The Impact of Innovation on Companies Performance: An Entropy-Based Analysis of the STAR Market Segment of the Italian Stock Exchange

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Abstract
This paper proposes the use of a class of concentration-based entropy measures as a new instrument to quantify business performances through an analysis of growth, profitability and productivity. Such measures are tested against a complex analysis of the link between innovation and performance for firms listed in the STAR market segment of the Italian Stock Exchange.
In so doing, two targets are achieved: 1) the identification of parameters that are relevant for explaining the relationship between innovation and performance for the considered sample, with special focus on innovation type, innovation level and business size; 2) the elaboration of a new methodology - based on information theory - for the analysis of the impact of innovation on performance.
The study shows that type of innovation and size play a key role in determining company performance.

Keywords: Entropy, innovation, business performance.

1. Introduction

The goal of the present paper is to introduce a class of concentration-based entropy measures in the field of management science. In particular, the impact of innovation on performance for a specific set of companies is here discussed. There are two main motivations for the present study: first, the impact of innovation on company performance is an important issue in management; secondly, and most important, there is a growing interest in the quantitative tools for measuring performances, and exploring their link with management strategies – such as innovation - and the characteristics of the companies.
The methodological proposal is tested on the STAR segment of the Italian Stock Exchange (STAR, hereafter) – which includes only medium-sized companies in terms of capitalization – for the period 2006-2010. In particular, the impact of innovation initiatives taken in 2006-2007 on company performance during 2008-2010 is considered. The sample and the reference period have been selected on the basis of data availability and scientific consistency (see Section 3).
Performance outcomes are measured in terms of growth (percentage sales variation and number of employees variation or, briefly, SalesV and EmplV), profitability (return on investment or, briefly, Roi), and productivity (sales per employee or, briefly, SpE).
A crucial feature of the introduced entropies is that they make possible to examine the variables that evidence how innovation affects performance. Special attention is paid to this aspect and companies are classified in terms of: 1) business size, 2) innovation type and 3) innovation level, in order to emphasize differences or similarities on performances in relation to these variables.
The entropies defined here are generally employed for economic-geographical problems, and their introduction in the present context is rather new (see next section). The entropies measure business performance concentration (*disorder,* in the language of information theory) over the triennium 2008-2010, and such a disorder varies dependently on the clustering of companies – in the period 2006-2007 – with respect to innovation level, innovation type and business size.
In particular, we show how the abovementioned variables can be associated with a homogeneous rather than heterogeneous distribution of companies indicators. By the point of view of a policymaker, low entropy is a desirable result when the business performances are positive, since homogeneity is associated to a general good situation. Differently, high entropy means highly inhomogeneous performances, which is a good news when the scope is to move from a recession phase. In saying this, we argue that high entropy is associated to the most significant variables which affect the relationship between innovation and performance.
The analysis shows that the role played by type of innovation (with a particular emphasis on process innovation) is important, whereas size is significant in companies that do not innovate in terms of tangible assets. The size is important also when companies innovate in terms of

intangible assets, mainly for process innovation. On the basis of above results, policymakers can plan and implement effective innovation strategies to improve performance.
The rest of the paper is structured as follows: Section 2 contains the literature review; Section 3 describes dataset and employed methodology; Section 4 discusses the main findings; Section 5 offers the conclusions. All the Tables and Figures are collected in the Appendix, along with a description of the questionnaires used to provide face validity to some assumptions of the model.

2. Literature review

We situate our paper in the research area of new instruments for measuring business performance, specifically information theory-type measurements.
This section elaborates only on this aspect. The reader is addressed to Sections 3 and 4 for a discussion of the methodology and the empirical findings in the context of a number of relevant references.
Many scholars share the idea of approaching economics and managerial science from the perspective of complexity. Such a point of view is grounded on the interpretation of economic and financial series as realizations of complex systems (Anderson et al. 1988, Vandewalle and Ausloos 1997, 1998, Arthur 1999, Ausloos and Ivanova 2003, Jacobs 2013). The STAR, in particular, can be viewed as a complex system, and the diversity within companies can be translated in terms of statistical disorder. Therefore, it makes sense to measure performance using the concept of entropy, as we do in the present paper.
A large strand of literature deals with the performance measurement of a system based on entropy, mainly of the Shannon type (see e.g. Stirling 2001, Harrison and Sin 2006, Harrison and Klein 2007, Chang 2007).
As for company performance, one of the most influential contribution is Jaquemin and Berry (1979), where Shannon entropy is adopted as a measure of corporate diversification for total sales and productivity of 460 U.S. industrial corporations. Matusik and Fitza (2012) use entropy to measure companies diversification and corresponding performance outcomes for 4,000 firms over the period 1960-2000. In general, entropy has been adopted to measure how business specialization and innovation affect performance, as it captures the concentration of companies activities (Palepu 1985, Ahuja and Katila 2001, Choi and Russell 2005, Park and Jang 2012).
However, Shannon entropy refers to the disorder of a set of quantities given in terms of *values* (total sales and productivity for Jaquemin and Berry, performance outcomes for Matusik and Fitza), while the understanding of the comparative relations between the key variables of the problem requires the introduction of quantities in terms of *rates*. A probabilistic explanation may be useful to capture this relevant difference: the former case is associated to the comparison between an empirical probability distribution and the uniform law, while the latter one compares two non-uniform empirical probability distributions. Therefore, the entropies adopted here should be of a *relative* (*rates* case) rather than *absolute* (*values* case) type. Moreover, here diversity refers to the performances of a collection of companies rather than to the corporate activities of individual companies.
We adapt a localization-type problem to our setting. Hence, our approach resembles that of the New Economic Geography (Krugman 1991), in that the economical features of the companies are evaluated by means of relative measures of concentration. Among the measure used in this field, we mention the absolute entropy index (e.g. Aiginger and Pfaffermayr 2004, Aiginger and Davis 2004). Kullback-Leibler distance (e.g. Mori et al. 2005), Gini location quotient (see e.g. Kim 1995 and Brülhart 2001) and K-concentration (or K-specialization) index (e.g. Krugman 1991 and Mulligan and Schmidt 2005) are noteworthy examples of relative measures. It is also

worth mentioning Ellison and Glaeser (1997), where a relative measure of concentration for performing analysis at regional levels is introduced. However, the relative measures quoted above are not able to deal with "too complex" problems and do not provide a satisfactory description of the economic-geographical aspects at a global and local level (see Cutrini 2009 for a discussion). A more convincing solution is offered by the generalized entropy measures. In particular, Brülhart and Traeger (2005) and Cutrini (2009, 2010), following Ellison and Glaeser, introduce entropy indices of Theil-type. Given that the large number of variables involved in the analysis of the STAR leads to a high degree of complexity, we have reasonably chosen to adopt the latter indices in the present paper.
Next section contains further details on this aspect.

3. Methodological instruments and data

3.1 Data collection

Our analysis focuses on the STAR which included, as of 31 December, 2010, 71 mid-sized companies in terms of capitalization value (between 40 million and 1 billion euros). To ensure homogeneity and relevance, banks and insurance institutes have been removed from the list, reducing the number of considered companies to 62.
The data (of qualitative and quantitative nature) have been manually collected from the consolidated section of the companies' annual reports (including balance sheet, income statement and descriptive notes) of the 2006-2010 period, as published on the companies' websites. No other sources have been employed to collect data, and this allows us to encompass validity problems often recurring when using existing datasets.
The classification of companies by industry is in Table A1.
Our decision to use STAR provides further consistency since unlisted companies do not usually show their annual reports on the website, which makes the analysis problematic. Moreover, the choice of the STAR allows us to avoid large companies, which may have several operating divisions (OECD 2005, p. 66) that are often not detailed in financial statements. Small and mid companies instead are more likely to focus on a single or few operating segment, which enhances the relevance of their financial statements.
Furthermore, the unit of analysis is the company intended as a business group. The analyses are performed at the group level through the consolidated financial statement for two important reasons: 1) financial data at legal entity level are not significant when innovation is performed at operating division intercompany level (see also OECD 2005, p. 66), while the consolidated balance sheet and income statement – included in the company's annual report – grant the full availability of data about all the legal entities included in the group; 2) when a company is listed on a stock exchange it has to comply with several disclosure requirements (for example it must grant free access to annual reports via the company website), and such requirement must be fulfilled only by the listed legal entity. Hence, it is not extended to all the participated not listed legal entities, which usually do not voluntarily disclose their accounts.
A delay is needed to evaluate how innovation affects performance (e.g. Teece 1988, Ravenscraft and Scherer 1982, Leonard 1971, Cainelli et al. 2004), and the triennial time-horizon taken here is consistent with the indications of the Oslo Manual (OECD 2005, p.130).
Furthermore, the selected time period is particularly suitable, because no significant changes occurred in European accounting standards in the 2006-2010 period.

