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The Role of Knowledge Heterogeneity on the Innovative Capability of Industrial Districts

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ABSTRACT

This paper seeks to contribute to the ongoing debate concerning the role of heterogeneity for the innovative capability of industrial districts. With this aim, using a knowledge-based approach, the paper focuses on different sources of industrial district knowledge heterogeneity and studies how the different level of heterogeneity affects the innovative capability of industrial districts. Four theoretical hypotheses concerning the effects of knowledge and knowledge heterogeneity on the Industrial District innovativeness are formulated. To test the hypotheses, an econometric analysis on 32 Italian District Provinces is applied. Empirical results show that knowledge heterogeneity matter for increasing the innovative capability of industrial districts.

Keywords: Industrial district, innovative capability, knowledge heterogeneity

JEL classification: O32, F14, R12

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Abstract

This paper seeks to contribute to the ongoing debate concerning the role of heterogeneity for the innovative capability of industrial districts. With this aim, using a knowledge-based approach, the paper focuses on different sources of industrial district knowledge heterogeneity and studies how the different level of heterogeneity affects the innovative capability of industrial districts. Four theoretical hypotheses concerning the effects of knowledge and knowledge heterogeneity on the Industrial District innovativeness are formulated. To test the hypotheses, an econometric analysis on 32 Italian District Provinces is applied. Empirical results show that knowledge heterogeneity matter for increasing the innovative capability of industrial districts.

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INTRODUCTION

Industrial districts (IDs) are geographically defined production systems, characterized by a large number of small and medium sized firms that are involved at various phases in the production of a homogeneous product family. These firms are highly specialized in a few phases of the production process, and integrated through a complex network of inter-organizational relationships[2].

The reasons underlying the ID competitiveness have been deeply studied in the related literature by adopting different theoretical perspectives coming from many research streams, namely regional economics, economic geography, political economy, and industrial organization. In particular, studies of regional scientists have explained the advantages of firms localized within IDs by using the notion of "localization economies", which are benefits mainly due to the presence of specialized input suppliers, a local pool of specialized labour skills, and specialized knowledge concerning the particular industry (Becattini, 1990; Marshall, 1920). Studies on industrial economics have highlighted the reduction of the transactional costs due to geographical proximity of firms and informal and face-to-face contacts among them as one of the most important benefits for local firms (Mariotti, 1989). Studies on innovation management have pointed out that IDs found the competitive success on their innovative capability, which is due to the presence of high specialized technical competencies, the existence of networks of formal and informal relationships, and the geographical proximity that creates an environment wherein information, codes, languages, routines, strategies, and knowledge are easy to be transferred and shared (Cainelli et al., 2007; Cooke and Morgan, 1998; Henry and Pinch, 2002; Lundvall and Johnson, 1994; Storper, 1997).

[2]The industrial district is a specific type of geographical cluster. The latter is defined by Porter (1998) as a geographically proximate group of interconnected companies and associated institutions (for example universities, standards agencies, and trade associations) in particular fields, linked by commonalities and complementarities. Geographical clusters also promote knowledge sharing, learning processes, and innovation development. Therefore, the topic we investigate in the paper is of interest not only in Italy but also in other countries.

In the recent years, where innovation and creative capacity are considered essential determinants of economic prosperity and knowledge has become the most important production factor, a number of studies, both in the field of strategic management and in the field of regional economics (Grant, 1996; Krugman, 1991; Maskell and Malmberg, 1999; Saxenian, 1996) have widely recognized that the sustainable competitive advantage is strictly related to the ability of firms and indeed IDs to increase their innovative capability. In line with this, some scholars have rethought the ID production model shifting their attention from the cost-based benefits to the knowledge-based benefits. These works have proposed a knowledge-based theory of IDs (Maskell, 2001; Maskell and Malmberg, 2004), by investigating the nature of local knowledge (Tallman *et al*., 2004), the frequency and the effectiveness of the knowledge transfer processes among ID firms (Gordon and McCann, 2000; Mesquita, 2007), and the learning processes activated within IDs (Albino *et al*., 2005; Maskell, 2001).

By adopting a knowledge–based perspective, the innovative capability of a system depends on its ability to create new knowledge by both acquiring complementary knowledge owned by external sources of knowledge and combining such external knowledge with its internal knowledge (Coombs and Hull, 1998; Leonard and Sensiper, 1998; Nonaka and Takeuchi, 1995). According to this perspective, the key source of IDs' competitive advantage is strictly related to their innovative capability, which in turn is due to their ability to have access to different sources of knowledge and to activate processes of knowledge transfer and creation.

Despite this wide literature, questions about how the IDs' innovative capability can be increased; how much important is the ID technical knowledge and how much the scientific knowledge; how much balanced should be the local knowledge with the external knowledge, are minimally addressed in the literature. Answering to these questions seems to be particularly critical in the highly innovative and fast changing scenario in which firms operate and compete, where successful innovation depends more and more on the combination of different and heterogeneous pieces of knowledge.

Furthermore, the question on the role of the heterogeneity for the ID growth and innovativeness is still opened both in the traditional and in the more recent literature (Beaudry and Schiffauerova, 2009; De Groot *et al*., 2009). In particular, the traditional literature (Jacobs, 1969; Glaeser et al, 1992), still poses the following questions: what kind of externalities, Marshall-Arrow-Romer (MAR) externalities or Jacobs externalities, is really the driving force of the local competitive advantage? Is the heterogeneity in the local industrial composition important for the success and the innovativeness? What types of IDs are more innovative, those specialized in a single industry or those spammed within different industries?

