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A measure of innovation performance: the Innovation Patent Index

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Abstract

Purpose – The measure of companies' Innovation Performance is fundamental for enhancing the value and decision-making processes of firms. The purpose of this paper is to present a new measure of Innovation Performance, called Innovation Patent Index (IPI), which makes it possible to quantitatively summarize different aspects of firms' innovation.

Design/methodology/approach – In order to define the IPI, a secondary source, i.e. patent data, has been used. The five dimensions of IPI, i.e. efficiency, time, diversification, quality and internationalization have been defined both analyzing the literature and applying three different machine learning algorithms (regularized least squares, deep neural networks and decision trees), considering patent forward citations as a proxy of the innovation performance.

Findings – Results show that the IPI index is a very useful tool, simple to use and very promptly. In fact, it is possible to get important results without making time consuming analysis with primary sources. It is a tool that can be used by managers, businessmen, policymakers, organizations, patent experts and financiers to evaluate and plan future activities, to enhance the innovation capability, to find financing and to support and improve innovation.

Research limitations/implications – Patent data are not widely used in all the sectors. Moreover, the pure number of forward citations is not the only forward looking indicator suggested by the literature.

Originality/value – The demand for a useable Innovation Performance tool, as well as the lack of tools able to grasp different aspects of the innovation, highlight the need to develop new instruments. In fact, although previous studies provide several measures of Innovation Performance, these are often difficult for managers to use, do not appreciate different aspects of the innovation and are not forward looking.

Keywords Innovation patent index, Innovation performance, Measure, Patents

Paper type Research paper

1. Introduction

Performance measurement is fundamental for enhancing the value of companies and improving the decision-making process. Thanks to a performance measurement system, based on sets of indicators (see for details Dziallas and Blind, 2019), people can be motivated, learning can be stimulated and coordination and communication can be improved (Govindarajan and Govindarajan, 1993; Schumann *et al.*, 1995; Kerssens-van Drongelen and Bilderbeek, 1999). In the few last years, the innovation process has become more and more complex, expensive and risky (Dziallas and Blind, 2019). The technological and competitive environments are changing dramatically and markets becoming dynamic and turbulent. The content of technological knowledge has increased within products and processes, knowledge comes out from the confluence of separate disciplines and stakeholders, and the life cycle is shortening.

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In this context, innovation performance measurement is extremely important for both firms' managers and policymakers. From a managerial point of view, new performance measurement systems are needed to efficiently manage innovation. Indeed, innovation is one of the main drivers of productivity performance (Cainelli *et al.*, 2005; Love and Roper, 2015). In addition, firms who can show themselves to be owners of good innovations may be better able to raise funds from investors. From the policymakers point of view, timely, accurate, clear and reliable indicators are needed to set directions and rules to stimulate a fruitful innovation environment, to select industrial sectors requiring special attention, to evaluate the proposals of different applicants for innovation projects and to assess the progress of the initiatives funded (Dziallas and Blind, 2019).

So far, several indicators have been proposed to evaluate innovation performance and its impact on company productivity (see for a complete review Dziallas and Blind (2019) and Chiesa *et al.* (2008)).

The main source for measuring innovation performance is primary data, i.e. interviews with managers or surveys. However, primary sources are based on small sets of data (Kitsios and Kamariotou, 2016) because of difficulties in terms of firm reachability, costs, insufficient data quality, not to mention, companies' willingness to answer sensitive questions about their processes (Walsh, 1994). In addition, when based on a Likert scale [1], they are affected by respondents' subjectivity. Often, in order to avoid subjectivity, dichotomous questions are proposed, but they do not allow the nuances of the phenomena under investigation to be captured; see for example the Community Innovation Survey (CIS) [2]. In fact, studies on binary variables (yes/no measures) are clear in terms of low bias and are also efficient, but they miss some of the complexity involved in the innovation process (De Jong and Vermeulen, 2006).