3.2 Variable definition

The data collected for the 2006-2007 biennium provide a classification of companies by size, level of innovation in terms of tangible and intangible fixed assets, and type of innovation.

Innovation in 2006-2007 is reflected in the performances in the triennium 2008-2010. Outcomes are measured in terms on growth, profitability and productivity on a yearly basis.
The *growth* indicators are SalesV and EmplV, while Roi and SpE are used to measure *profitability* and *productivity*, respectively.
To be scientifically consistent, only innovation which can be detected based on the information available in financial statements is considered.
In particular, we have considered only innovation involving investments in tangible and intangible assets measurable as the variation recognized in those items, appropriately reported in the balance sheet (see below).
To assess the type of innovation, the reading of the management report attached to the consolidated financial statement is needed. Specifically, we analyze the section containing the description of research and development, which contains information on innovation activities carried out or in progress. The searching of the strings "nuov*" and "innov*" (the Italian translations of the English strings "new" and "innov*") in the full annual report has been also used.
The categorization of the initiatives is based on Damanpour (2010), where the definition of product and process innovation is given.
Our classification therefore focuses mainly on product and process innovations, and summarizes actions which previous studies classify more in detail (Gunday et al. 2011). However, in the codification, we have also taken into account cases of joint realization of product and process innovation and cases characterized by lack of innovation or absence of information.
R&D are largely used in research at firm level (Lichtenberg and Siegel 1991, Hall and Mairesse 1995, Mairesse and Mohnen 2005, Marsili and Salter 2006, Parisi et al. 2006). The majority of authors takes the position that R&D does not capture all aspects of innovation but may represent an important part of it (OECD 2005). In particular, the probability that R&D expenditure leads to an underestimation of the impact of innovation on performance is particularly high in smaller companies (Kleinknecht 1987; Hall et al. 2009).
Furthermore, a distortion may occur in the data from the company annual reports, since innovation expenditures are not usually specified in the companies' financial accounts (OECD 2005, p. 40). According to the Oslo Manual, this problem can be addressed by measuring a company's innovation effort through its tangible and intangible (fixed) assets (OECD 2005, p. 35).
Tangible assets correspond to the sum of the balance sheet items: plants, machineries and equipments. These items are assumed to entail innovation, at least at a technological level (OECD 2005, p.93). In our study, properties have been excluded because their variation may not necessarily express an innovation effort.
Intangible assets are computed in the balance sheet, and are mainly composed of development costs, patents, trademarks, licences and concessions. Goodwill is not considered in the set of the intangible fixed assets, because its variation is mainly due to mergers or acquisition of new companies. Those initiatives are often designed to obtain new financial or fiscal advantages rather than achieving product or process innovation.
Company size is one of the most influential variables for the impact of innovation on performance. Furthermore, as shown in Damanpour (2010), the choice of different measurements of size (financial indicators and personnel) may influence the relation between size and type of innovation. In order to reduce this bias, companies are classified through a mix of employee number, total sales and total assets.

3.3 Variable measurement

The *level of innovation* is assessed in terms of *intensity* and *relevance* of the initiatives. The intensity is measured as percentage variation of tangible and intangible assets in the biennium 2006-2007, while the relevance is their average weights on total assets in the same period.
Companies are then grouped into two categories: Low Innovation (LI) and High Innovation (HI). This clustering is made by considering innovation intensity and innovation relevance separately for intangible and tangible innovation (see Table A2). The clustering thresholds are based on the empirical evidence of the STAR. For intensity, 20% is the approximate median value of the percentage variation of intangible assets, and it is consistently used also for tangible assets. Such threshold is validated by interviewing managers (see the Appendix for some details on the employed questionnaires). Results show that this threshold is reasonable and prudent (20% is the maximum value indicated by the respondents), hence allowing the identification of the most innovative behaviours. The relevance threshold is fixed at 10%, which is the average of the two most recurring answers (5% and 15%).
As for *size,* companies are grouped into three categories: small, medium and large. The thresholds employed for personnel have been defined on the basis of the literature (Acs and Audretsch 1990, Phillips and Kirchhoff 1989, Brock and Evans 1989 and Baldwin et al. 2002).
The classification of companies based only on financial measures is controversial, since the size of a firm describes different levels of complexity. The soundness of the adopted thresholds is validated through "face validity" interviews (see the Appendix). The mode and the median of the thresholds identified by the managers coincide with the values adopted here (150.000 and 500.000 for total sales; 140.000 and 400.000 for total assets, see Table A1). The mean of the values in the responses is higher, but comparable with the present ones (157.500 and 447.500 for total sales; 197.000 and 533.750 for total assets).
Each company satisfies at least two thresholds conditions for one of the three categories in Table A1, and its size has been identified according to this criterion and employing the average values in the years 2006-2007.
Tables A2 and A3 show the distribution of companies grouped by size and innovation level both for tangible and intangible assets.
The distributions of companies by type of innovation and size is shown in Table A4.
Some descriptive statistics of the considered variables are reported in Table A5.

3.4 Methodological instruments: preliminary notations.

The qualitative parameters that cluster the set of companies are denoted as follows:

- $i=1,2,3$ is the size of the company, and $i=1,2,3$ means small, medium and large companies, respectively.
- $j=1,2,3,4$ is the type of innovation of the company and $j=1,2,3$ stands for innovation in product, in process, and in product and process, respectively. Case $j=4$ means no innovation or no information. It is reported for the sake of completeness but results are reasonably not discussed.
- $h=1,2$ is the level of innovation for tangible assets. "Low innovation" is $h=1$, while "High innovation" is $h=2$.
- $k=1,2$ is the level of innovation for intangible assets. "Low innovation" is $k=1$, while "High innovation" is $k=2$.

As already mentioned, with the term *indicators* we mean the quantities measuring company performance: SalesV, EmplV, Roi, SpE.
They are denoted as x and the subscript, when it appears, indicates the considered cluster. Specifically, fix one of the four indicators listed above. Then:

- x is the sum of the absolute values of the indicator for all the companies of the STAR.
- x_i represents the sum of the absolute values of the indicator for the companies with size i. Analogously, one can define x_j, x_h and x_k.

- x_{ij} is the sum of the absolute values of the indicator for companies with size *i* and type of innovation *j*. The same applies for x_{ih}, x_{ik}, x_{jh}, x_{jk} and x_{hk}.
- x_{ijk} is the sum of the absolute values of the indicator for companies with size *i*, type of innovation *j* and level of innovation for intangible assets *k*. The terms x_{ijh}, x_{ihk} and x_{jhk} are analogously defined.

3.5 Methodological instruments: entropy measures.

The adopted entropy measures capture the localization of companies (see Brülhart and Traeger 2005 and Cutrini 2009, 2010) and, in contrast with Shannon entropy, the higher their values, the less uniformly shaped is the distribution of the related parameter in the clusters, and the more scattered the performances. Moreover, entropies satisfy a decomposition property for which concentration depends on how companies are clustered. In this paper, subfamilies of the original set of companies determined by a fixed value of one (or two) of the parameters *i,j,k,h*, are considered, and the concentration of the performance indicators when such subfamilies are clustered with respect to one of the remaining parameters is measured. Results are not biased by the probability estimates of the empirical data, being entropy-type measures based on empirical distributions (no hypothesis test or best fit of known probability distribution of data is required).