Even in the latest works, in which IDs are interpreted as “cognitive systems”, namely social-productive systems in which knowledge, social experiences, mental, models and collective beliefs are accumulated in a specific space through time (Becattini and Rullani, 1996; Belussi and Pilotti, 2002), the relevance of heterogeneity for the ID competitive advantage is an open question. In fact, heterogeneity in firms’ competencies and capabilities evokes the notion of cognitive and technological proximity (Boschma, 2005; Schamp *et al.*, 2004). The level of cognitive and technological proximity characterizing a system affects the effectiveness of inter-organizational knowledge exchanges and learning processes. In particular, it is widely recognized that too little cognitive and technological proximity increases the difference between the cognitive maps and technological capabilities of two firms and then decreases the capacity of one firm to identify, interpret, and exploit the knowledge possessed by the other firm (Cohen and Levinthal, 1990). However, too much cognitive and technological proximity may be not effective for learning and innovation, as it means a lack of novelty. As a consequence, a natural question arises: there is an optimal value for the level of heterogeneity in firms’ competencies and capabilities within an ID?

Spurred into filling the gap of the literature and contributing to the ongoing debate, this paper analyses the role of knowledge and knowledge heterogeneity for the innovative capability of Italian IDs.

Drawing on various streams of the literature, the study tests whether the innovative capability of the Italian IDs is positively related both with the amount and the heterogeneity of the local knowledge, and the ID absorptive capacity (Asheim 2007; Asheim *et al*., 2011; Berliant and Fujita, 2011; Boschma and Iammarino, 2009). To do this, an econometric analysis on 32 Italian District Provinces over the period 2000-2008 is applied.

The analysis here is of relevance to scholars who are interested in either ID- or firm-level outcomes. At the ID level, the study suggests ways to improve IDs' innovative capability. This knowledge is invaluable, considering the importance of regional innovativeness for a nation's competitive advantage (Porter, 1990; 2000). At the firm level, the investigation provides a better understanding of factors that enhance firms' knowledge creation. This is crucial since knowledge is considered to be a firm's most important competitive asset (Teece and Pisano, 1994; Winter, 1987)

The paper is organized as follows. The second section provides the theoretical framework and develops the research hypotheses. The third section illustrates the methodology and the data employed to empirically test the hypotheses. The fourth section reports and discusses the econometric findings, while the fifth section concludes with summary remarks and suggestions for future research.

KNOWLEDGE AND INDUSTRIAL DISTRICTS

Knowledge-based Industrial District Competitive Advantage

Recently, strategic management literature has pointed out that in today economy the source of sustainable competitive advantage for firms can not more be limited to cost and differentiation advantages and has recognized the importance of knowledge as a fundamental factor in creating economic value and competitive advantage for firms (Barney 1991; Grant, 1996; Leonard-Barton, 1995). What firm knows, how it uses what it knows, and how fast it can develop new knowledge are key aspects for firm success (Hamel and Prahalad 1994; Prusak 1997). Therefore, knowledge is a key asset for competing firms and, consequently, learning is a key process. This in fact increases the firm cognitive capital (knowledge stock).

These new strategic management theories have forced new studies in the field of economic geography and regional economics. In the last two decades, some scholars have rethought the ID production model shifting their attention from competitive advantages that are based purely on lower costs to knowledge-based competitive advantages. These works have proposed a knowledge-based theory of IDs (Cooke, 2002; Etzkowitz and Klofsten, 2005; Maskell, 2001; Maskell and Malmberg, 2004), by investigating: the nature of knowledge circulating in IDs (Tallman *et al.*, 2004); the role of physical proximity for the diffusion of local knowledge (Gerosky, 1995); the effect of knowledge spillovers and collective learning in local innovation processes (Audretsch and Vivarelli, 1994; Capello and Faggian, 2005); the effectiveness of the knowledge transfer processes among ID firms (Gordon and McCann, 2000; Mesquita, 2007), the learning processes activated by firms within IDs (Albino *et al*., 2005; Maskell, 2001), the conditions to create Learning and Innovating Regions (Etzkowitz and Klofsten, 2005).

According to these studies, the sustainable competitive advantage of IDs lies in their superior capacity to support processes of knowledge accumulation and creation, and to facilitate innovation.

The Role of Knowledge on the Industrial District Innovative Capability: A Theoretical Framework

Using a knowledge-based perspective, IDs can be considered as cognitive systems (Maskell, 2001) with a knowledge-base that is the combination of information, know-how, skills and capabilities owned by local firms and individuals. The ID's knowledge-base is not static but continually evolves and increases due to processes of knowledge creation, acquisition, combination, and diffusion.

In particular, new technological knowledge is created by R&D activities carried out by firms, university, and research centers. Yet, new knowledge results by processes of learning by doing and by using, which give rise to incremental improvements of the existing technological knowledge-base. Processes of knowledge acquisition and combination are activated by means of formal and informal interactions established both within the network of relationships among actors located inside the ID and through relationships with actors located outside the ID. In the first case, the consequent learning process (learning by interaction) is based on knowledge sources external to the firm but internal to the geographical area in which the ID is localized. In the second case, the knowledge sources are external both to the firm and to the geographical area. The spatial diffusion of knowledge is mainly based on knowledge spill-overs and its effectiveness increases when the geographical proximity of firms increases (Anselin *et al*., 1997). All the above knowledge generating processes affect the competitiveness and foster economic growth of IDs by increasing the IDs' knowledge-base and then their innovative capability (Asheim, 1996; Tallman *et al*., 2004).

