CDTI credits (Fig. 2).

4.4 *Elaboration of the Model Variables*

4.4.1 The Dependent Variable

The dependent variable of the model is the innovation per employee in the LPS, measured by simple and weighted indicators. In both cases, for each LPS the innovations of the period 2001–2005 are added and are then divided by the number of LPS employees obtained from the 2001 Census.

4.4.2 The Explanatory Variables

The explanatory variables use data from 2001 to avoid, as far as possible, problems of simultaneity and endogeneity. Following the model presented in Sect. 3, the variables are expressed as logarithms, so that the estimated coefficients can be interpreted as elasticities. We arrange them into three groups: indicators of input to the innovative process, indicators of localization economies and indicator of urbanization economies.

(a) Indicators of input to the innovative process. The R&D expenditure of the firms is obtained from the balance sheets of SABI (Bureau van Dijk). The aggregate expenditure of the public sector and universities in R&D activities is allocated to each LPS based on the regional expenditure per person employed in R&D provided by the INE, multiplied by the number of R&D jobs in the public sector and universities in each LPS.[2] It is assumed that there is a positive relationship between R&D expenditure (public or private) and innovative capacity.

(b) Indicators of localization economies (Marshallian economies). These are grouped into five categories, which assume a positive relationship between the indicator and the generation of innovation per employee:

(b.1) Percentage of productive specialization (or non-diversity) in each LPS, calculated as a Hirschman-Herfindahl diversity index of employment E at 2-digit level of NACE sector i in each LPS j. This indicator also assumes that there is a positive relationship with the innovation indicators. Higher values of the index indicate higher specialization (less diversity) of the economic structure:

$$\mathrm{DIV}_j = \sum_j \left(E_{ij}/E_j \right)^2 \tag{7}$$

(b.2) Share of specialized industrial workers in each LPS, calculated as the percentage of manufacturing employment in each LPS. A greater share of

[2]The fact that the R&D expenditure of universities is concentrated in a few LPSs and that in the rest it is zero presents difficulties in expressing the variables in logarithms; this is the reason why we have opted to add it to the public sector expenditure.

manufacturing workers is related to greater ease of transmission of practical knowledge, either between workers in the same sector or in different industrial sectors, which facilitates their use in productive activity (through innovations). On the other hand, a greater share of industrial workers is associated with a greater availability of skilled workers for handcrafted products in the LPS and greater generation of synthetic knowledge. The relation of the capacities of this type of workers through their craftsmanship, carrying out innovation in LPSs where mass production is not dominant, has recently been highlighted in Sennett (2008) and Micelli (2011). In these LPSs, the manufacturing worker is a *maker* who has direct experience with the material world and establishes a dialogue between action and reflexivity, from which new processes and products emerge.

(b.3) Presence of suppliers in each LPS. This indicator is inspired by Dumais et al. (2002) and allows, based from the symmetric input-output table (SIOT) of the Spanish economy of the 2000, prepared by the INE,[3] to obtain an indicator of the employment in the supplier sectors of the sector i in area j (in our case, the 806 LPSs):

$$P_{ij} = \sum_{i \neq z} \vartheta_{is} E_{zj}, \text{with } \vartheta_{is} = v_{is} / \sum v_{is} \tag{8}$$

where v_{is} is the volume of purchases of the sector i acquired from each of the other economic sectors (calculated for all sectors of the SIOT), ϑ_{is} is the proportion of total inputs that sector i acquires from each of the other sectors and E_{zj} is the employment in each of these other activities (calculated from the 2001 Census employment data at 3-digit level of CNAE93, in order to build the sectors equivalent to those employed in the SIOT[4]).

Once the employees in each supplier activity were obtained, we added them for each LPS, obtaining a weighted total of employment. We compare this weighted sum with the actual employment total of each LPS, and this is then placed in relation to the value that is obtained from considering the whole of Spain as a single area (S_{Spain}), with which we obtain SS_j:

$$SS_j = \left(\sum_i P_{ij} / \sum_i E_{ij} \right) / S_{\text{Spain}} \tag{9}$$

If SS_j is higher than 1, the weight of employment in the supply sectors in LPS j is greater than the weight of employment in the supply sectors in the

[3]The INE only offers the symmetric tables of the years 2000 and 2005, so we used the year 2000. When using a single table for all geographic areas, it is assumed that the inter-sector supplier-customer relationships are similar between LPSs.

[4]The table of equivalences used is that published by the INE along with the SIOT.

whole of Spain. This indicator also assumes that there is a positive relationship with the innovation indicators.