In order to overcome the above mentioned problems, other measures based on secondary data, such as patents or publications have been proposed (Garg and Padhi, 1998; Burrus *et al.*, 2018). Patents provide rich qualitative and quantitative information on technological change (Scherer, 1992); in fact the criteria behind patentability of any invention are its utility (industrial application), novelty and non-obviousness (inventive step) (Encaoua *et al.*, 2006). Patents are collected in free databases after being checked and verified by specialists. The availability of online patent databases means that patents are a simple and immediate source to measure innovation performance both for academic and industrial researchers. So far, many innovation measures based on patent data have been proposed in the literature Dziallas and Blind (2019). However, in opposition to the literature that suggests a multidimensional approach, the innovation measures based on patents are usually related only to a specific patent feature such as the number of patents issued by a firm or the number of patents forward citations. It is worth remembering that the patents forward citations are the citations received by a patent from the time of its issue. Even if the number of patents issued by a firm or the number of patents forward citations are two of the main proxies of innovation performance (Carayannis and Provance, 2008), measures based only on a specific patent feature, are restrictive, not promptly to be used and allow only an ex post evaluation. As the issue for academics, managers and policymakers is to use timely, concrete, flexible, adaptable and measurable indicators to evaluate the innovation process and its impacts on the productivity of a company (e.g., Becheikh *et al.*, 2006; Dewangan and Godse, 2014), the existing measures present limitations from both the managerial and policy maker point of view.

Thus, in this scenario, the aim of the paper is to define a multidimensional, promptly and simple to use innovation measure based on patent data, which is richer than the number of patents and more promptly than the number of forward citations, in order to overcome the limits of existing measures. Thus, the main research question of this paper is to define a new innovation measure, that will be called Innovation Patent Index (IPI), based on secondary

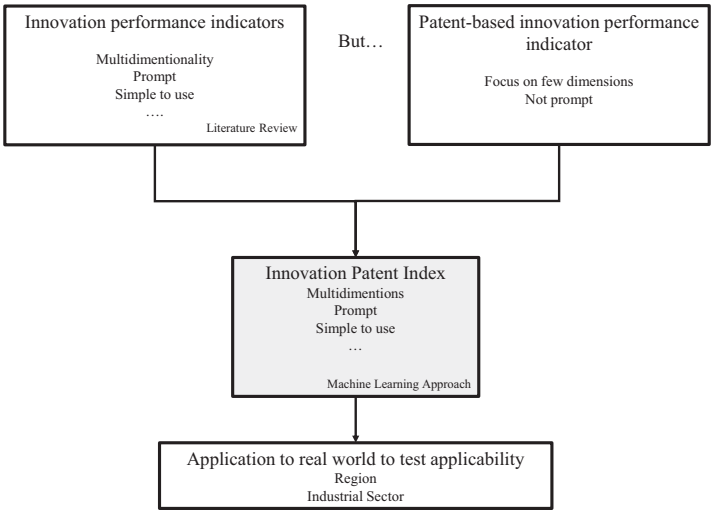
data, i.e., the patent database, that attempts to enrich the classical innovation measures, considering not only the number of patents but also other patent information identified using different machine learning algorithms. It is worth remembering that the machine learning approach is a very useful tool because it makes it possible to manage huge amounts of data and to capture the complex nonlinear relationships among the data features. In particular, in this paper, as described in Ponta *et al.* (2020a, b), three different algorithms, i.e., regularized least squares (RLS), deep neural networks (DNNs) and decision trees (DTs), have been employed to identify the most relevant patent features, in predicting innovation performance. Finally, the identified features have been aggregated in dimensions in order to create a user-friendly instrument, i.e. the Innovation Patent Index (IPI), for academics, managers and policymakers. Figure 1 shows the goal of the paper and the process of analysis.

2. Literature review

2.1 Innovation performance and its measures

Innovation is one of the main processes of a firm organization and its management and measurement should be defined as a structured process (Janssen *et al.*, 2011). Innovation is one of the determinants of firm performance and results (Hou *et al.*, 2019) and the promotion of an innovation culture is of fundamental importance (Hanifah *et al.*, 2019). For these reasons, innovation performance and its antecedents have been studied in several different contexts, from multinational and subsidiaries (Nuruzzaman *et al.*, 2019; Gaur *et al.*, 2019; Bahl *et al.*, 2020) to SMEs (Hanifah *et al.*, 2019; Saunila, 2016). The definition of appropriate innovation measures contributes to the understanding of the innovation itself, gives the opportunity to enhance the performance and increases the innovation culture (Saunila, 2016).