Drawing on the above, it is argued that the innovative capability of an ID rises with the amount of the ID knowledge, this brings to the following hypothesis:

Hp1: The higher the amount of the ID knowledge, the higher will be the ID innovative capability.

However, numerous studies show that IDs vary widely with respect to their competitive advantage.

In line with a knowledge-based approach, such a variance among IDs is explained by the fact that the accumulation of knowledge *per se* is not sufficient to create competitive advantage. In the current climate of rapid technological change and increased competition, no firm can rely entirely on its internal knowledge capacities and sources to develop successful innovations and that innovative performance are strictly associated with the heterogeneity of knowledge present in the ID (Prahalad and Hamel, 1990; Teece and Pisano, 1994). Where the knowledge heterogeneity refers to the variety of knowledge, know-how, and expertise to which a system has access. Exposure to heterogeneous knowledge should improve both the creative potential of the ID as well as its ability to develop innovation (Rodan and Galunic, 2004).

According to regional scientists, the competitive differences among IDs are explained by the different types of agglomeration externalities (Glaeser *et al.*, 1992; Saviotti, 1996): Marshall (1920)-Arrow (1962)-Romer (1986) (MAR) externalities and Jacobs (1969) externalities. Where MAR externalities are due to the concentration of a particular industry within a specific geographic region, Jacobs externalities regards inter-industry spillovers as they results by the agglomeration of different industries within an urban region. The former facilitates knowledge spillovers across firms and the latter fosters innovation because the heterogeneity of available local knowledge sources will spark creativity, new ideas and innovations. In particular, as argued by Jacobs (1969) and confirmed by further empirical studies (Glaeser *et al.*, 1992; Duranton and Puga, 2000), only in a context of industrial diversity, rather than industrial specialization, does the exchange of complementary knowledge leads to cross-fertilization of ideas and new knowledge combinations, which in turn favors innovation.

As a consequence of these reflections, the heterogeneity of ID's knowledge-base can be considered as an important factor to explain the competitive success of IDs based on their superior innovative capability.

Drawing on the above, it is argued that the innovative capability of an ID rises with the heterogeneity of the ID knowledge. This heterogeneity derives from the complementarity of knowledge within the ID and it is fed by the amount of knowledge coming from external knowledge sources (Asheim 2007; Asheim *et al*., 2011; Berliant and Fujita, 2011; Boschma and Iammarino, 2009).

These lead the authors to formulate the following hypotheses:

Hp2: The higher the complementarity of knowledge within the ID, the higher will be the ID innovative capability.

Hp3: The higher the amount of the external knowledge brought into the ID, the higher will be the ID innovative capability.

The above reflections open a further issue concerning the ability of an ID to manage the knowledge heterogeneity. With this regard, the literature on knowledge management and organizational learning highlights that having access to a great amount of knowledge flowing into a system (whether it is an organization or a region) is not *per se* a sufficient condition for building new and complementary knowledge that increases the heterogeneity of the system knowledge base. Although new and complementary knowledge is important for an organization, its identification, acquisition, and above all, its implementation are by no means simple processes and depend on the “absorptive capacity” of the organization (Veugelers,

1997). Absorptive capacity is the ability of any firm and region to acquire, assimilate, adapt, and apply new knowledge – that is to learn (Tallman *et al*., 2004; Zahra and George, 2002). Cohen and Levinthal (1990) argue that investment in R&D activities produces not only new knowledge but contributes also to the absorptive capacity of the firm by increasing the skills of the employees who have been involved in the R&D process. These stocks of skills or of prior knowledge determine the ability to assimilate and utilize external knowledge. Tripsas (1997) finds that a combination of internal investment in absorptive capacity of the firm and an external communication infrastructure to facilitate the transmission of external knowledge enables firms successfully to integrate knowledge outside its boundaries. Rothwell and Dodgson (1991) emphasize the importance for small and medium enterprises in having highly qualified technical specialists, scientist and engineers in order to access external knowledge.
A fourth hypothesis is formulated in order to consider the effect of the absorptive capacity as follows:

Hp4: The higher the absorptive capacity of the ID, the higher will be the ID innovative capability.

THE EMPIRICAL ANALYSIS

The Data

The data set is represented by the 32 Italian District Provinces (DPs). According to Becattini and Coltorti (2004), the DPs are those Provinces that satisfy the following requirement: the percentage of manufacturing employees working in firms with fewer than 250 employees must be higher than the national average[3]. In other words, DPs are geographical areas whose production system is predominately that one of the ID, strongly characterized by the presence of small and medium firms operating in the manufacturing sectors. We choose the province as territorial unit of analysis instead of the Local Labour Systems (LLSs), because provinces provide a more suitable level of analysis in terms of data availability[4].

Once specified the territorial unit of analysis, it is worth explaining the industrial sector classification used in the empirical analysis. The 14 manufacturing industries have been grouped into 4 sectors of activity: food, household and personal goods (textile and clothing, leather and footwear, furniture), mechanics, and heavy industry (paper products, chemicals, rubber, transport equipment). In Table 1 each sector of activity is defined according to the two-digit NACE classification[5].

Table 1. Classification of the sector of activity.