(b.4) Social organization of production, using as an indicator the index of social capital developed by the IVIE (Pérez et al. 2005). This indicator is calculated for the provinces and indicates if the province has a higher, equal or lower level of social capital than the country average. Each LPS is assigned the value of its province. In the case of LPSs that cover more than one province, they are assigned the mean of the different provincial values and weighted by the percentage of employment of LPS in each province. The influence of this indicator on innovation variables is also assumed to be positive.

(b.5) Weight of employment in small- and medium-sized firms (up to 249 employees) in each LPS. This indicator aims to control which organizational model is most related to innovation capacity. It is calculated from the following expression, differentiating small firms and medium-sized firms

$$SME1_j = \sum E_{SME1,j} / \sum E_j \tag{10}$$

$$SME2_j = \sum E_{SME2,j} / \sum E_j \tag{11}$$

where $E_{SME1,j}$ is the occupation in small firms (up to 49 workers) in the LPS j and $E_{SME2,j}$ is its equivalent for medium-sized firms (from 50 to 249 workers). The relationship with innovation can be assumed positive because the agglomeration of SMEs can facilitate the processes of diffuse creativity. However, in some LPS the average firm size is so small that it could make diffused creativity difficult to operate, so that there could be a negative relationship between specialization in SMEs and innovative behaviour.

(c) Indicator of urbanization economies: indicator of physical density, the result of dividing the resident population in each LPS by the area in square kilometres of the corresponding LPS. The hypothesis that justifies the consideration of this indicator is that a higher density can facilitate the circulation of knowledge and, consequently, a greater capacity for innovation.

Table 4 presents the descriptive statistics of the dependent and independent variables.

5 Results

Following Boix and Galletto (2009) and Boix and Trullén (2010), we proceed to estimate the models sequentially. First, the analytic knowledge model (Eq. 5) is estimated for the weighted and non-weighted indicator (Table 5). The estimation is made with a fixed effects model, where the fixed effects pick up the individual effect

Table 4 Descriptive statistics: variables in levels

Variables in levels	Observations	Mean	Median	Std dev	Min	Max
Simple indicator	806	201.09	118.58	318.63	0.00	3285.22
Weighted indicator	806	47.91	9.01	129.22	0.00	1999.84
Private R&D	806	0.13	0.08	0.12	0.01	0.59
Public R&D	806	0.80	0.65	0.62	0.07	5.52
Specialization	806	2.70	2.02	2.23	1.00	13.68
Specialization in manufacturing	806	17.85	14.49	11.97	1.53	63.36
Suppliers	806	0.12	0.10	0.07	0.03	0.41
Social capital	806	1.90	2.00	0.86	1.00	3.00
SME1	806	0.80	0.86	0.23	0.01	1.00
SME2	806	0.13	0.08	0.17	0.01	1.00
Population density per km^2	806	41.18	14.22	107.66	0.95	1634.68

Source: Authors' elaboration

of each of the seven types of LPS, including the IDs. The model is estimated first for the 604 LPS that have innovation records and then for the 806 LPS using the Heckman two-step model, which allows it to control the existence of selection biases. Second, the model of analytical-synthetic knowledge is estimated, which includes the variables that explain the individual effects, that is, the localization economies (Marshallian economies) and the urbanization economies (Table 6).

The hypothesis of this article is that the I-district effect exists whether all types of utility models and patents are accounted for by the same value or they are weighted by the expected value of patents, which would mean that the ID does not specialize only in low-cost, low-quality patents. The results of the estimates clearly show that the district effect continues to be maintained by weighting patents by an indicator of their expected value and that the relative differential is not altered: in the unweighted indicator, the innovative differential of the IDs (I-district effect) is between 40% and 43% above the LPS average, like that of Boix and Galletto (2009) and Boix and Trullén (2010). In the weighted indicator, the differential is 42% higher than the mean LPS. In all cases the coefficients are statistically and economically significant. As in the previous works, localization and urbanization economies explain the differentials, reducing the coefficients of the typologies of LPS and making them statistically insignificant.

