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# Industrial district heterogeneity and competitive advantage: Evidence from Italy

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# Industrial District Heterogeneity and Competitive Advantage: Evidence from Italy

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## Abstract

This paper seeks to contribute to the ongoing debate concerning the role of heterogeneity for the competitive advantage of Industrial Districts (IDs). With this aim, it focuses on different sources of heterogeneity and highlights how the different level of heterogeneity affects the ID performance.

This study has been based on an empirical research conducted on 32 Italian District Provinces. A cluster analysis methodology has been applied to process the data collected, in order to highlight whether there is a relation between the level of heterogeneity and the performance of District Provinces and how the different level of heterogeneity affects on the District Province performance.

**Keywords:** Industrial district, competitive advantage, heterogeneity, cluster analysis

## 1. Introduction

The literature on the different forms of industrial districts (IDs), such as Marshallian industrial districts, geographical cluster, local industrial systems, *milieux innovateur*, is very reach and involves different streams of research, such as social sciences, regional economics, economic geography, political economy, and industrial organization. These studies share a common interest to explain the reasons of ID competitive advantage. Theoretical and empirical investigations have identified several critical factors governing the ID competitive advantages such as: physical and cultural proximity of many small and medium sized firms; division of labor among firms; presence within the area of complementary competencies and skills; high degree of specialization of both firms and workforce; existence of a dense network of inter-firm relationships where firms co-operate and compete at the same time; presence of a dense network of social relationships based mainly on face-to-face contacts; and the easy and fast circulation of knowledge and information in the area.

Earlier studies have explained how and why these factors generate pecuniary externalities. In his seminal study on Britain's industrial districts, Marshall (1920) observed that the spatial polarization of firms active in similar industries generate three externalities, namely knowledge spillovers among firms; pecuniary externalities through forward and backward linkages; and a better access to specialized skills. For Krugman (1991), the benefits of geographical cluster in essence depend on three factors: i) substantial increasing returns to scale, both at the level of single firm (internal economies) and the industry (external economies); ii) sufficiently low transport costs; and iii) large local demand. In opposition to Marshall, Jacobs (1969) argues that the agglomeration of different industries within a region fosters innovation due to the diversity of available local knowledge sources. She observes that

only the contexts characterized by industrial diversity, rather than industrial specialisation, favour innovation and economic growth.

So far, in these studies there are still open questions, such as: what kind of externalities, 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 economic growth? What types of IDs are more innovative, those specialized in a single industry or those spanned within different industries?

More recently, scholars started shifting their attention to the role played by agglomeration on the innovation processes and knowledge creation (Baptista, 2000; Maskell, 2001; Tallman et al., 2004). According to this shift, the latest works have studied how IDs features can enhance the processes of knowledge transfer and creation, the learning processes activated by firms in IDs, and the innovation processes (Tallman et al., 2004). The theory holds that the co-location of many firms competing in the same industry or collaborating across related industries tend to trigger processes of learning and innovation. In fact the geographic proximity increases the frequency of interactions between firms and the local culture with specific norms, values, and institutions (both formal and informal) makes it possible to transfer also tacit knowledge. In this new view the competitive advantage of IDs is mainly based on their superior capacity of enhancing firms' knowledge creation.

Even in these studies the relevance of heterogeneity for the ID competitive advantage is an open question. In fact, heterogeneity in firms' competencies and capabilities evokes the notions 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 a ID?

A further question on the role of heterogeneity for the ID competitive advantage emerges by the studies on the balance of competition and co-operation in the ID and how this affects performances. In fact, competition takes place mainly between homogeneous firms that exhibit similar resources, cost structures, mental models, and competitive behaviour (Pouder and St. John, 1996), whereas co-operation takes place, to a greater extent, between different and complementary firms generally involved in different phases of the production process (Albino et al., 2007).

This paper seeks to contribute to the ongoing debate concerning the role of heterogeneity for the competitive advantage of IDs. With this aim, the study focuses on different sources of heterogeneity and highlights how the different level of heterogeneity affects the ID performance.

The paper is organized as follows. The second section briefly discusses the notion of ID heterogeneity and introduces the dimensions of heterogeneity used for the quantitative analysis to assess the level of ID heterogeneity.