Sector of activity	NACE two digit codes
Household and personal goods	DB17-18, DC19, DD20, DN36, DI26
Mechanics	DK29, DL30-31-32-33, DJ28
Heavy industry	DJ27, DF23, DE21-22, DG24, DH25, DM34-35
Food	DA15-16

To each DP (or ID) have been associated one ore more sectors of activity on the basis of the manufacturing specialization of the IDs located inside the ID. Table 2 summarizes the main characteristics of the IDs.

Table 2. Characteristics of the District Provinces (DPs).

District provinces	Sector of specialization	Total manufacturing employees	Employees in the sector of specialization	Total manufacturing firms	Firms in the sector of specialization
Ancona	Household-personal goods/ Mechanics	65.138	49.947 *(77%)*	4.869	3.729 *(77%)*
Arezzo	Household-personal goods	45.274	32.707 *(72%)*	5.730	4.018 *(70%)*
Ascoli Piceno	Household-personal goods	47.191	31.784 *(67%)*	6.352	4.086 *(64%)*
Bergamo	Mechanics/Heavy industry	164.884	107.969 *(65%)*	12.358	7.166 *(58%)*
Biella	Household-personal goods	33.697	26.190 *(78%)*	2.658	1.542 *(58%)*
Brescia	Mechanics/Heavy industry	176.131	130.539 *(74%)*	18.113	11.217 *(62%)*
Como	Household-personal goods	77.912	39.784 *(51%)*	7.949	4.131 *(52%)*
Cremona	Mechanics	36.711	13.879 *(38%)*	3.588	1.534 *(43%)*
Firenze	Household-personal goods	108.422	52.997 *(49%)*	15.363	9.238 *(60%)*
Lecco	Mechanics/Heavy industry	52.976	41.095 *(78%)*	4.677	3.312 *(71%)*
Lucca	Heavy industry	37.803	11.477 *(30%)*	5.202	719 *(14%)*
Macerata	Household-personal goods	41.705	26.654 *(64%)*	4.983	3.025 *(61%)*
Mantova	Household-personal goods	58.013	25.154 *(43%)*	4.860	2.168 *(45%)*
Modena	Household-personal goods/ Mechanics	122.783	96.505 *(79%)*	11.087	9.014 *(81%)*
Novara	Mechanics	48.371	21.995 *(45%)*	4.139	2.054 *(50%)*
Padova	Household-personal goods	114.694	40.111 *(35%)*	12.016	5.296 *(44%)*
Parma	Food	55.873	18.044 *(32%)*	5.509	1.263 *(23%)*
Pesaro-Urbino	Household-personal goods/ Mechanics	48.860	41.451 *(85%)*	5.494	4.577 *(83%)*
Pistoia	Household-personal goods	28.493	18.574 *(65%)*	5.169	3.603 *(70%)*
Prato	Household-personal goods	45.423	38.649 *(85%)*	7.958	6.713 *(84%)*

[3] Becattini and Coltorti (2004) have classified the 103 Italian provinces into four groups: provinces of large firms, district provinces, residual provinces, and mixed provinces.
[4] In our study, DPs (District Provinces) is the same as IDs (Industrial Districts).
[5] NACE is the statistical classification of economic activities in the European Community.

Ravenna	Household-personal goods/ Food	31.213	13.885 *(44%)*	3.441	1.719 *(50%)*
Reggio Emilia	Mechanics/Heavy industry	82.339	50.952 *(62%)*	7.482	4.250 *(57%)*
Rovigo	Household-personal goods	23.025	10.633 *(46%)*	2.847	1.480 *(52%)*
Siena	Household-personal goods	21.074	9.749 *(46%)*	2.773	1.513 *(55%)*
Teramo	Household-personal goods	36.818	20.402 *(55%)*	3.693	2.014 *(55%)*
Treviso	Household-personal goods	141.743	67.956 *(48%)*	12.008	5.418 *(45%)*
Udine	Household-personal goods/ Mechanics	56.509	44.227 *(78%)*	5.698	4.614 *(81%)*
Varese	Household-personal goods	128.382	35.739 *(28%)*	11.370	4.308 *(38%)*
Verbano-Cusio-Ossola	Mechanics	13.726	7.850 *(57%)*	1.862	911*(49%)*
Vercelli	Household-personal goods	17.761	5.701 *(32%)*	1.789	629 *(35%)*
Vicenza	Household-personal goods/ Mechanics	171.327	139.414 *(81%)*	14.294	12.203 *(85%)*
Viterbo	Household-personal goods	11.731	7.037 *(60%)*	2.129	918 *(43%)*

Source: ISTAT data.

To build our dataset we used different statistical sources: the Italian Office of National Statistics (ISTAT) databases; the European Patent Office (EPO) database; the Ministry of University and Research (MIUR) database, and the UNIONCAMERE database. Data for import and export are provided by the Coeweb database from ISTAT; population and R&D investment come from ISTAT databases, data on employment in two-digit NACE codes are provided by the ASIA database from ISTAT, data on graduates and university are extracted by the MIUR database, data on firms in two-digit NACE codes come from the UNIONCAMERE database, finally data on patents are provided by the IPO database.

Data have been collected for each IDs and refer to the period 2000-2008.