The measurement systems should act as a managerial tool that supports R&D decisions, providing information about strengths and weaknesses of companies' innovation activities. In addition, they should act also as monitoring and evaluation tools for institutional bodies, who can "see" the behavior of firms or groups of firms. Moreover, it should be a



Source(s): Authors' conceptualization

Figure 1.
Research goal and process of analysis

benchmarking tool, allowing the company to compare its own results with other companies or also contexts (Lazzarotti *et al.*, 2011).

Over the years the measurement of innovation has raised different issues. Disparities emerging between the studies have failed to develop a unique understanding of innovative performance systems and a common set of indicators at the organization level. A review of more recent studies provides some principles to develop an appropriate measurement system (Dewangan and Godse, 2014). These principles claim that performance measurement systems should be focused also on firm level, should be multi-dimensional, process based, meet stakeholders' goals, propose a cause and effect relationships between measures, as well as being promptly and easy to implement and use (Dewangan and Godse, 2014; Scalera *et al.*, 2014; Lazzarotti *et al.*, 2011). The measurement of innovation performance has often been analyzed at a project or technological level. The analysis at the firm level has been less examined (Carayannis and Provance, 2008). Project-level studies provide a shaded understanding of the innovation mechanisms; this limits the controls that managers have to make decisions in uncertain and dynamic environments. Multiple or composite measures should be preferred in determining a firm's innovation level and a multidimensional view of performance should be provided. Composite indicators allow the multiple determinants of innovation performance to be captured. The assumption behind a multiple-composite indicator is that superior innovation occurs when firms maximize all dimensions of the innovation activity (Lazzarotti *et al.*, 2011; Tohumcu and Karasakal, 2010; Ojanen and Vuola, 2006). The advantage of this approach is that it provides a more informative measure of the innovation performance level of a company. Indeed, each indicator has a different meaning. When one specific indicator diverges from the others, it can be analyzed separately as it contributes to the "innovative performance." The indicators should include throughput measures of innovation (Hagedoorn and Cloodt, 2003). Considering process performance is important in order to focus on continuous improvement and to facilitate the competitive benchmarking and identification of potential problems or inefficiencies. Stakeholder goals should be addressed and merged to take into account those of multiple stakeholders. The performance measurement should be built on the basis of cause and effect linkages between the measures. It should address past and probable future performance by including both leading and lagging indicators. This allows managers to evaluate the value of different activities and relate them to specific results. An effective performance measurement should include indicators that can be measured promptly. In a turbulent environment, managers should take action in advance with respect to their competitors (Liu *et al.*, 2015; Soosay and Chapman, 2006). If the proposed indicators can be evaluated only after a lapse of time or if a long time is needed to collect these data, the information about the performance may no longer be useful. The scheme should be easy for the different firm areas to implement and use.

2.2 Innovation performance and their measures with patents

In the literature, many researchers present patents as a source for innovation measurement (Scherer, 1965; Pakes and Griliches, 1980; Griliches, 1990; Jaffe and Palmer, 1997; De Rassenfosse *et al.*, 2013; Acs *et al.*, 2002; Lanjouw and Schankerman, 2004; Nagaoka *et al.*, 2010). Most scientific works investigate the relationship between patent counts and innovation performance, considering patents as an R&D output. In Svensson (2015), the number of patents per capita is used to estimate the rank of sectors and countries in terms of technology intensity or innovation. De Rassenfosse *et al.* (2013) present a new methodology to assess innovation performance by counting priority patent applications filed by a country's inventors regardless of the patent office. Hagedoorn and Cloodt (2003) analyze innovation performance of countries proposing two ratios: inventive performance and invention productive performance based on the total patent count and R&D indicators. Dechezleprêtre