The third section describes the methodology used. The fourth section presents the results of the empirical analysis. Finally, the last section suggests some conclusions.

## 2. Sources of heterogeneity in Industrial Districts

The notion of heterogeneity is used in many different studies on IDs and understanding the role of heterogeneity on the agglomeration economies is a central question in the field of economic geography and regional economics (Audretsch and Feldman, 1999; Duranton and Puga, 2000; Essletzbichler, 2007; Paci and Usai, 1999; 2000).

Although heterogeneity can be defined and measured in many different ways, it is possible to identify three main explanations for the ID heterogeneity: i) the production specialization/diversity, ii) the knowledge specialization/diversity, and iii) the organizational similarity/diversity.

Specifically, most of the studies on this topic associate the ID heterogeneity to the specialization of economic activity. Glaeser et al. (1992) measure the level of production specialization by using location quotients, i.e. the share of local industry production in a specific industry in relation to the average national share. Diversity is simultaneously measured by taking the share of local employment of the top five industries (other than the one in question) of total employment. Audretsch and Feldman (1999) test whether the specialization of economic activity within a narrow concentrated set of economic activities is more conducive to knowledge spillovers or if diversity, by bringing together complementary activities, better promotes innovation. Greunz (2004) investigates whether the composition of industrial activity influences innovation. He measures the degree of production diversity of a region by using the reciprocal of the Gini coefficient and the Theil index, calculated by using the employment data.

The firm size has been used mainly in the field of strategy and in the business literature as a variable to explain differences in firms' competitive capabilities. In fact firm size may be a proxy for the firm assets, the firm innovation strategies, and the firm level of intellectual capital (Barney, 1991; Sonnier et al., 2009; Tang, 2008). Moreover firm size is a basic measure to describe the structure of an industry. With particular reference to the localized industry, Baum and Mezias (1992) use firm size to evaluate the level of similarity in the Manhattan hotel industry.

More recently, much emphasis has been put on the role of knowledge for the economic growth and innovation development. In line with this perspective the ID heterogeneity has been related to the ID knowledge base heterogeneity. Some authors relate the level of heterogeneity of the ID knowledge base to the heterogeneity of knowledge bases of the ID firms (Giuliani, 2007). Yet, another way to estimate the heterogeneity of the ID knowledge base is by considering the variety of external knowledge flowing into the ID. With this regard, Iammarino and Boschma (2009) measure the amount of extra-regional knowledge that flows inside a region by means of import and export. The authors also highlight that having a great amount of knowledge flowing into the region is not *per se* a sufficient condition for building new and complementary knowledge that increases the variety of the ID knowledge base. They argue that the heterogeneity of the ID knowledge base depends on the regional absorptive capacity, that is the ability of a region to understand and absorb external knowledge and it is dependent on its own knowledge base (Cohen and Levinthal, 1990; Giuliani, 2005; Owen-Smith and Powell, 2004; Simmie, 2003).

Based on the above, in order to assess the role of heterogeneity on the ID competitive advantage, I explain the ID heterogeneity as due to: 1) the variety in the firms' technological specialization; 2) the diversity in the firms' organization; 3) the variety of the external knowledge brought into the ID; 4) the ID absorptive capacity.

### 3. Empirical analysis

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<sup>1</sup>. In other words, DPs are geographical areas whose production model is predominately that one of the ID, strongly characterized by the presence of small and medium firms operating in the manufacturing sectors. I 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.

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.

**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 have been associated one or more sectors of activity on the basis of the manufacturing specialization of the IDs located inside the DP. Table 2 summarizes the main characteristics of the DPs.

#### 3.1. Data

The data employed in this research combine information on patents provided by the Italian Patent Office with Census statistics provided by ISTAT (Italian Office of National Statistics) and MIUR (Ministry of University and Research).

Specifically, the 2001 Census of Industry and Services has been used to collect data on number of firms, identified for each provinces up to the three-digit level, and number of employees, disaggregated for province, industry and class of employees. The ISTAT foreign trade statistics have been used to collect data on export, classified for province, industry, and geographical area of destination. The MIUR database provides data on graduates, disaggregated for province and scientific field. The Italian Patent Office has been used to collect data on patents, disaggregated for province. The Infocamere database has been used to collect data on the number of firms closed in each year. Finally, the ISTAT database provides data on GDP.