The Econometric Model

In order to estimate the relationship between regional innovation capability and its determinants, we apply a non-linear estimator, i.e. negative binomial. The reason for choosing such estimator is because of the special feature of our dependent variable. The dependent variable *patent application* is a count data which is considerably over-dispersed because the sample variance is 43 times the sample mean, as reported in tables 4. In order to handle this situation, the literature suggests several models such as negative binomial, zero-inflated negative binomial, and hurdle models (Cameron and Trivedi, 2008)[6]. The dependent variable has only one zero value (out of 287 observations). Therefore, the zero-inflated models are not

[6] Since the mean and variance are not equal, the estimations based on Poisson and Zero-inflated Poisson models are not the preferred options.

necessary, intuitively. Even if there would be the excess of the zero in our data, it does not necessarily mean that zero-inflated models can be the best option (Cameron and Trivedi, 2008), since it must be possible to distinguish between 'true zeros' and 'excess zeros' in order to be reasonable to use zero-inflated models. The mechanism for distinguishing these two types of zero is not clear in the patent application data, hence the use of zero-inflated models seems to be implausible[7]. Nevertheless, in order to be sure, we perform the Vuong test of zero-inflated negative binomial vs. (standard) negative binomial. The test is slightly in favor of negative binomial. The hurdle model is not a preferred model, too, for the same reason as for the zero-inflated models. The formulation for the innovation capability of ID r in year t is written as follows:

$$\Pr(y_{rt} = \tilde{y}_{rt} \mid \mathbf{X}_{1rt} \mathrm{X}_{2rt} X_{3rt} \mathrm{Z}_{rt}, \sigma_{rt}) = \frac{e^{-\lambda_{rt}} (\lambda_{rt})^{\tilde{y}_{rt}}}{\tilde{y}_{rt}!} \qquad \tilde{y}_{rt} = 1, 2, 3, \ldots \qquad (1)$$

Where,

$$\lambda_{rt} = \exp(\beta_1 X_{1rt} + \beta_2 \mathrm{X}_{2rt} + \beta_3 \mathrm{X}_{3rt} + \beta_4 \mathrm{Z}_{rt}) * \exp(\sigma_{rt})$$

Where y_{rt} is the number of patent applications in ID r in year t, $\mathbf{X}_{1rt}$ is the vector of the amount of the ID knowledge variables (both internal and external variables), X_{2rt} is the variable of the ID knowledge heterogeneity variables, X_{3rt} is the absorptive capacity variable, Z_{rt} represents the control variables, and σ_{rt} is normally assumed to have a gamma distribution with mean 1 and variance *alpha*, which can be estimated from the data. Alpha is the over-dispersion parameter, which corrects for the overdispersion by adjusting the variance independently from the mean (Cameron and Trivedi, 2008). We will use both pooled and panel application (Random Effect) of the negative binomial model in the subsequent analyses, while the panel application is the preferred one (more elaboration is provided in table 5)[8].

[7] An example of the a situation where it is possible to distinguish between true zeros and excess zero is when we want to explain the amount of cigarettes smoked per day, while we have a survey containing both smokers (can causing true zeros) and non-smokers (causing excess zeros) (Cameron and Trivedi, 2008, p.584).

[8] The Hausman test reveals that the difference in coefficients between random effect and fixed effect are not systematic.

The dependent variable

As the phenomenon under investigation is the innovativeness of Italian IDs, we use the number of patents developed in each ID during the period 2001-2008, as an indicator of innovative performance (see Jaffe and Trajtenberg (2005) and Acs *et al*. (2002)). Patents have been found to be a good proxy of innovative activity in general (Griliches, 1990) and for regional-level analysis in particular (Acs *et al*., 2002)[9]. This is because patents are granted for inventions which are novel, inventive, and have industrial application (Andersson and Lööf, 2011).

Note that in order to exclude endogeneity problems, the independent variables have been measured in the period 2000-2007, lagged of 1 year respect to the dependent variable.

The independent variables

The independent variables considered in the model refer to the conceptual framework illustrated in the second section. Therefore, they have been classified as proxies for the amount of the IDs knowledge, the IDs knowledge heterogeneity, and the IDs absorptive capacity.

Amount of the IDs knowledge

The amount of IDs knowledge has been measured by the amount of R&D investments. The variable has been constructed by disaggregating at the province level the data available at the regional level. In particular, R&D by ID was assigned from regional data on the basis of the regional R&D investments per employee in each institutional sector (business sector, universities and public administration) and multiplied by the employees in each ID (Boix and Galletto, 2009). Therefore, the value for each province has been computed by:

[9] Acs *et al.* (2002) compared innovation and patents across US regions and conclude; ‘‘the empirical evidence suggests that patents provide a fairly reliable measure of innovative activity’’ (p. 1080).

$$R\&D_r = \frac{R\&D_k^i}{E_k} * E_r \qquad (2)$$

Where:

- $R\&D_k^i$ is the amount of R&D investments in Region *k* where the District Province *i* is located.

- E_k is the total number of employees in Region *k*.

- E_i is the total number of employees in ID *i*.

R&D expenditure has been frequently used as a proxy for the local capability to generate new knowledge. Cohen and Klepper (1991; 1992) point out that the greatest source generating new economic knowledge is generally considered to be R&D.

A critical problem associated to this variable is that R&D activities produce formal and codified knowledge that can be easily protected by firms (Brouwer and Kleinknecht, 1999) and than cannot be considered as a public good that increases the IDs knowledge-base. However, empirical studies prove the existence of R&D knowledge spillovers within geographically bounded area. For example, Jaffe (1989), Acs *et al*. (1992), and Audretsch and Feldman (1996) found that the knowledge created through R&D activities spills over to contribute to the generation of new technical knowledge.