The family of mono-subscript entropy measures is now introduced. Since *h* and *k* give information on the innovation level from two different perspectives, it is illogical to consider them jointly, and we have therefore avoided clustering companies with respect to both parameters. Hence, for *φ=k,h,* we have:

$$H_{\varphi}^{1}=\sum_{i=1}^{3}\sum_{j=1}^{4}\frac{x_{ij\varphi}}{x_{\varphi}}\ln\left(\frac{x_{ij\varphi}/x_{i\varphi}}{x_{ij}/x_{i}}\right)$$

$$H_{\varphi}^{2}=\sum_{i=1}^{3}\sum_{j=1}^{4}\frac{x_{ij\varphi}}{x_{\varphi}}\ln\left(\frac{x_{ij\varphi}/x_{j\varphi}}{x_{ij}/x_{j}}\right)$$

$$H_{j}^{1}=\sum_{i=1}^{3}\sum_{\varphi=1}^{2}\frac{x_{ij\varphi}}{x_{j}}\ln\left(\frac{x_{ij\varphi}/x_{ij}}{x_{i\varphi}/x_{i}}\right)$$

$$H_{j}^{2}=\sum_{i=1}^{3}\sum_{\varphi=1}^{2}\frac{x_{ij\varphi}}{x_{j}}\ln\left(\frac{x_{ij\varphi}/x_{j\varphi}}{x_{i\varphi}/x_{\varphi}}\right)$$

$$H_{i}^{1}=\sum_{j=1}^{4}\sum_{\varphi=1}^{2}\frac{x_{ij\varphi}}{x_{i}}\ln\left(\frac{x_{ij\varphi}/x_{ij}}{x_{j\varphi}/x_{j}}\right)$$

$$H_{i}^{2}=\sum_{j=1}^{4}\sum_{\varphi=1}^{2}\frac{x_{ij\varphi}}{x_{i}}\ln\left(\frac{x_{ij\varphi}/x_{i\varphi}}{x_{j\varphi}/x_{\varphi}}\right)$$

To distinguish the case with *k* from that with *h*, we denote $H_{j}^{1}=H_{j}^{1\varphi},H_{j}^{2}=H_{j}^{2\varphi},H_{i}^{1}=H_{i}^{1\varphi},H_{i}^{2}=H_{i}^{2\varphi}$, where *φ=k,h.*

The quantities introduced above make it possible to evaluate the impact of one of the three parameters *i, j, h* or *k* when only one of the remaining parameter is fixed. H_{k}^{1} and H_{k}^{2} capture information on *x* for the level of innovation on tangible assets *k*, when such an aggregation involves companies with size *i* and type of innovation *j*, respectively. As the value of $H_{k}^{1}(H_{k}^{2})$ grows, the scatter effect of *i* (*j*) in the aggregation *x* of companies with a level of intangible assets innovation *k* increases. Specifically, the disorder of the companies with regard to the indicator is high, and scarce concentration occurs. Conversely, if entropy has a low value, then the system of companies is concentrated with respect to the examined indicator. The same arguments apply to the other *H*'s. Table 1 summarizes the action of each mono-subscript entropy measures.

Entropy measure	H_k^1	H_k^2	H_j^{1k}	H_j^{2k}	H_i^{1k}	H_i^{2k}	H_h^1	H_h^2	H_j^{1h}	H_j^{2h}	H_i^{1h}	H_i^{2h}
Fixed parameter	*k*	*k*	*j*	*j*	*I*	*i*	*h*	*h*	*J*	*j*	*i*	*i*
Scatter parameter	*i*	*j*	*i*	*k*	*J*	*k*	*i*	*j*	*I*	*h*	*j*	*h*

Table 1: Action of the mono-subscript entropy measures. Given the companies with a fixed parameter (second line), the corresponding entropy (first line) is measured for companies clustered with respect to the scatter parameter (third line).

Now the family of entropy measures with double subscript is defined. The scatter effect of one of the three parameters *i*, *j*, *h* or *k*, when the other parameters are fixed, is explored.

$$H_{ij}^{k} = \sum_{k=1}^{2} \frac{x_{ijk}}{x_k} \ln\left(\frac{x_{ijk} / x_k}{x_{ij} / x} \right)$$

$$H_{ik} = \sum_{j=1}^{4} \frac{x_{ijk}}{x_j} \ln\left(\frac{x_{ijk} / x_j}{x_{ik} / x} \right)$$

$$H_{jk} = \sum_{i=1}^{3} \frac{x_{ijk}}{x_i} \ln\left(\frac{x_{ijk} / x_i}{x_{jk} / x} \right)$$

k is replaced with *h* to define $H_{ij}^{h}, H_{ih}, H_{jh}$.

H_{ij}^{k} is the entropy measure that gives information on the value of *x* for companies with innovation type *j* and size *i* as *k* varies. Specifically, as H_{ij}^{k} grows, the scatter effect of *k* increases when *i* and *j* are fixed. The disorder of the system is high and scarce concentration takes place. When the entropy is low, companies are clustered through similar values by the related scatter parameter. A similar discussion applies to all the double-subscript entropy measures. Table 2 synthesizes such arguments.

Entropy measure	H_{ij}^k	H_{ik}	H_{jk}	H_{ij}^h	H_{ih}	H_{jh}
Fixed parameters	*i,j*	*i,k*	*j,k*	*i,j*	*i,h*	*J,h*
Scatter parameter	*k*	*j*	*i*	*h*	*j*	*I*

Table 2: Action of the double-subscript entropy measures. Given the companies with a fixed couple of parameters (second line), the corresponding entropy (first line) is measured for companies clustered with respect to the scatter parameter (third line).

4. Results and discussion

In the following subsections, entropy values (in Tables A6 and A7 for mono-and double-subscript measures, respectively) are commented by considering separately how size, type of innovation, intangible and tangible assets may influence the relationship between innovation and performance.
Table 3 summarizes the most relevant results, showing the cluster of companies and the performance measures where each considered variable produces the most significant impacts.

Scatter Parameter	Relevant cluster	Performance influenced

Size (*i*)	Low and high innovative companies in tangible assets (indexes 19 and 20 – Table A6)	Growth, Profitability
	Companies performing product and product/process innovation (indexes 23 and 25 – Table A6)	Growth, Profitability, Productivity
	Companies performing process innovation (index 6 – Table A6)	Productivity
Type of innovation (*j*)	Companies (any size) innovative in tangible assets (Indexes 39-43 – Table A7)	Productivity
Tangible Assets (*h*)	Companies performing process innovation (Index 28 – Table A6)	Growth
	Large companies (Index 36 – Table A6)	Growth, Productivity
Intangible Assets (*k*)	Companies performing different types of innovation (Indexes 9-12 – Table A6)	Growth, Profitability, Productivity
	Small companies (Index 16 – Table A6)	Growth
	Large companies (Index 18 – Table A6)	Productivity

Table 3 – Summary of the major findings

4.1 Size

Several studies assess the likelihood of smaller and larger companies to be innovative, showing mixed results (see Damanpour 2010 for a survey).

Hall et al. (2009) point out that large firms often implement multiple innovation initiatives. Large size leads to positive performances thanks to scale and scope economies, even if performances may be bounded by the high level of costs due to administrative and bureaucratic constraints (Irwin et al. 1998, Gopalakrishnan 2000). Thus, large companies pursue more likely innovation, but such innovation is not always effective. Empirical studies show an inverse relationship between productivity of R&D investments and size, hence supporting the theory that managers of large-sized companies focus on existing products and spend less time developing new ones (Acs and Audretsch 1990, Cohen and Klepper 1996, Plehn-Dujowich 2007).

The entropy measures provide interesting and original insights because they allow to highlight the role played by size on performance when innovation occurs.

In particular, row 19 in Table A6 shows high entropy, particularly for growth and profitability. This means that size could be a relevant explanatory variable of company performance, when companies show low innovation on their tangible assets.

This finding is of particular interest when compared to row 20, which shows lower entropy in highly innovative companies in tangible assets. The combined results of indexes 19 and 20 suggest that innovation in tangible assets produces higher homogeneity in company performance, while when innovation (in tangible assets) is not occurring, company size influences performance.

The results confirm existing literature: company performance is significantly affected by size (Hall et al. 2009; Horta et al. 2012), but only when innovation is not occurring to a significant extent. Conversely investments in tangible assets seem to smooth the impact produced by size on company performance.

It is also possible to analyze the role of size in companies performing different types of innovation. Previous studies focused on the relation between company size and type of innovation, and show that smaller firms are more likely to perform product innovation initiatives (Cohen and Levin, 1989; Fritsch and Meschede, 2001; Scherer, 1980), because they can be easily translated into market outcomes (new sales or licensing), whereas larger firms tend to

invest in process innovation, looking for organizational changes which may foster cost savings (Scherer, 1980 p.414).
Table A6 shows other interesting facts: when companies invest in tangible assets, size does not seem to impact on performance, as the entropies are generally low, particularly when companies implement product and product/process innovations (indexes 23 and 25); conversely, size seems to influence performance in companies investing in intangible assets, and particularly in cases of process innovation (index 6).