Two other relevant results emerge from the weighted indicator. First, the primacy of IDs as the most innovative LPS is now superseded by manufacturing LPS of large firms ($\beta = 0.51$) and large metropolitan areas specialized in business services ($\beta = 0.62$), although in the latter case, the coefficient is not statistically significant. This result would be expected to some extent because in these two environments the greater average size and typology of firms make the cost of European and world patents more affordable and it is also easier to exploit the potential value of these innovations. Secondly, the estimated R&D expenditure coefficients double their value with respect to the unweighted indicator, and the coefficients more clearly related to the Marshallian economies tend to be reduced and/or not to be statistically

Table 5 Estimation of the function of simple knowledge production and district effect

	Dependent variable: simple innovation indicator		Dependent variable: weighted innovation indicator	
	Fixed effects (a–d)	Fixed effects Heckman (a–e)	Fixed effects (a–d)	Fixed effects Heckman (a–e)
Constant	5.7439*	5.6995*	4.1349*	4.1370*
	(0.000)	(0.000)	(0.000)	(0.000)
Private R&D	0.2250*	0.2467*	0.4522*	0.4512*
	(0.000)	(0.000)	(0.000)	(0.000)
Public R&D	0.1838*	0.2450*	0.4728*	0.4701*
	(0.001)	(0.000)	(0.001)	(0.000)
Fixed effects				
Industrial districts	0.4016*	0.4370*	0.4213*	0.4194*
	(0.000)	(0.000)	(0.007)	(0.007)
Manufacturing LPS of large firms	0.0968	0.1356	0.5143*	0.5122*
	(0.369)	(0.209)	(0.013)	(0.015)
Other manufacturing LPS	0.3463*	0.2871*	−0.2438	−0.2395
	(0.006)	(0.024)	(0.314)	(0.335)
Large metropolitan areas	0.1215	0.1267	0.6178	0.6175
	(0.715)	(0.702)	(0.335)	(0.336)
Other LPS services	−0.2298*	−0.2005*	−0.0987	−0.0999
	(0.019)	(0.040)	(0.599)	(0.596)
Construction	−0.2884*	−0.2657	−0.2794	−0.2812
	(0.040)	(0.057)	(0.300)	(0.300)
Agriculture and extractive activities	−0.4480*	−0.5202*	−0.9315*	−0.9283*
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects *F*-test	22.15*	23.49*	15.55*	12.80
F-test	28.04*	21.70*	36.18*	24.08
LR selection Test	9.59*	9.59*	0.00	0.00
VIF	1.04	1.19	1.04	1.19
Condition number	6.51	7.42	6.51	7.42
R^2-adj/Pseudo R^2	0.2845	0.2932	0.2674	0.2662
Log-L	−684.69	−680.48	−1080.00	−1080.00
Akaike	1387.38	1380.97	2178.00	2178.00
BIC	1427.02	1425.00	2217.63	2224
Number of observations	604	806	604	806

Notes: (a) All variables are natural logarithms; (b) P-values in parentheses; the asterisks represent statistical significance at 5%; (c) estimators of the effects *within* model; (d) fixed effects calculated under the constraint that $\Sigma\ \alpha i = 0$, so that the dummy coefficients represent deviations from the average effect of the group (intercept); (e) in case of rejecting the independence of the equations (Test LR), we compute the adjusted coefficients of Heckman

Table 6 Modelling the determinants of innovative intensity

	Dependent variable: simple innovation indicator		Dependent variable: innovation weighted innovation indicator	
	Fixed effects (a–d)	Fixed effects Heckman (a–e)	Fixed effects (a–d)	Fixed effects Heckman (a–e)
Constant	4.1714*	3.0499*	2.1329*	1.4951
	(0.000)	(0.000)	(0.003)	(0.097)
Private R&D	0.1362*	0.1499*	0.3102*	0.3180*
	(0.001)	(0.000)	(0.000)	(0.000)
Public R&D	0.1581*	0.1590*	0.3490*	0.3494*
	(0.006)	(0.005)	(0.003)	(0.003)
Specialization	0.1510*	0.1305*	0.2399	0.2283
	(0.013)	(0.029)	(0.053)	(0.067)
Specialization in manufacturing	0.5372*	0.6507*	0.4313*	0.4959*
	(0.000)	(0.000)	(0.008)	(0.004)
Suppliers	0.2934*	0.0823	0.1554	0.0353
	(0.000)	(0.272)	(0.198)	(0.823)
Social capital	0.2421*	0.2279*	0.4087*	0.4005*
	(0.001)	(0.002)	(0.008)	(0.009)
SME1	−0.1240	−0.0894	−0.1140	−0.0944
	(0.053)	(0.115)	(0.385)	(0.476)
SME2	−0.0089	−0.0001	0.3253	0.0303
	(0.740)	(0.998)	(0.648)	(0.584)
Density	0.0954*	0.1449*	0.1407*	0.1689*
	(0.001)	(0.000)	(0.015)	(0.007)
Fixed effects				
Industrial districts	0.0921	0.0755	0.1604	0.1511
	(0.327)	(0.411)	(0.405)	(0.433)
Manufacturing LPS of large firms	−0.0642	−0.0760	0.4006	0.3940
	(0.567)	(0.490)	(0.082)	(0.088)
Other manufacturing LPS	0.0714	0.0119	−0.3435	−0.3773
	(0.573)	(0.924)	(0.186)	(0.149)
Large metropolitan areas	−0.0111	−0.1130	0.2582	0.2003
	(0.972)	(0.718)	(0.691)	(0.758)
Other service LPS	0.0125	0.0865	−0.0239	0.0181
	(0.910)	(0.434)	(0.916)	(0.937)
Construction	−0.0084	0.1194	0.0042	0.0769
	(0.951)	(0.385)	(0.988)	(0.788)
Agriculture and extractive	−0.0922	−0.1044	−0.4561*	−0.4630
	(0.292)	(0.226)	(0.011)	(0.010)
Fixed effects *F*-test	0.72	1.12	2.39*	2.54
F Test	20.22*	22.95*	11.88*	10.84