and Martin (2010) compare both relative levels and trends in clean innovation activity between different countries taking patent counts as an innovation measure to portray a picture of where UK is standing in terms of climate change mitigation innovation. Thus, patent count is still considered as a satisfactory measure for innovation. However, De Rassenfosse *et al.* (2013) outline some major drawbacks of patent counts: the value distribution of patents is skewed as many patents do not have industrial applications; many inventions are not patented and many inventions are not patentable when other means of protection, i.e. trade secrecy, lead-time on the market or reputation are more useful; counting patents has become difficult due to the differences in patent regulations across countries (Papageorgiadis and Sofka, 2020). The OECD Patent manual of 1994 also underlines that patent statistics should be interpreted with caution due to the variations in propensity to patent across time, firms, industries and countries. These limitations have led researchers to consider other indicators along with patent counts such as forward and backward citations, patent family size, patent renewal, opposition and litigation information and also build patent related indexes (Papageorgiadis and Sofka, 2020; Datta *et al.*, 2015). In particular, patent forward citations appear to be one of the most widely used indicators (Hall *et al.*, 2005). They are the citations received by a given patent from other patents. For that reason, they are partially available only after a substantial time since the granting. Forward citations are particular in that they to grasp not only the technological value of an innovation and its originality, but also its relevance toward the market (Aristodemou and Tietze, 2018). Forward citations may be a measure to understand emerging technologies or to evaluate the economic value of a technology and the innovation capacity of a company (Hall *et al.*, 2005). Moreover, Mueller (2015) states that patent information provides more indicators than just the sheer number of patents over time. For example, the origin of inventor the can represent an excellency of the higher education system when the population of the country is taken into account, or statistical evaluation of jurisdictions in which patent family members were granted can give information about the priority markets for the country considered. Finally, Lanjouw and Schankerman (2004) suggest measuring innovation with a composite index of patent quality using different indicators of patents in order to reduce a measured variance in quality.

The main purpose of this paper is to define an Innovation Patent Index based on secondary data that can overcome the limitation of the indicators based only on one feature of patents, such as the number of patents and also be able to appreciate the value the market gives to the patented technology.

3. Methodology

In order to build an innovation performance indicator based on secondary data, i.e. the patents database, that can overcome the serious limitations of existing innovation indicator underlined in Section 1, first of all the relevant patent features have been extracted from all the information included in the patents database. In particular, starting from all the data in the patent database, the 24 patent features, reported in Table 1 were identified. As said above in section 1, the paper aims to build a multidimensional, promptly and simple to use measure of the innovation performance. Thus, starting from the 24 patents features identified we wanted to build an indicator that considers all this information. To do this, the number of forward citations, i.e. the number of citations received by a patent, was considered as a proxy of the innovation performance, whereas the other features were considered as potentially predictive of the innovation performance (Narin *et al.*, 1984; Ponta *et al.*, 2020a, b). In this way we are able to create a simple index that is multidimensional because it considers all the information inside the patent database, is timely because it considers all the features that are directly available when the patent is issued and is simple because it considers only a reduced

Description	Definition	Usage
Date of the first application for the family	Date of the origin of the novelty	Predictive
Date of application of the patents	Time when the company presents a novelty toward the world, receives the approval from authorities and expires	
Date of publication		
Date of grant		
Date of expire		
Technical concepts	Technical concepts: knowledge owned by the company since they report the core information content about technology Choi and Hwang (2014)	
Technological domain	Technical domains and technological classes based on The Ipc: "Breadth" and the "Scope" of a patent, identifying where the company invests Moaniba *et al.* (2018)	
IPC classification with 9 digits		
First country of application	Place where the knowledge arises Mahnken and Moehrle (2018)	
Backward citations	Knowledge owned within the company that is recombined in order to have a novelty step Harhoff *et al.* (2003), Hall *et al.* (2007)	
Independent claims	Breadth of a patent, it reveals information about its inventive step (non-obviousness). the claims are the expression of the value in stock of the company Bessen (2008), Reitzig (2004)	
Dependent claims		
Number of assignees	Strategy adopted by the company to create a network for developing technology Belderbos *et al.* (2014)	
Months between the publication date of the youngest and the oldest patent of the family	Number of months between the date of publication of youngest and the oldest patent of the patent family: period needed by the maturation process of innovations to reach a higher level of maturity Dechezleprêtre *et al.* (2017)	
Number of words in the document	Features related to the patent structure (for example the number of words in the document or in the abstract): ability of company to explain the knowledge owned inside Reitzig (2004)	
Number of technical terms in the abstract		
Number of words in the description		
Number of authorities		
Number of figures		
Number of priorities	Market of the technologies and the countries where the technology must be protected (Harhoff *et al.*, 2003)	
Size of the family	Number of patents that share the same novelty and belong to an unique family	
Forward citations	Number of citing patents	To be predicted