4.2 Type of innovation

The impacts of different innovation typologies are explored by several empirical studies, which generally tend to assess whether the different types of innovations are more likely to impact growth, profitability, productivity or additional performance perspectives.
Edquist et al. (2001), Pianta (2005), Artz et al. (2010) argue that product innovation can improve occupation and earnings, whereas process innovation can reduce operating costs and lead times, or improve the quality of invested capital, internal capabilities and competitiveness in the long term (Geroski et al. 1993, Damanpour 2010).
Fagerberg et al. (2005) argue that, while product innovation is supposed to produce a positive impact on income and employment growth, a new process can have a more indeterminate effect, because of its cost-cutting nature. Differently, Oke (2007) emphasizes that product and process innovations are correlated and their joint implementation is fruitful, since the improvement of the processes is necessary to successfully create new products or services.
Therrien et al. (2011) and Lin and Chen (2007) argue that organizational innovation, rather than technological innovation, is a crucial factor in explaining sales improvement.
The relevance of the type of innovation is strongly confirmed by the double sub-script indexes in Table A7. Rows 39-43 show remarkably high level of entropy for all the considered performance indicators and for each covered year. Such indexes strongly evidence that different types of innovation have relevant impacts on performance (in particular, on productivity) of companies clustered by a given size and level of innovation in tangible assets. This may be interpreted as a confirmation that the number of employees is conditioned by the type of innovation.
According to indexes 13-18 (Table A7), the type of innovation seems to impact on performance also when companies invest in intangible assets and mainly in the case of small-sized companies.

4.3 Tangible assets

Rows 27-30 on Table A6 show that entropies are rather high when companies performing the same kind of innovation are sub-clustered in terms of level of innovation in tangible assets. The level of tangible capital investments could therefore be a significant driver of performance (Lotti and Santarelli 2001), in particular among companies performing process innovation (index 28) and for growth outcomes. The level of tangible assets innovation may deserve thus further consideration in studies aiming at assessing effectiveness and accuracy of innovation measures based on current or capital expenditures. As said before, these variables may not fully represent the wide range of innovation initiatives performed by the companies (Crépon et al. 1998, Cohen and Levin 1989) and could therefore be weak predictors of innovation outcomes, considering also that the success of innovation is based on how well firms introduce innovation and adapt it to competitive environments, rather than on the amount of expenditure (Kitching et al. 2009).
The scatter parameter *(h)* seems significant when the fixed parameter is the size (indexes nr 34-36 in Table A6). This may suggest that, when the companies are clustered on the basis of a given size, performance (growth and productivity in particular) is influenced by innovation in tangibles assets.

4.4 Intangible assets

The level of innovation in intangible assets is the dimension which generates the lowest entropy when the type of innovation is assumed as fixed (rows 9-12 in Table A6). Therefore, when clustering companies on the basis of a fixed type of innovation (*j=1,2,3,4*), the comparison between sub-clusters determined by the level of innovation in intangible assets does not show significant variability. In other words, given a particular type of innovation, the performances in companies with high innovation level in intangible assets do not differ significantly from those of low innovation ones. This means that the distributions in the sub-clusters do not show significant changes. Hence, when companies are implementing the same type of innovation, the level of innovation in intangible assets is not supposed to be significant for the investigation of the relation between innovation initiatives and company performance. This finding holds for all the performance indicators considered and in all the three output years covered.
The exceptional low entropy of indexes 9-12 (and therefore also the high homogeneity in the clusters obtained through each type of innovation) allows us to address additional considerations about the type of innovation (assumed as fixed parameter). Figure A1 shows the average deciles on SalesV, calculated for the considered types of innovation clusters. The deciles make it possible to overcome the bias represented by the different company size when calculating central tendency measures based on financial ratios (Lev and Sunder 1979).
Cluster 2 (Figure A1) – referred to process innovation – shows higher performance on productivity for all the three output years. The low entropy ensures that the average performance should be highly representative of the general level of performance among the clustered companies. We performed the same analysis also considering the outcomes in terms of growth, and profitability and in all cases we found similar results. Results are coherent with those studies asserting that process innovation makes it possible to improve the company outcomes through a better environmental adaptation (Hall et al. 2009; Therrien et al. 2011; Lin and Chen 2007). Companies which aim to successfully implement innovation activities must first overcome the structural inertia that inhibits the process (Makkonen et al. 2014).
When companies are clustered by size (indexes nr 16 and 18 in Table A6) the relevance of the scatter parameter *(k)* appears rather high, showing that high or low intangibles assets innovation affects performance, determining growth in small companies and productivity in large companies. This result confirms that the relationship between innovation investments in intangible assets and performance deserves further consideration in studies which try to explain differences in performance of companies of similar size (Mansfield 1981; Pavitt et al. 1987; Acs and Audretsch 1991; Plehn-Dujowich 2007).

5. Conclusions

A new perspective based on entropy for measuring company performance has been advanced in this paper. To test the methodology, the analysis of the impact of innovation on performances for the STAR has been carried out. The introduction of entropy measures offers insights on the distribution of growth, profitability and productivity. By taking into account the statistical properties of the data, the central characteristics of the performances of companies can be inferred, along with information on the impact of innovation on them. In this respect, the present paper can be used as the basis of further studies on management and innovation.
The technicalities used in this work may be adopted to explore the structure of different microeconomic data. This may suggest policies for assessing the more effective innovation types in terms of performance. Moreover, the analysis of the less impacting parameters – in terms of low level of entropy – leads to the identification of aggregation criteria which maintain the performance indicators of the companies in a small range of variation. In this respect, a comparative analysis between indices – including the industrial sectors of the single components

– could provide several insights. An exhaustive treatment of such aspects is left to future research.

References

Acs, Z.J., Audretsch, D.B., 1990. The determinants of small-firm growth in US manufacturing. *Applied Economics*, 22(2), 143-153.

Acs, Z.J., Audretsch, D.B., 1991. Innovation and size at the firm level, *Southern Economic Journal*, 57(3), 739-744.

Ahuja, G., Katila, R., 2001. Technological acquisition and the innovation performance of acquiring firms: a longitudinal study. *Strategic Management Journal* 22, 197-220.

Aiginger, K., Davies, S.W., 2004. Industrial specialization and geographic concentration: two sides of the same coin? Not for the European Union. *Journal of Applied Economics,* 7(2), 231–248.

Aiginger, K., Pfaffermayr, M., 2004. The Single Market and geographic concentration in Europe. *Review of International Economics*, 12(1), 1–11.

Anderson, P., Arrow, K.J., Pines, D., Eds., 1988. The Economy As an Evolving Complex System. Addison-Wesley, Reading, MA.

Arthur, W.B., 1999. Complexity and the Economy. *Science,* 284(5411), 107-109.

Artz, K.W., Norman, P.M., Hatfield, D.E., Cardinal, L.B., 2010. A Longitudinal Study of the Impact of R&D, Patents, and Product Innovation on Firm Performance, *Journal of Product Innovation Management*, 27(5), 725-740.

Ausloos, M., Ivanova, K., 2003. Dynamical model and nonextensive statistical mechanics of a market index on large time windows. *Physical Review E*, 68(4), 046122.

Baldwin, J., Hanel, P., Sabourin, D., 2002. Determinants of innovative activity in Canadian manufacturing firms. In Kleinknecht A., Mohnen P., (eds), Innovation and Firm Performance. New York: Palgrave.

Brock, W.A., Evans, D.S., 1989. Small business economics. *Small Business Economics*, 1,7-20.

Brülhart, M., 2001. Evolving geographical concentration of European Union. *Weltwirtschaftliches Archiv*, 137(2), 215–243.

Brülhart, M., Traeger, R., 2005. An account of geographic concentration patterns in Europe. *Regional Science and Urban Economics*, 35(6), 597-624.

Cainelli, G., Evangelista, R., Savona, M., 2004. The impact of innovation on economic performance in services. *Service Industries Journal*, 24(1), 116-130.

Chang, A.Y., 2007. On the measurement of routing flexibility: A multiple attribute approach. *International Journal of Production Economics,* 109(1-2), 122-136.