Having acknowledged this point, according to the conceptual framework, this variable is expected to impact positively on the IDs innovative capability.

ID knowledge heterogeneity

The ID knowledge heterogeneity has been captured by using two variables intended to explain two different sources of knowledge heterogeneity: one internal to the ID, related to the complementarity of knowledge within the ID, and the other external to the ID, due to the amount of knowledge coming from external knowledge sources.

- The complementarity of knowledge within the ID has been associated to the degree of production diversity of the ID. Such production diversity has been measured, as in previous empirical studies (Greunz, 2004; van Oort, 2002; Paci and Usai, 1999; Feldman and Audretsch, 1999), by concentration measures. In particular, this study uses the Gini coefficient. The index aims at capturing the level of concentration of employees in a specific manufacturing sector.

The Gini coefficient is defined as follows:

$$G\_prod = \frac{\sum_{i=1}^{n-1}(Q_i - P_i)}{\sum_{i=1}^{i=n-1} P_i} \qquad (3)$$

Where:

- i indexes the manufacturing sector (i = 1….n), classified into the two-digit NACE codes;
- $Q_i = \frac{\sum_{j=1}^{i} E_j}{CE}$
- $P_i = \frac{i}{n}$

Where:

- $\sum_{j=1}^{i} E_j$ is the cumulative sum of employees in each manufacturing sector, classified into the two-digit NACE codes, when the sector employment is ordered in increasing order;
- CE is the total number of employees.

The Gini coefficient ranges from a minimum value of zero to a theoretical maximum of one. Values of *G_prod* close to zero indicate that ID firms are specialized into different manufacturing sectors, on the contrary values of *G_prod* close to one indicate that the ID manufacturing specialization is concentrated in very few sectors. Therefore, the *G_prod* aims at capturing Jacobs externalities, it decreases together with the production diversity of the firms. Lower is the *G_prod*, higher is the complementarity of knowledge within the ID, thus higher is the ID knowledge heterogeneity.

- the amount of external knowledge that is brought into the ID has been proxied by using the amount of the international trade linkages of each ID (Boschma and Iammarino, 2009). The variable has been calculated by the amount of imports and exports – expressed in monetary terms and weighted on the number of employees – recorded by each ID:

$$Ext\_Knowledger\ r = \frac{import_r + Export_r}{CE_r} \qquad (4)$$

Where:

- $Import_i$ and $Export_i$ are the amount of imports and exports of the ID *i*, respectively;
- CE *r* is the number of employees in ID *r*.

Trade indicators have been traditionally very important in assessing knowledge flows in open economic systems, particularly when there is an emphasis on extra-regional linkages. Boshma and Iammarino (2009) used the degree of export and import diversification to measures the degree of knowledge variety into a region. Camagni (1991) pointed out that external connections bring new knowledge into a region. In this way, sectoral lock-in at the regional level may be counterbalanced by the inflow of a high degree of variety of knowledge through inter-regional relationships.

By using the international trade linkages of each ID as a proxy of the external knowledge brought into the ID, the higher is the value of *Ext_Knowledge*, the greater is the external knowledge that flows into the ID, thus the higher is the ID knowledge heterogeneity.

According with the conceptual framework, both the above variables are expected to impact positively on the ID's innovative capability.

Absorptive capacity

The ID absorptive capacity has been proxied by a variable expressing the availability of high-educated human resources within the ID. Namely, the variable has been measured by the incidence of graduates in technical-scientific fields on the total population of the ID:

$$AbsorptiveCapacity_r = \frac{Graduates_r}{Population_r} \qquad (5)$$

Where:

- $Graduates_r$ = number of graduates in technical-scientific fields in the ID $_r$.
- P_r = population of the ID $_r$.

Although the proxy may appear rather rough, it takes into account an important aspect of IDs, namely the large presence of small and medium sized firms specialized in low-tech sector that build up their absorptive capacity mainly on high-educated individuals working in the organization (Rothwell and Dodgson, 1991) rather than on R&D activities. In line with this, Mangematin and Nesta (1999) argue that high-educated employees naturally by their daily task will increase the stock of knowledge in the organization. Carter (1989) argues that higher educated employees are the main contributors of know-how trading due to high level of knowledge embodied in these people. This statement in further supported by Guellec (1996) who emphasizes skilled labor to be in a better position to generate new knowledge because they master the state of the art and thus is better to manage new technology.

According to the conceptual framework, the variable is expected to impact positively on the ID's innovative capability.

Table 3 summarizes all the independent variables showing the used measure and the data source.

Table 3. Measures of the independent variables.

Variables	Measures	
Intensity of R&D activities	$R\&D_r = \frac{R\&D_k^i}{E_k} * E_r$	R&D_r = R&D investment in the ID *r*
Variety of the technological knowledge	$G\_prod = \frac{\sum_{i=1}^{n-1}(Q_i - P_i)}{\sum_{i=1}^{i=n-1} P_i}$	G_prod = Gini coefficient of the employees in each manufacturing sector
Amount of external knowledge	$Ext\_know = \frac{import_r + Export_r}{E_r}$	$Import_{pr}$/$Export_{pr}$ = amount of Import and Export of the ID *r*
Absorptive Capacity	$Absorptive\ Capacity_i = \frac{Graduates_i}{Population_i}$	$Graduates_{pr}$ = number of graduates in the ID *r*

The control variables

The analysis includes several controls variables. First, in order to take into account the general economic conditions of the district areas, the authors used a dummy for IDs localized in the Northern, that is a more advanced and developed area (Mariotti *et al*., 2008). Two other controls have been considered for factors that may affect the ID innovative capability through production of new knowledge. Specifically, the first variable is a density index that measures the geographic proximity among firms and it is considered as a factor that facilitates spillovers and the growth of knowledge (Audretsch and Feldman, 1996; Carlino et al., 2001; 2006; Knudsen et al., 2007). The index has been measured as the ratio between the population of manufacturing firm and the ID land area.