Table 1.
Features' description of patents

number of features. In order to identify which features are predictive of the forward citations the machine learning approach was chosen. Despite their "dark side" (Siau and Wang, 2020) in terms of ethics, machine learning algorithms let to manage a huge amount of data such as the one embodied in patents and to discover linear and not linear relations (Tu, 1996).

3.1 Data and patent features

The data analyzed in building the innovation performance index, are the patents collected from 1st January 2005 to 31st December 2018 for 32 states, i.e., the 28 members states of the EU plus Iceland, Liechtenstein, Norway and Switzerland. A total of about 8 million patents were considered. In particular, the analysis was performed for each country considering where firms have the registered office or where inventors have their residence. The data source chosen was The Orbit Intelligence database, provided by Questel [3] one of the world's leading intellectual property management companies.

3.2 Artificial intelligence approaches

The problem of identifying which patents features are relevant in predicting innovation performance, approximated with the forward citations, can be mapped into a conventional regression framework. The main steps are: first, the identification of the relation $\mathfrak{R}$ between the input $\mathscr{X}$, namely the features described in Table 1, and an output space $\mathscr{Y} \subseteq \mathbb{R}$, namely the number of forward patent citations (Shalev-Shwartz and Ben-David, 2014); second, the discovery of the most influencing factors in the input space for predicting the correct associated element in the output space (Altmann *et al.*, 2010); third, understanding how the influencing factors in the input space influence the associated value in the output space. The goal is to identify a model/function $\mathfrak{M}$: $\mathscr{X} \rightarrow \mathscr{Y}$, for approximating $\mathfrak{R}$, through a learning algorithm $\mathscr{A}_{\mathscr{H}}$ characterized by a particular set of hyperparameters $\mathscr{H}$. The accuracy of approximation $\mathfrak{M}$ in representing the unknown relation $\mathfrak{R}$ is measured with the Mean Absolute Percentage Error (MAPE) (Cincotti *et al.*, 2014). The interpretability, namely the possibility to understand how it behaves, ranks the features based on their effect on the learned model (Guyon and Elisseeff, 2003; Altmann *et al.*, 2010). Three different machine learning algorithms have been implemented to determine the most important features, i.e., RLS, DNNs and DTs.

These algorithms are fast to train, powerful in managing non-linear relations, easy to exploit in practice and interpretable (Lulli *et al.*, 2018). For details in solving the problem described above with RLS, DNNs and DT algorithms, see Ponta *et al.* (2020a, b)

3.3 Machine learning results

The results of the three machine learning algorithms used to predict forward citations show that the most relevant features identified are the technological classes (4 and 7 digit), based on the IPC, the technological domain and the number of backward citations (Ponta *et al.*, 2020a, b). Moreover, the size of the patents family, representing the geographical extension of the patent, is a valuable feature for estimating the market value of a patent, as suggested by Harhoff *et al.* (2003). Another important feature is represented by the time-related determinant of months between the date of publication of the youngest and the oldest patent of the family. This feature provides information on how companies invest in innovation over-time and build their capabilities (Dechezleprêtre *et al.*, 2017).

It is worth noting that all the three algorithms extracted the same patents features as important in predicting the forward citations, i.e. innovation performance. See Ponta *et al.* (2020a, b) for further details.