Choi, J., Russell, J.S. 2005. Long-term entropy and profitability change of United States public construction firms. *Journal of Management Engineering,* 21(1): 17–26.

Cohen, W.M., Klepper, S., 1996. Firm size and the nature of innovation within industries: the case of process and product R&D. *Review of Economies & Statistics,* 78(2), 232-43.

Cohen, W., Levin, R.C., 1989. Empirical studies of innovation and market structure, Handbook of Industrial Organization, 2, Edited by Schmalensee, R., Willig, R.D., Elsevier, 1059-1107

Crépon, B., Duguet, E., Mairesse, J., 1998. Research, innovation and productivity. An econometric analysis at the firm level, *Economics of Innovation & New Technology,* 7(2), 115-159

Cutrini, E., 2009. Using entropy measures to disentangle regional from national localization patterns. *Regional Science and Urban Economics*, 39(2), 243-50.

Cutrini, E., 2010. Specialization and concentration from a twofold geographical perspective: Evidence from Europe. *Regional Studies*, 44(3), 315-36.

Damanpour, F., 2010. An integration of research findings of effects of firm size and market. Competition on product and process innovations. *British Journal of Management*, 21(4), 996–1010.
Edquist, C., Hommen, L., McKelvey, M., 2001. Innovation and employment: Process versus product innovation, Cheltenham: Elgar.
Ellison, G., Glaeser, E., 1997. Geographic concentration in U.S. manufacturing industries: a dartboard approach. *Journal of Political Economy*, 105(5), 889-927.
Fagerberg J., Mowery D.C., Nelson R.R., 2005. The Oxford Handbook of Innovation, Oxford: Oxford University Press.
Fritsch, M., Meschede, M., 2001. Product innovation, process innovation, and size. *Review of Industrial Organization*, 19, 335–350.
Geroski, P., Machin, S., Van Reenen, J., 1993. The profitability of innovating firms. *Journal of Economics*, 24(2), 198-211.
Gopalakrishnan, S., 2000. Unraveling the links between dimensions of innovation and organizational performance, *Journal of High Technology Management Research*, 11(1), 137-154.
Gunday, G., Ulusoy, G., Kilic, K., Alpkan, L., 2011. Effects of innovation types on firm performance. *International Journal of Production Economics*, 133(2), 662-76.
Hall, B.H., Lotti, F., Mairesse, J., 2009. Innovation and productivity in SMEs. Empirical evidence for Italy. *Small Business Economics*, 33(1), 13-33.
Hall, B.H., Mairesse, J., 1995. Exploring the relationship between R&D and productivity in French manufacturing firms, *Journal of Econometrics*, 65(1), 263-293.
Harrison, D. Klein, K. (2007) What's the difference? Diversity constructs as separation, variety, or disparity in organizations, *The Academy of Management Review*, 32(4), 1199–1228.
Harrison, D. Sin, H.P. (2006). What is diversity and how should it be measured? In A.M.Konrad, Prasad, P., and Pringle, J.K., Handbook of Work Place Diversity. SAGE publications ltd.
Horta, I. M., Camanho, A.S., Moreira da Costa J., 2012. Performance assessment of construction companies: A study of factors promoting financial soundness and innovation in the industry. *International Journal of Production Economics*, 137(1), 84-93.
Irwin, J.G., Hoffman, J.J., Geiger, S.W., 1998. The effect of technological adoption on organizational performance: Organizational size and environmental munificence as moderators. *The International Journal of Organizational Analysis*, 6(1), 50-64.
Jacobs, M.A., 2013. Complexity: Toward an empirical measure. *Technovation*, 33, 111-118.
Jacquemin, A.P., Berry, C.H., 1979. Entropy measure of diversification and corporate growth. Journal of Industrial Economics, 27(4), 359-369.
Kim, S., 1995. Expansion of markets and the geographic distribution of economic activities: the trends in US regional manufacturing structure, 1860–1987. *Quarterly Journal of Economics*, 110(4), 881–908.
Kitching, J., Blackburn, R., Smallbone, D. Dixon, S., 2009. Business strategies and performance during difficult economic conditions. (Project Report) London, U.K., Department for Business Innovation and Skills (BIS), Kingston University
Kleinknecht, A., 1987. Measuring R&D in Small Firms: How Much are we Missing?, *The Journal of Industrial Economics*, 36(2), 253-256.
Krugman, P., 1991. Geography and Trade. MIT Press, Cambridge.
Leonard, W.N., 1971. Research and development in industrial growth. *Journal of Political Economy*, 79(2), 232-56.
Lev B., Sunder S., 1979. Methodological issues in the use of financial ratios, *Journal of Accounting and Economics*, 1(3), 187–210.
Lichtenberg, F.R., Siegel, D., 1991. The Impact of R&D Investment on Productivity: New Evidence using Linked R&D-LRD Data, *Economic Inquiry*, Vol. 29(2), 203-228

Lin, C.Y., Chen, M.Y., 2007. Does innovation lead to performance? An empirical study of SMEs in Taiwan. *Management Research News*, 30(2), 115-32.
Lotti, F., Santarelli, E., 2001. Linking knowledge to productivity. *Empirica*, 28, 293-317.
Mairesse, J., Mohnen, P., 2005. The Importance of R&D for Innovation: A Reassessment Using French Survey Data, *The Journal of Technology Transfer*, 30(1-2), 183-197.
Makkonen, H., Pohjola, M., Olkkonen, R., Koponen, A., 2014. Dynamic capabilities and firm performance in a financial crisis, *Journal of Business Research*, 67(1), 2707-2719
Mansfield, E., 1981. Composition of R&D expenditures. Relationship to size of firm, concentration and innovative output, *Review of Economics and Statistics*, 63(4), 610-615.
Marsili, O., Salter, A., 2006. The dark matter of innovation: design and innovative performance in Dutch manufacturing. *Technology Analysis & Strategic Management*, 18(5), 515-34.
Matusik, S.F. Fitza, M.A., 2012. Diversification in the venture capital industry: leveraging knowledge under uncertainty. *Strategic Management Journal*, 33(4), 407-26.
Mori, T., Nishikimi, K., Smith, T.E., 2005. A divergence statistic for industrial localization. *Review of Economics and Statistics*, 87(4), 635–651.
Mulligan, G.F., Schmidt, C., 2005. A Note on Localization and Specialization, *Growth and Change*, 36(4), 565-576.
Oke, A., 2007. Innovation types and innovation management practices in service companies. *International Journal of Operations & Production Management*, 27(6), 564-87.
OECD, 2005, Oslo Manual, Guidelines for collecting and interpreting innovation data, OECD Publishing.
Palepu, K.,1985.Diversification strategy, profit, performance and the entropy measure. *Strategic Management Journal*, 6, 239–255.
Parisi, M.L., Schiantarelli, F., Sembenelli, A., 2006. Productivity, innovation and R&D: micro evidence for Italy. *European Economic Review*, 50(8), 2037-61.
Park, K., Jang, S. (2012). Effect of diversification on firm performance: Application of the entropy measure. *International Journal of Hospitality Management*, 31, 218-228.
Pavitt, K., Robson, M., Townsend, J., 1987. The size distribution of innovating firms in the UK: 1945-1983. *The Journal of Industrial Economics*, 35(3), 297-316.
Phillips, B.D., Kirchhoff, B.A. 1989. Formation, growth and survival: small firm dynamics in the U.S. economy. *Small Business Economics*, 1,65-74.
Pianta, M., 2005. Innovation and employment, in Fagerberg J., Mowery D. C., Nelson R. R., The Oxford Handbook of Innovation, Oxford: Oxford University Press.
Plehn-Dujowich J., 2007. Innovation, Firm Size and R&D Search, *Economics Bulletin*, 12(18) 1-8.
Ravenscraft, D.J., Scherer, F.M., 1982. The lag structure of returns to research and development. *Applied Economics*, 14(6), 603-20.
Scherer, F.M., 1980. Industrial Market Structure and Economic Performance. Chicago, IL: Rand McNally.
Stirling, A., 2001. A general framework for analyzing divirsity in science, technology and society. SPRU Working Papers, (156).
Teece, D.J., 1988. Capturing value from technological innovation: integration, strategic partnering, and licensing decision. *Interfaces*, 18(3),46-61.
Therrien, P., Doloreux, D., Chamberlin, T., 2011. Innovation novelty and (commercial) performance in the service sector: A Canadian firm-level analysis. *Technovation*, 31(12), 655-65.
Vandewalle, N., Ausloos, M., 1997. Coherent and random sequences in financial fluctuations. *Physica A*, 246(3), 454-459.
Vandewalle, N., Ausloos, M., 1998. Multi-affine analysis of typical currency exchange rates, *The European Physical Journal B*, 4(2), 257-261.