(continued)

Table 6 (continued)

	Dependent variable: simple innovation indicator		Dependent variable: innovation weighted innovation indicator	
	Fixed effects (a–d)	Fixed effects Heckman (a–e)	Fixed effects (a–d)	Fixed effects Heckman (a–e)
LR selection test	12.45*	12.45*	0.49	0.49
VIF	1.51	1.90	1.51	1.91
Condition number	29.37	40.93	29.37	40.93
R^2-adj/Pseudo R^2	0.3949	0.4127	0.2965	0.2969
Log-L	−630.48	−620.98	−1064.20	−1063.48
Akaike	1292.96	1273.96	2160.41	2160.97
BIC	1363.42	1344.41	2230.86	2235.83
Number of observations	604	806	604	806

Notes: (a) All variables are natural logarithms; (b) P-values in parentheses; the asterisks represent statistical significance at 5%; (c) estimators of the effects *within* model; (d) fixed effects calculated under the constraint that $\Sigma\ \alpha i = 0$, so that the dummy coefficients represent deviations from the average effect of the group (intercept); (e) in case of rejecting the independence of the equations (Test LR), we compute the adjusted coefficients of Heckman

significant (the exception is social capital). The latter can be interpreted as a greater relationship between the use of innovation protection figures of higher expected value and innovation of an analytical type.

Finally, other indicators and complementary effects have been considered. In relation to urbanization economies, the total population of each LPS, employment density (employment over population) and physical density (population per km^2) were initially tested (separately), although they create collinearity problems. Other control variables related to human capital were also introduced, namely, educational levels, knowledge and creativity (percentage of university graduates among workers, employment in knowledge-intensive activities, percentage of people employed in ICT, in creative activities and in R&D activities), although they were economically and statistically non-significant. We also rejected the existence of significant spatial correlation between LPS in the form of lags of the endogenous or exogenous variable or in the error term.

6 Conclusions

Previous research that has addressed the I-district effect finds evidence in its favour, although they do not consider that the types of patentable records used to measure technological innovation may have different economic value.

The ID theory supports the hypothesis that the I-district effect should be maintained even if we consider different weights for patents, but it does not indicate how much it will vary. To verify this, a weighted indicator of technological innovation has been developed, adjusting the patents by their expected value, and two functions of knowledge production have been estimated econometrically, considering in the first an analytical knowledge base and in the second an analytical-synthetic base.

The conclusion is that the hypothesis of the robustness of the I-district effect cannot be rejected: the I-district effect remains economically and statistically significant and shows very similar values for the weighted and unweighted indicator (an innovative intensity of around 42% above the average of LPSs). The reason for this is that the combination of decentralized industrial creativity and DUI (doing, using and interacting) innovation generate a multitude of small innovations that integrate and consolidate into higher value innovations, both coexisting.

However, by weighting patents by the indicator used to approximate their expected value, manufacturing LPS of large firms and the centres of the large metropolitan areas show an innovative effect superior to that of the ID, as a result of the metropolitan environment and the larger size of their firms that allows them to approach larger markets, to cover the costs of international patents and to have greater expectations to obtain yields from them.

The main implication of these results is that the ID is not a weak innovator, since it does not specialize only in innovations of reduced value and is even capable of generating disruptive innovations that renew their cycles of production and reproduction. In addition, the results also show that the higher production of patents with higher expected value is also related to higher levels of private and public R&D in the LPS.

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