- $Density_r = \frac{F_r^{manufacturing}}{A_r}$ = measure of the density of the manufacturing firms in the ID *r*.

Where:

$F_r^{manufacturing}$ = number of manufacturing firms in ID *r*.

A_r = land area covered by ID *r*.

The second variable refers to the presence of universities within the district area, which are considered as sources of new knowledge (Benneworth and Hospers, 2007; Cooke and Piccaluga, 2004).

Results

Table 4 contains the descriptive statistics and the correlation matrix of the variables. The dependent variable *patent application* is considerably over-dispersed because the sample variance is 43 times the sample mean for this variable. Hence, there is the lack of equidispersion for this variable which violate the assumption of Poisson model. The formal test of the significance of overdispersion parameter (*Alpha*), reported in Table 5, provides further evidence for overdispersion of our dependent variable. All explanatory variables are positively correlated with the dependent variable, except *G_prod* which has a negative correlation as expected.

Given the high correlation value of some independent variables, we perform the variance inflation factor (VIF) test to check for multicollinearity between independent variables. The VIF score for each variable is well below five (and the mean VIF is 2.37), hence we can expect that multicollinearity does not substantially bias the regression results[10].

Table 4. Descriptive statistics and correlation matrix of the variables

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Mean	53.5	11.73	0.6313	22.237	6.40	4.106	0.594	0.65
Variance	2285	0.38	0.003	0.42	0.42	16.23	0.50	0.23
Standard dev.	47.8	0.611	0.0539	0.9022	0.643	4.03	0.702	0.48
Minimum	0	10.5	0.534	19.708	4.522	0.674	0	0
Maximum	191	13.32	0.833	23.865	7.659	24.16	3	1
(1) *Patent*	1							
(2) *R&D (log)*	0.6833	1						
(3) *G_prod*	-0.449	-0.28	1					
(4) *Ext_know(log)*	0.7935	0.7136	-0.29	1				
(5) *AbsorpCapacity(log)*	0.7165	0.6855	-0.471	0.7238	1			
(6) *Density*	0.1974	0.0929	0.4052	0.2837	0.0685	1		
(7) *Nr of University*	0.1314	0.2131	-0.339	0.0642	0.3179	-0.172	1	
(8) *North dummy*	0.4115	0.5029	-0.113	0.2741	0.1735	-0.137	-0.33	1

For the dependent variable and most of the regressors, the vast majority of the variation in the data consists of the between-variation rather than the within-variation. Therefore, the fixed-

[10] The VIF test is performed after the conventional OLS regressions. There is no formal threshold for VIF score, but as a rule of thumb the VIF score below 10 is said to be the evidence of quite mild multicollinearity.

effects estimator may not be very efficient, since it relies on within-variation, and therefore we use random-effects estimator in our panel models[11].

The results of negative binomial estimation of determinants of patent application for Italian IDs over the period of 2001 to 2008 are reported in Table 5. Both pooled and panel regressions (RE) are performed, while the panel models are the preferred ones, as discussed before. We add one explanatory variable in each model (column), while controlling for the set of control variables in all the models. This is done first for pooled models (column 1 to 4) and then for panel models (column 5 to 8). The Likelihood-ratio (LR) test vs. pooled is always in favor of panel models, hence the preferred models are 5 to 8. In the first model (column) we start with the amount of the ID knowledge, measured by the intensity of *R&D* activities. This variable is positive and significant and the results remained almost robust in the later models, especially for panel models. In the second model *G_prod* is introduced. It is significant and negative and the results remained robust in all the later models. This is what we expected, as the lower *G_prod,* means the higher the production diversity within an ID. In the third model we introduce the variable used as proxy of the amount of external knowledge that is brought into the ID (*Ext_knowledge*). This variable is positive and highly significant, which remained robust in all the later models. The result confirms our third hypothesis: the greater is the external knowledge that flows into the ID, the higher will be the ID innovative capability. Finally in the fourth model, we include absorptive capacity of IDs and this variable also shows positive and significant effect on patent application of Italian IDs.

[11] Nevertheless, the formal Hausman test reveals that the difference in coefficients between random effect and

Table 5. Determinants of patent applications in Italian regions (2001-2008)