APPENDIX

Industries	Nr of companies	%	Total Sales (€ millions)			Total Assets (€ millions)			Nr of employees			Size		
			0 - 150	**150 - 500**	**> 500**	**0 - 140**	**140 - 400**	**> 400**	**0 - 500**	**500 - 1000**	**> 1000**	**Small**	**Medium**	**Large**
Hotels & Restaurants	1	1,61%			1			1		1				1
Manifacturing Companies	28	45,16%	8	17	3	9	13	6	5	13	10	8	13	7
Construction Companies	3	4,84%		1	2			3			3			3
Energy Suppliers	3	4,84%	2	1		1		2	3			2	1	
Health Care Providers	2	3,23%	1		1		1	1			2		1	1
ICT Companies	7	11,29%	5	2		4	3		6	1		5	2	
Industrial and commercial services	3	4,84%	2	1		2	1		1	1	1	1	2	
Hi-Tech Producers	14	22,58%	7	6	1	7	5	2	4	6	4	7	5	2
Overseas Transportation services	1	1,61%			1			1			1			1
Totals	**62**	**100,00%**	**25**	**28**	**9**	**23**	**23**	**16**	**19**	**22**	**21**	**23**	**24**	**15**
			40,3%	**45,2%**	**14,5%**	**37,1%**	**37,1%**	**25,8%**	**30,6%**	**35,5%**	**33,9%**	**37,1%**	**38,7%**	**24,2%**

Table A1: Classification of companies by industry and size attributes.

	Intensity (% Variation of fixed assets)			Relevance (average weight of fixed assets)		Level of Innovation	
	High (Var. above 20%)	**Low** (Var. between 0% and 20%)	**Negative** (negative var.)	**High Relevance** (avg. weight below or equal 10%)	**Low Relevance** (avg. weight above 10%)	**LI** (Low Innovation)	**HI** (High Innovation)
Small	7	12	4	7	16	**1**	**14**
Medium	8	10	6	3	21	**10**	**14**
Large	1	5	9	2	13	**10**	**13**
	25,8%	**43,6%**	**30,6%**	**19,4%**	**80,6%**	**33,9%**	**66,1%**

Table A2: Distribution by size of the level of innovation in intangible fixed assets

	Intensity			Relevance		Level of Innovation	
	High	**Low**	**Negative**	**High**	**Low**	**I**	**NI**
Small	8	8	7	3	20	**9**	**14**
Medium	2	17	5	13	11	**12**	**12**
Large	1	9	5	6	9	**5**	**10**
	17,7%	**54,9%**	**27,4%**	**35,5%**	**64,5%**	**41,9%**	**58,1%**

Table A3: Distribution by size of the level of innovation in tangible fixed assets

	Product	**Process**	**Product & Process**	**Not Declared**	**Totals %**
Small	11	2	5	5	**37,1%**
Medium	9	4	7	4	**38,7%**
Large	9	2	2	2	**24,2%**
	46,8%	**12,9%**	**22,6%**	**17,7%**	**100%**

Table A4: Companies classification by dimension and type of innovation

	Average	**Std. Dev.**	**Skewness**	**Kurtosis**
Total Assets 2007 (€/1.000)	356,154	381,872	2.70	8.92
Total Assets 2006 (€/1.000)	317,603	337,945	2.56	8.03
Total Sales 2007 (€/1.000)	329,896	395,774	3.04	12.23
Total Sales 2006 (€/1.000)	289,186	358,457	3.14	13.11
Nr. of Employees 2007	1,281	1,570	2.84	9.38
Nr. of Employees 2006	1,143	1,350	2.54	6.80
Intangible Assets 2007 (€/1.000)	14,196	21,868	2.64	8.20
Intangible Assets 2006 (€/1.000)	12,970	23,214	2.89	8.99
Tangible Assets 2007 (€/1.000)	46,341	95,328	3.48	13.31
Tangible Assets 2006 (€/1.000)	42,252	88,494	3.48	13.05
% Intangible Assets on Total Assets 2007 (Relevance of Intangible Assets)	5.35%	7.53%	2.28	5.64
% Intangible Assets on Total Assets 2006 (Relevance of Intangible Assets)	5.10%	7.75%	2.71	8.72
% Tangible Assets on Total Assets 2007 (Relevance of Tangible Assets)	10.07%	12.37%	2.13	4.80
% Tangible Assets on Total Assets 2006 (Relevance of Tangible Assets)	10.52%	13.91%	2.20	4.64
Sales % Variation 2008	16.56%	37.32%	1.84	8.97
Sales % Variation 2009	-5.95%	25.42%	2.11	6.82
Sales % Variation 2010	13.24%	25.40%	1.94	6.99
Nr Employees % Variation 2008	23.60%	74.93%	6.16	43.79
Nr Employees % Variation 2009	1.39%	23.04%	4.45	31.96
Nr Employees % Variation 2010	-0.17%	13.51%	-0.03	10.01
Roi % Variation 2008	6.11%	6.96%	-0.04	2.03
Roi % Variation 2009	2.60%	6.96%	-0.07	-0.60

Roi % Variation 2010	5.87%	10.82%	5.25	35.43
Sales per employee 2008	374	463	3.06	9.61
Sales per employee 2009	347	421	2.87	8.51
Sales per employee 2010	377	431	2.77	8.29

Table A5: Descriptive statistics of the considered parameters.