4. Innovation indicators and Innovation Patent Index

Starting from both the literature and the results described in Section 3.3, an index composed of the simplest and most common measures of innovation used in literature, i.e. the number of patents and of the patents' features identified above was defined. The index is formed of five different indicators: (a) Efficiency: the normalized number of patents (b) Internationalization: the number of extensions (c) Diversification: the number of IPC classes (d) Quality: the number of backward citations (e) Time: the number of months between the publication date of the youngest and the oldest patent of the family. The efficiency indicator makes reference to

the literature, whereas the others make reference to the main patents' features, empirically derived by the machine learning algorithms, i.e. RLS, DNNs and DTs, as described in Section 3.3. In fact, machine learning is a well suited tool to extract significant relevant information from complex, nonlinear and noisy data (Tkáč and Verner, 2016). For this reason, in recent years and, thanks to the large availability of data, authors have applied machine learning algorithms to various problems such as financial topics, for example, credit scoring, financial analysis, or stock performance prediction, and costs monitoring and sales analysis (Tkáč and Verner, 2016). Recently, the use of these tools has been extended to the field of management in order to support business research and managers in their decision making process. Table 2 summarizes all the patent indicators, derived by the machine learning algorithms or by the literature, that form the IPI index.

Before defining each indicator, let's define the main characteristics of patent p

(1) e_p number of extensions of patent p;

(2) b_p number of backward citation of patent p;

(3) c_p number of classes patent p;

(4) m_p number of months between the publication date of the youngest and the oldest patent of the family.

4.1 Efficiency

The efficiency indicator is defined as the normalized number of patents. Given a company i, its efficiency $E_{i,t}$ at time t is given by the following formula:

$$E_{i,t} = \frac{\sum_{t=0}^{T} n_i(t)}{N_i} \tag{1}$$

where N_i is the total number of employees of firm i. In the case of a region or a country i, the efficiency is evaluated according to Eq. (1), where $n_i(t)$ is the number of patents published in region i at time t and N_i is the total number of employees of region or country i.

4.2 Diversification

The diversification indicator is defined as the number of IPC classes (4 digit) of each patent. Given a company i, the diversification $D_{i,t}$ is given by:

$$D_{i,t} = \frac{\sum_{t=0}^{T} \sum_{n=1}^{n_i(t)} c_{p,i}(t)}{\sum_{t=0}^{T} n_i(t)} \tag{2}$$

This indicator is important because it has been proven that small incremental innovations do not enhance firms innovation performance, see for example (Moaniba *et al.*, 2018), whereas the kind and not the number of technical domains selected by the company are significant.

Symbol	Description	Definition	Source
E	Efficiency	Normalized number of patents	Scientific literature
M	Time	Number of months between the publication date of the youngest and the oldest patent of the family	Machine learning results
D	Diversification	Number of IPC classes (4 digit)	
Q	Quality	Number of backward citations	
I	Internationalization	Number of extensions	

Table 2.
Innovation indicators

4.3 Quality

The quality indicator is defined as the number of backward citations. Given a company i, the quality indicator is given by:

$$Q_{i,t} = \frac{\sum_{t=0}^{T}\sum_{n=1}^{n_i(t)} b_{p,i}(t)}{\sum_{t=0}^{T} n_i(t)} \tag{3}$$

Backward citations play a main role in predicting IC, so companies must be aware that their capacity to absorb previous knowledge and make use of it will strongly affect future innovation and the ability to be competitive (Harhoff *et al.*, 2003; Hall *et al.*, 2007).

4.4 Internationalization

The internationalization indicator is defined as the number of geographical extensions of a patent. Given a company i, the internationalization $I_{i,t}$ indicator is given by:

$$I_{i,t} = \frac{\sum_{t=0}^{T}\sum_{n=1}^{n_i(t)} e_{p,i}(t)}{\sum_{t=0}^{T} n_i(t)} \tag{4}$$

4.5 Time

The time indicator is defined as the road chosen by the firm to patent. Given a company i, the time dimension $R_{i,t}$ is given by:

$$M_{i,t} = \frac{\sum_{t=0}^{T}\sum_{n=1}^{n_i(t)} m_{p,i}(t)}{\sum_{t=0}^{T} n_i(t)} \tag{5}$$

4.6 Innovation Patent Index

Given the five previously defined indicators, an index that summarizes the five values is defined. The Innovation Patent Index (IPI) is defined by five dimensions, which are the five indicators just described: efficiency, time, diversification, quality and internationalization, as shown in Figure 2. The IPI is evaluated as a weighted average of the normalized five indicators, in formula,

$$IPI_{i,t} = \alpha_1 E_{i,t} + \alpha_2 D_{i,t} + \alpha_3 Q_{i,t} + \alpha_4 I_{i,t} + \alpha_5 M_{i,t} \tag{6}$$

where $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and α_5 are real numbers. So far, the α coefficients are positive and all equal. Thus, IPI is a real number that ranges between 0 and 10. Moreover, it is important to underline that in order to evaluate the IPI for a firm or a region it is necessary to define the period of observation T, i.e. the number of years.