	Pooled negative binomial				Panel negative binomial (RE)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Patent application	Patent application	Patent application	Patent application	Patent application	Patent application	Patent application	Patent application
R&D	1.182***	0.971***	0.0847	0.0692	0.163**	0.171**	0.122*	0.122*
(lagged 1 year) (log)	(0.115)	(0.0861)	(0.0660)	(0.0599)	(0.0751)	(0.0748)	(0.0742)	(0.0729)
G_prod		-8.391***	-4.985***	-4.303***		-3.123*	-4.660***	-3.834***
(lagged 1 year)		(0.770)	(0.535)	(0.562)		(1.835)	(1.029)	(1.071)
Ext_Knowledge			0.818***	0.730***			0.772***	0.664***
(lagged 1 year) (log)			(0.0437)	(0.0626)			(0.0719)	(0.0836)
Absorptive Capacity				0.219**				0.281**
(lagged 1 year) (log)				(0.0932)				(0.116)
Density	0.0207	0.0582***	0.0145**	0.0118*	0.106**	0.107***	0.0224	0.0181
(lagged 1 year) (log)	(0.0177)	(0.00960)	(0.00587)	(0.00612)	(0.0467)	(0.0415)	(0.0155)	(0.0152)
Nr of University	0.0349	-0.0593	0.0967**	0.0548	0.477**	0.401**	0.109	0.0514
	(0.0718)	(0.0577)	(0.0420)	(0.0486)	(0.191)	(0.180)	(0.0855)	(0.0865)
North dummy	0.0773	0.0956	0.269***	0.257***	1.255***	1.165***	0.301**	0.259**
	(0.148)	(0.120)	(0.0730)	(0.0694)	(0.289)	(0.271)	(0.134)	(0.131)
Alpha	-0.994***	-1.450***	-2.633***	-2.689***				
(log)	(0.109)	(0.126)	(0.175)	(0.166)				
Observations	256	256	256	256	256	256	256	256
Number of IDs	32	32	32	32	32	32	32	32
Year Dummy	YES	YES	YES	YES	YES	YES	YES	YES
LR test vs. pooled					443.40 (0.000)	343.03 (0.000)	111.51 (0.000)	109.11 (0.000)
AIC	2348.984	2248.651	2027.116	2021.484	1912.118	1911.315	1862.837	1859.061
BIC	2395.072	2298.284	2080.294	2078.207	1961.751	1964.493	1919.560	1919.329

Dependent variable in all eight models: Number of patent applications in Italian regions over 2001 to 2008.
For pooled negative binomial, Robust standard errors in parentheses ()
For panel models, standard errors in parentheses ()
For LR test vs. pooled, Prob>=chibar2 in parentheses ()
*** p<0.01, ** p<0.05, * p<0.1
AIC: Akaike Information Criterion,
BIC: Bayesian Information Criterion

Among control variables, all of them are positive, while density and north dummy show more robust behavior in terms of significance. They are positively and significantly associated with the patent applications, which is in line with previous literature.

fixed effect are not systematic.

Describing the full model in the preferred estimator (model 8), all the determinants of patent application are significant and showing the expected sign.

Since we used the Maximum Likelihood Estimation (MLE), in order to compare the models with each other, we used Bayesian information criterion (BIC) and Akaike information criterion (AIC). Both criteria get smaller when we move from model 1 to 4 (pooled models) and when we moved from model 5 to 8 (panel models). This means that by gradually adding the variables from model 1 to 4 (and 5 to 8), the models are getting better in terms of fitness, while there is no evidence of over-fitting. This is also obtained by LR test of restricted vs. unrestricted models, which is always in favor of unrestricted models. In other words, internal knowledge, external knowledge, and absorptive capacity of the region all together can produce the better fit for modeling the patent application in compare with including only one or two of them. The values in panel models are lower than their counterparts in pooled models, indicating a better fit of panel models.

The alpha, over-dispersion parameter, is reporter in table 5, too, for the pooled models. When the over-dispersion parameter is zero, the negative binomial distribution is equivalent to a Poisson distribution. In our case, however, alpha is significantly different from zero in all (pooled) models and thus shows again that the negative binomial is a preferred estimation strategy over the Poisson or zero-inflated Poisson models.

CONCLUSIONS

This paper seeks to contribute to the ongoing debate concerning the role of knowledge and knowledge heterogeneity for the innovative capability of IDs. With this aim, using a knowledge-based approach, the study tests whether the innovative capability of IDs is positively related both with the amount and the heterogeneity of the ID knowledge, and the ID absorptive capacity.

Four theoretical hypotheses concerning the effects of knowledge and knowledge heterogeneity on the ID innovativeness are formulated. To test the hypotheses, an econometric analysis on 32 Italian District Provinces is applied.

The paper's findings confirm the hypothesized positive relation between knowledge and the ID innovative performance. In particular, results confirm our first hypothesis regarding the positive relationship between the availability of knowledge and the ID innovative performance. As far as the ID knowledge heterogeneity, we test the effects of both sources of knowledge heterogeneity, namely the internal source, related to the complementarity of knowledge within the ID, and the external one, due to the amount of knowledge coming from external knowledge sources. We find that ID knowledge heterogeneity positively affects the ID innovative capability, whether it is due to production diversity of the ID firms whether it is due to the external knowledge brought into the ID.

Finally, results highlight the important role played by the absorptive capacity of the ID, confirming that the higher the absorptive capacity of the ID, due to the higher density of graduates in technical-scientific fields, the higher will be the ID innovative capability.

In addition to this consideration, it is interesting to note that the *G_prod* variable, which measures the ID knowledge heterogeneity due to the complementarity of knowledge within the ID, has the highest magnitude in compare with other variables. This is a remarkable outcome of our analysis for two main reasons. First, it is a counterintuitive result respect to the traditional studies that recognize R&D investment has the major driver of patent applications. Second, since the *G_prod* variable captures Jacobs externalities, our result emphasizes the important role played by externalities that may come from a diversity of related industries in IDs (Frenken *et al.*, 2007). Thus, the more variety across related sectors in an ID, the higher the number of technologically related sectors, and the more learning opportunities there are for local industries. This will result in more inter-sectoral knowledge spillovers, which enhance the ID innovative performance.

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