				Growth						Profitability			Productivity		
Index nr.		F	S	SalesV 08	SalesV 09	SalesV 10	EmplV 08	EmplV 09	EmplV 10	Roi 08	Roi 09	Roi 10	SpE 08	SpE 09	SpE 10
1	$H_k^1\,(k=1)$	k	i	-14%	-5%	-11%	-12%	-12%	-11%	-16%	-19%	-12%	-11%	-12%	-11%
2	$H_k^1\,(k=2)$	k	i	28%	21%	19%	16%	22%	37%	12%	17%	17%	39%	44%	41%
3	$H_k^2\,(k=1)$	k	j	22%	9%	18%	11%	17%	13%	6%	5%	15%	13%	11%	12%
4	$H_k^2\,(k=2)$	k	j	51%	38%	37%	31%	26%	30%	25%	29%	30%	33%	34%	33%
5	$H_j^{1k}\,(j=1)$	j	i	1%	2%	7%	0%	25%	0%	1%	3%	5%	4%	4%	4%
6	$H_j^{1k}\,(j=2)$	j	i	21%	41%	25%	24%	13%	41%	28%	32%	45%	52%	51%	52%
7	$H_j^{1k}\,(j=3)$	j	i	78%	18%	20%	31%	20%	45%	6%	5%	16%	33%	40%	43%
8	$H_j^{1k}\,(j=4)$	j	i	1%	14%	6%	7%	19%	34%	5%	5%	5%	13%	14%	11%
9	$H_j^{2k}\,(j=1)$	j	k	-180%	-206%	-210%	-177%	-230%	-200%	-208%	-203%	-216%	-228%	-227%	-227%
10	$H_j^{2k}\,(j=2)$	j	k	-101%	-108%	-106%	-129%	-61%	-159%	-180%	-192%	-193%	-113%	-120%	-123%
11	$H_j^{2k}\,(j=3)$	j	k	-185%	-177%	-179%	-148%	-207%	-122%	-165%	-171%	-127%	-177%	-174%	-170%
12	$H_j^{2k}\,(j=4)$	j	k	-152%	-129%	-151%	-189%	-132%	-162%	-203%	-202%	-140%	-183%	-185%	-185%
13	$H_i^{1k}\,(i=1)$	i	j	26%	12%	21%	17%	29%	12%	17%	16%	25%	26%	22%	21%
14	$H_i^{1k}\,(i=2)$	i	j	40%	22%	24%	11%	10%	30%	3%	7%	12%	17%	18%	18%
15	$H_i^{1k}\,(i=3)$	i	j	39%	29%	41%	43%	31%	27%	22%	18%	30%	14%	14%	14%
16	$H_i^{2k}\,(i=1)$	i	k	26%	16%	21%	26%	40%	12%	12%	10%	15%	27%	23%	23%
17	$H_i^{2k}\,(i=2)$	i	k	28%	17%	12%	17%	9%	33%	8%	9%	16%	18%	20%	19%
18	$H_i^{2k}\,(i=3)$	i	k	7%	19%	11%	15%	36%	10%	14%	9%	20%	33%	33%	34%
19	$H_h^1\,(h=1)$	h	i	73%	71%	35%	75%	50%	46%	52%	40%	26%	33%	29%	28%
20	$H_h^1\,(h=2)$	h	i	-8%	19%	7%	-7%	44%	-14%	7%	11%	66%	17%	27%	31%
21	$H_h^2\,(h=1)$	h	j	14%	11%	19%	11%	23%	5%	4%	6%	9%	17%	19%	20%
22	$H_h^2\,(h=2)$	h	j	39%	15%	20%	16%	15%	17%	4%	10%	7%	6%	7%	9%
23	$H_j^{1h}\,(j=1)$	j	i	-36%	-36%	-37%	-25%	-11%	-33%	-42%	-44%	-39%	-34%	-34%	-33%
24	$H_j^{1h}\,(j=2)$	j	i	13%	18%	-1%	25%	11%	-17%	-17%	-27%	-3%	-14%	-16%	-15%
25	$H_j^{1h}\,(j=3)$	j	i	-33%	-24%	-18%	-5%	-13%	-14%	-25%	-35%	-4%	3%	2%	-4%
26	$H_j^{1h}\,(j=4)$	j	i	3%	10%	-20%	-16%	11%	11%	-16%	-9%	-26%	-32%	-26%	-25%
27	$H_j^{2h}\,(j=1)$	j	h	12%	11%	11%	6%	44%	10%	5%	2%	5%	8%	9%	11%
28	$H_j^{2h}\,(j=2)$	j	h	39%	48%	26%	48%	31%	24%	8%	13%	32%	5%	3%	5%
29	$H_j^{2h}\,(j=3)$	j	h	16%	10%	12%	21%	23%	17%	10%	7%	27%	16%	16%	15%
30	$H_j^{2h}\,(j=4)$	j	h	31%	25%	11%	44%	40%	9%	16%	13%	9%	9%	13%	12%
31	$H_i^{1h}\,(i=1)$	i	j	17%	10%	20%	8%	23%	5%	2%	4%	5%	8%	10%	12%
32	$H_i^{1h}\,(i=2)$	i	j	30%	19%	18%	9%	13%	16%	4%	8%	4%	7%	9%	11%
33	$H_i^{1h}\,(i=3)$	i	j	22%	10%	22%	34%	21%	13%	7%	15%	22%	22%	24%	21%
34	$H_i^{2h}\,(i=1)$	i	h	18%	12%	8%	19%	39%	7%	4%	5%	11%	3%	5%	6%
35	$H_i^{2h}\,(i=2)$	i	h	35%	17%	12%	17%	23%	20%	9%	7%	13%	5%	7%	7%
36	$H_i^{2h}\,(i=3)$	i	h	26%	32%	37%	46%	62%	30%	14%	9%	22%	26%	26%	26%

F = Fixed parameter; S = Scatter Parameter

Table A6: Values of the mono-subscript entropy measures

Index nr.		F1	F2	S	Growth: SalesV 08	Growth: SalesV 09	Growth: SalesV 10	Growth: EmplV 08	Growth: EmplV 09	Growth: EmplV 10	Profitability: Roi 08	Profitability: Roi 09	Profitability: Roi 10	Productivity: SpE 08	Productivity: SpE 09	Productivity: SpE 10
1	$H_{ij}^{k}\left(i=1;\ j=1\right)$	i	j	k	0%	-2%	1%	-8%	1%	-3%	-5%	-2%	2%	1%	0%	1%
2	$H_{ij}^{k}\left(i=2;\ j=1\right)$	i	j	k	15%	10%	20%	5%	15%	16%	7%	4%	8%	6%	5%	5%
3	$H_{ij}^{k}\left(i=3;\ j=1\right)$	i	j	k	-2%	-1%	-2%	0%	-6%	1%	-1%	0%	0%	-1%	-1%	-1%
4	$H_{ij}^{k}\left(i=1;\ j=2\right)$	i	j	k	2%	-3%	-6%	6%	0%	-1%	-1%	0%	9%	-1%	-1%	-1%
5	$H_{ij}^{k}\left(i=2;\ j=2\right)$	i	j	k	5%	7%	7%	4%	19%	7%	3%	2%	-5%	3%	4%	4%
6	$H_{ij}^{k}\left(i=3;\ j=2\right)$	i	j	k	3%	-1%	1%	5%	2%	1%	3%	2%	5%	7%	7%	6%
7	$H_{ij}^{k}\left(i=1;\ j=3\right)$	i	j	k	9%	4%	-1%	16%	1%	6%	16%	16%	0%	0%	1%	0%
8	$H_{ij}^{k}\left(i=2;\ j=3\right)$	i	j	k	-2%	-2%	-2%	0%	-3%	-3%	-5%	-3%	-4%	2%	5%	4%
9	$H_{ij}^{k}\left(i=3;\ j=3\right)$	i	j	k	31%	15%	21%	17%	55%	4%	4%	6%	4%	37%	34%	32%
10	$H_{ij}^{k}\left(i=1;\ j=4\right)$	i	j	k	15%	17%	17%	2%	1%	49%	12%	10%	6%	10%	14%	16%
11	$H_{ij}^{k}\left(i=2;\ j=4\right)$	i	j	k	-3%	-6%	-4%	-3%	-2%	-2%	0%	1%	31%	-2%	-3%	-3%
12	$H_{ij}^{k}\left(i=3;\ j=4\right)$	i	j	k	4%	14%	10%	4%	-1%	0%	-1%	0%	-1%	-6%	-6%	-6%
13	$H_{ik}\left(i=1;\ k=1\right)$	i	k	j	21%	33%	18%	20%	56%	91%	37%	20%	15%	11%	15%	16%
14	$H_{ik}\left(i=1;\ k=2\right)$	i	k	j	52%	21%	25%	6%	43%	44%	5%	6%	16%	41%	47%	54%
15	$H_{ik}\left(i=2;\ k=1\right)$	i	k	j	34%	7%	7%	38%	13%	0%	6%	0%	26%	34%	29%	23%
16	$H_{ik}\left(i=2;\ k=2\right)$	i	k	j	9%	46%	15%	21%	25%	-1%	13%	22%	44%	22%	21%	21%
17	$H_{ik}\left(i=3;\ k=1\right)$	i	k	j	7%	-2%	7%	31%	31%	5%	-4%	-1%	4%	0%	0%	0%
18	$H_{ik}\left(i=3;\ k=2\right)$	i	k	j	1%	0%	2%	0%	4%	1%	4%	5%	9%	13%	15%	15%
19	$H_{jk}\left(j=1;\ k=1\right)$	j	k	i	20%	46%	37%	2%	64%	35%	23%	10%	23%	15%	13%	14%
20	$H_{jk}\left(j=1;\ k=2\right)$	j	k	i	5%	2%	9%	22%	6%	1%	1%	1%	1%	23%	20%	18%
21	$H_{jk}\left(j=2;\ k=1\right)$	j	k	i	18%	5%	6%	10%	8%	28%	7%	6%	22%	2%	4%	3%
22	$H_{jk}\left(j=2;\ k=2\right)$	j	k	i	22%	6%	10%	45%	24%	0%	3%	3%	6%	-3%	-3%	-3%
23	$H_{jk}\left(j=3;\ k=1\right)$	j	k	i	10%	3%	0%	10%	1%	5%	4%	8%	3%	15%	18%	17%
24	$H_{jk}\left(j=3;\ k=2\right)$	j	k	i	42%	16%	28%	12%	51%	13%	6%	7%	12%	19%	18%	17%
25	$H_{jk}\left(j=4;\ k=1\right)$	j	k	i	6%	5%	7%	6%	4%	7%	10%	8%	7%	8%	7%	9%
26	$H_{jk}\left(j=4;\ k=2\right)$	j	k	i	2%	9%	8%	3%	1%	2%	5%	4%	24%	2%	1%	2%
27	$H_{ij}^{h}\left(i=1;\ j=1\right)$	i	j	h	0%	1%	3%	1%	0%	9%	1%	0%	1%	0%	0%	0%
28	$H_{ij}^{h}\left(i=2;\ j=1\right)$	i	j	h	1%	0%	1%	0%	5%	-1%	0%	3%	1%	3%	2%	1%
29	$H_{ij}^{h}\left(i=3;\ j=1\right)$	i	j	h	0%	0%	0%	0%	2%	0%	1%	1%	7%	12%	11%	10%
30	$H_{ij}^{h}\left(i=1;\ j=2\right)$	i	j	h	9%	4%	11%	-1%	7%	8%	-1%	2%	2%	-3%	-2%	0%
31	$H_{ij}^{h}\left(i=2;\ j=2\right)$	i	j	h	34%	7%	11%	11%	19%	2%	0%	1%	0%	5%	4%	5%
32	$H_{ij}^{h}\left(i=3;\ j=2\right)$	i	j	h	2%	1%	3%	4%	3%	3%	1%	2%	3%	5%	5%	4%
33	$H_{ij}^{h}\left(i=1;\ j=3\right)$	i	j	h	0%	6%	4%	3%	4%	1%	1%	2%	8%	8%	7%	7%
34	$H_{ij}^{h}\left(i=2;\ j=3\right)$	i	j	h	2%	0%	0%	3%	1%	0%	0%	0%	5%	7%	6%	4%
35	$H_{ij}^{h}\left(i=3;\ j=3\right)$	i	j	h	0%	2%	4%	0%	0%	4%	0%	0%	0%	0%	0%	0%
36	$H_{ij}^{h}\left(i=1;\ j=4\right)$	i	j	h	6%	0%	1%	2%	6%	10%	2%	14%	21%	0%	0%	0%
37	$H_{ij}^{h}\left(i=2;\ j=4\right)$	i	j	h	6%	11%	11%	5%	3%	4%	10%	15%	11%	12%	13%	15%
38	$H_{ij}^{h}\left(i=3; j=4\right)$	i	j	h	1%	1%	2%	1%	0%	3%	2%	0%	0%	0%	0%	0%
39	$H_{ih}\left(i=1;\ h=1\right)$	i	h	j	309%	321%	215%	93%	164%	191%	67%	81%	63%	627%	696%	804%
40	$H_{ih}\left(i=1;\ h=2\right)$	i	h	j	128%	94%	98%	105%	94%	104%	47%	60%	100%	408%	428%	414%
41	$H_{ih}\left(i=2;\ h=1\right)$	i	h	j	203%	97%	99%	250%	72%	59%	106%	90%	106%	566%	557%	503%
42	$H_{ih}\left(i=2;\ h=2\right)$	i	h	j	119%	199%	211%	176%	143%	26%	77%	54%	93%	1318%	1209%	1224%
43	$H_{ih}\left(i=3;\ h=1\right)$	i	h	j	125%	60%	65%	179%	52%	62%	49%	53%	54%	370%	381%	397%
44	$H_{ih}\left(i=3;\ h=2\right)$	i	h	j	33%	45%	80%	33%	69%	30%	29%	13%	19%	234%	206%	213%
45	$H_{jh}\left(j=1;\ h=1\right)$	j	h	i	16%	93%	22%	17%	56%	38%	92%	62%	79%	96%	95%	89%
46	$H_{jh}\left(j=1;\ h=2\right)$	j	h	i	-19%	75%	6%	10%	25%	-1%	21%	5%	1%	33%	27%	19%