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<sup>1</sup> Becattini and Coltorti (2004) have classified the 103 Italian provinces into four groups: provinces of large firms, district provinces, residual provinces, and mixed provinces.

**Table 2. Characteristics of the District Provinces (2001).**

District provinces	Sector of specialization	Total N. of employees in manufacturing sector	N. of employees in the sector of specialization	Total N. of firms in manufacturing sector	N. of 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%)
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%)

### 3.2. The variables

In the empirical analysis on the 32 Italian DPs, for each DP the level of heterogeneity and the performance have been measured. To do this, a set of variables both for the sources of heterogeneity and for the performance has been defined.

In particular, the variety in the firms' technological specialization has been measured by using 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:

$$G_{tech} = \frac{\sum_{i=1}^{n-1} (Q_i - P_i)}{\sum_{i=1}^{n-1} P_i}$$

Where:

- $i$  indexes the manufacturing sector ( $i = 1 \dots n$ ), classified into the three-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 three-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. The  $G_{tech}$  decreases together with the firms' technological specialization diversity.

The diversity in the firms' organization has been computed by using the Gini coefficient. In this case the index measures the level of concentration of firms in a specific class of employees.

$$G_{org} = \frac{\sum_{i=1}^{n-1} (Q_i - P_i)}{\sum_{i=1}^{n-1} P_i}$$

Where:

- $i$  indexes the class of employees ( $i = 1 \dots n$ ),  $n = 10$

- $$Q_i = \frac{\sum_{j=1}^i F_j}{CF}$$

- $$P_i = \frac{i}{n}$$

Where:

- $\sum_{j=1}^i F_j$  is the cumulative sum of firms in each class of employees when the number of firms in each class is listed in increasing order;
- CF is the total number of firms.

A low  $G_{org}$  indicates a more unequal distribution of the firms' organization, while higher  $G_{org}$  indicates that firms are equally distributed among the different classes of employees.



In addition to technological specialization and organization diversity, the variety of the external knowledge brought into the ID has been measured.

To do this we have evaluated the breadth of the international trade linkages of each DP. Specifically, by using the Gini coefficient, the level of concentration of exports in a specific macro-geographical area of destination has been calculated (Boschma and Iammarino, 2009).

The applied measure is the Gini coefficient expressed as follows:

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

Where:

-  $i$  indexes the macro-geographical area ( $i = 1 \dots n$ ),  $n = 4$

$$- Q_i = \frac{\sum_{j=1}^i E_j}{CE}$$

$$- P_i = \frac{i}{n}$$

Where:

- $\sum_{j=1}^i E_j$  is the cumulative sum of the export in each macro-geographical area when the export is listed in increasing order;
- CE is the total export.

Higher values of  $G\_ExtKnowledge$  indicate that export is equally distributed among the four different macro-geographical areas, namely Europe, Asia, America, rest of the World. By using export as a proxy of the new external knowledge brought into the ID, higher the value of  $G\_ExtKnowledge$  more diversified the knowledge that flows into the ID.

As for the ID absorptive capacity, I have calculated the number of graduates in technical-scientific fields in each DP as follows:

$$Graduates_i = Graduates_r * \frac{F_i}{F_r}$$

Where:

- $i = 1, \dots, 32$  DPs.
- $Graduates_r$  = number of graduates in technical-scientific fields in the region  $r$  in which DP  $i$  is located.
- $F_i$  = number of firms in DP  $i$ .
- $F_r$  = number of firms in the region  $r$ .

Finally, as measures of performance, I have considered three indicators:

1) the GDP, as an indicator of the economic performance

- 2) the number of patents developed in each DP, as an indicator of innovative performance (see Jaffe and Trajtenberg (2005) and Acs et al. (2002))
- 3) the firms' death rate, as a proxy for measuring the competitive success of the ID firms.
- All the three indicators have been measured in the 2003 and 2004.

#### 4. The cluster analysis

A cluster analysis has been applied to process the data collected, in order to highlight whether there is a relation between the level of heterogeneity and the performance of DPs and how the different level of heterogeneity affects on the DP performance.