47	$H_{jh}(j = 2;\ h = 1)$	j	h	i	23%	-12%	19%	16%	3%	30%	-14%	-2%	0%	10%	9%	9%
48	$H_{jh}(j = 2;\ h = 2)$	j	h	i	51%	4%	56%	10%	109%	12%	3%	8%	18%	56%	37%	32%
49	$H_{jh}(j = 3;\ h = 1)$	j	h	i	11%	-2%	17%	4%	-8%	24%	30%	40%	30%	-15%	-15%	-12%
50	$H_{jh}(j = 3;\ h = 2)$	j	h	i	-10%	10%	-1%	-12%	-21%	20%	12%	5%	6%	-16%	-15%	-15%
51	$H_{jh}(j = 4;\ h = 1)$	j	h	i	46%	24%	-5%	49%	63%	-6%	-4%	-7%	-14%	0%	7%	9%
52	$H_{jh}(j = 4;\ h = 2)$	j	h	i	19%	12%	6%	10%	15%	2%	4%	22%	106%	29%	31%	30%

F1 = Fixed Parameter nr.1; F2 = Fixed Parameter nr.2; S = Scatter Parameter

Table A7: Values of the double-subscript entropy measures

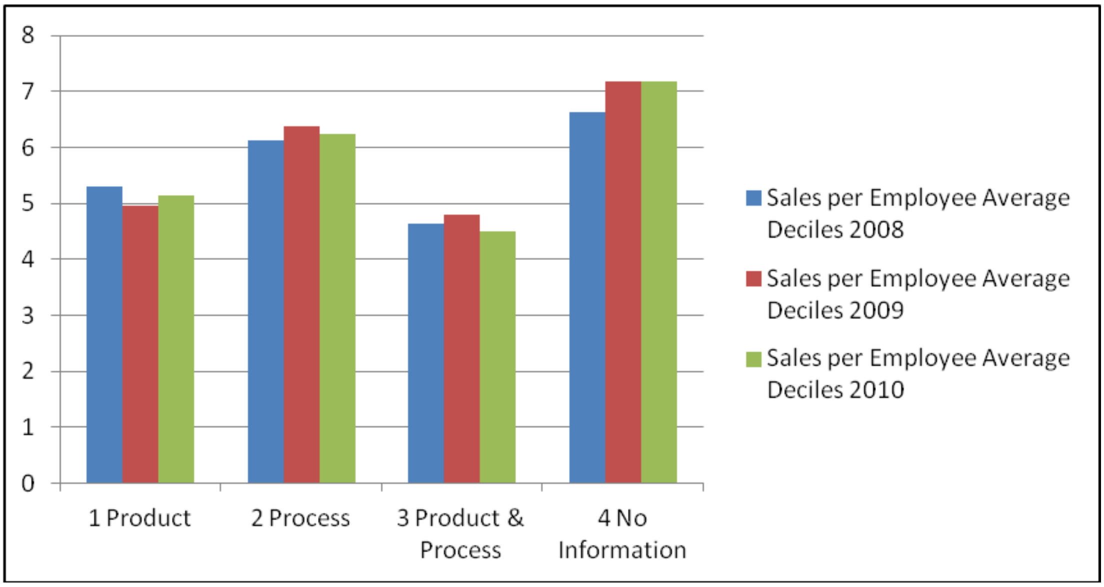

Figure A1: Sales per employee average deciles in 2008-2010 for type of innovation clusters

Face Validity Questionnaires

Following the suggestions of the Reviewer, some assumptions in our model have been validated through interviewing managers. In particular, a short questionnaire has been sent by e-mail to the managers of all the companies listed in the STAR Market, asking them to express their opinion about the following main issues:

- Which are reasonable thresholds to classify companies (intended as a group of separate legal entities) on the basis of the same characteristics of those analysed in the paper.
- Which are meaningful thresholds to assess intensity and relevance of the company innovation efforts.

The short questionnaires has been sent to the investor-relations managers because they have a deep knowledge of the innovation activities implemented by the company and, at the same time, a high level of expertise on their representations in the financial statements.

Each single manager has been contacted by telephone, in order to solicit her/him to answer the questionnaire. Unfortunately, responses have been received only by 2 of the 62 STAR Market companies. Then, to collect additional information, questionnaires have been submitted to managers of other companies which are comparable to the STAR Market ones, because they are listed on the Italian Stock Exchange (even if in a separate market) or share analogous characteristics (size, level of internationalization, etc.) At the end of this procedure, other 6 questionnaires (2 by listed companies) have been collected. The final list of 8 companies is the following: Biesse, Elica (listed in the STAR Market), Indesit, Navigazioni Montanari (listed in the Italian Stock Exchange), Fintel, Svila, Eusebi, Rainbow (not listed).

Results confirm the soundness of the values of the thresholds taken for performing the analysis of the STAR Market. More details on this can be found in the main text of the paper.