A two-stage clustering technique to identify different profiles of DPs in terms of heterogeneity has been followed. Specifically, the use of agglomerative hierarchical cluster analysis has been combined with the k-means cluster analysis (Zhang et al., 2008).

The empirical results of the cluster analysis are given in Table 3.

At the end of clustering procedures three clusters are obtained. Each cluster is characterized by a different profile of heterogeneity:

- Cluster 1 groups those DPs with a low variety in the firms' technological specialization, a high variety in the firms' organization, a high variety of the external knowledge brought into the DP, and a high absorptive capacity;
- Cluster 2 groups those DPs with a low variety in the firms' technological specialization, a low variety in the firms' organization, a low variety of the external knowledge brought into the DP, and a low absorptive capacity;
- Cluster 3 groups those DPs with a high variety in the firms' technological specialization, a high variety in the firms' organization, a high variety of the external knowledge brought into the DP, and a high absorptive capacity.

I used the three performance indicators for the period 2003-2004 to compare the three clusters.

**Table 3. The cluster analysis results.**

<b>Variables</b>	<b>Cluster 1</b>	<b>Cluster 2</b>	<b>Cluster 3</b>	<b>Centroid</b>
<i>G_tech</i>	0,730	0,788	0,690	0,710
<i>G_org</i>	0,526	0,573	0,515	0,551
<i>G_ExtKnowledge</i>	0,387	0,441	0,370	0,418
<i>Graduates<sub>i</sub></i>	804,300	368,976	1.397,33	601,423
<b><i>Number of DPs in each cluster</i></b>	<i>10</i>	<i>19</i>	<i>3</i>	

Results in Table 4 show that Cluster 3 holds the higher performances (except for the firms' death rate in 2003). This finding allows to give a first answer to the paper's research question: does heterogeneity matter on the ID performance? In fact the results indicate that IDs characterized by a higher level of heterogeneity, resulting from the variety in the firms' technological specialization, the diversity in the firms' organization, the variety of the external knowledge brought into the ID; and the absorptive capacity, have superior performance. On the contrary, IDs characterized by a lower level of heterogeneity do not show high performance.

**Table 4. The cluster profiles and performance.**

	Cluster 1	Cluster 2	Cluster 3
<i>G_tech</i>	A	A	B
<i>G_org</i>	B	A	B
<i>G_ExtKnowledge</i>	B	A	B
<i>Graduates</i>	A	B	A
<b><i>GDP/Number of employees (€/employees)</i></b>			
<i>2003</i>	57.967	55.802	60.648
<i>2004</i>	60.219	57.311	62.175
<b><i>Patents/Number of firms</i></b>			
<i>2003</i>	0,0125	0,0077	0,0128
<i>2004</i>	0,0133	0,0086	0,0141
<b><i>Firms' death rate (%)</i></b>			
<i>2003</i>	6,15	6,68	6,36
<i>2004</i>	6,23	7,76	5,11

## 5. Conclusions

This paper seeks to contribute to the ongoing debate concerning the role of heterogeneity for the competitive advantage of IDs.

The notion of heterogeneity has been already used in several studies to explain the innovative capability and the economic growth of ID (Jacobs, 1969; Greunz, 2004; Shaver and Flyer, 2000). Nevertheless, these studies present two main drawbacks. From an empirical point of view, they refer to specific industrial districts or geographical clusters (Lissoni, 2001; Saxenian, 1994); from a theoretical point of view, they left an open questions on the relationship between the level of heterogeneity and the competitive advantage of IDs. The present paper tries to overcome these drawbacks.

With this aim, the study focuses on different sources of heterogeneity and by conducting an empirical analysis on Italian IDs it highlights whether there is a relation between the level of heterogeneity and the performance of industrial districts and how the different level of heterogeneity affects the ID performance.

The paper's findings indicate that IDs characterized by a higher level of heterogeneity (resulting from the variety in the firms' technological specialization, the diversity in the firms' organization, the variety of the external knowledge brought into the industrial district, and the absorptive capacity) have superior performance. On the contrary, IDs characterized by a lower level of heterogeneity do not show high performance.

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