5. Application to real world

In order to show how the IPI, defined in Section 4, can be used, this section shows how it has been applied in two cases. In case (a) IPI was employed to evaluate the innovation performance of the Lombardy region and of its provinces, whereas in case (b) IPI was used to measure the innovation performance of the firms belonging to the AMAPLAST [4] association. AMAPLAST is the association of the most important Italian firms working in the plastic materials sector. The data source used in these analyses is The Orbit Intelligence database [5]. All the patents published by inventors with residence in Lombardy or by firms with registered office in Lombardy, or belonging to the AMAPLAST association were

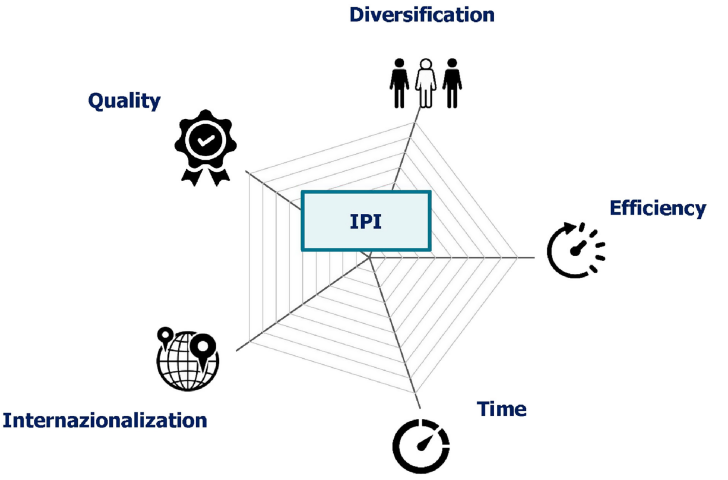


Figure 2.
The five dimensions of IPI

collected over the period, 2000 to 2017. For each patent, the list of all considered features is shown in Table 1.

5.1 IPI and Lombardy region (case (a))

Figure 3 shows the IPI measure in case (a), the Lombardy region in the period 2012–2017. The different colors on the map represent the classification. The province in dark blue represents the one with the largest IPI, and thus the most innovative province, whereas the province in light blue represents the one with the smallest IPI. All the shades of blue represent the IPI classification.

As said in Section 3.3 IPI is defined by five indicators, so it is possible to investigate in more detail the results shown in Figure 3, to give information to managers about the reasons for the classification. Thus, an analysis of the five IPI dimensions was performed. Figure 4 shows the IPI dimensions in the period after the economic crisis for three Lombardy provinces, Varese, Milan and Lodi. The same analysis was performed for all the provinces and the results are shown in Appendix. The green line represents the province and the pink line the region. It is possible to observe that provinces that are ranked as most innovative by the IPI have very different IPI indicators. For example, the province of Milan has a very high efficiency score whereas Lodi, a very small province of Lombardy, has a very high quality and time score. The province of Varese, that is ranked in the upper half of the classification, is only higher than the other provinces in terms of diversification. Moreover, it is possible to investigate more each dimension in more detail considering its evolution during the time period of analysis. Figure 5 shows the five dimensions of IPI for the provinces of Varese, Milan and Lodi for each year and thus their evolution over time. The analysis of all the provinces of the Lombardy region is presented in Appendix. In particular, it is possible to observe that, in the time range considered, in Figure 5a the diversification is the most important dimension in the IPI evaluation, in Figure 5b the efficiency and in Figure 5c time and quality. The analysis of each dimension of IPI for each year gives further information about the innovation trend of the companies belonging to the same province. For companies this information has very important results because they have information about what to improve in order to increase the innovation performance.Moreover, it is possible to investigate the results in the period 2012–2017 (post crisis) comparing different time ranges. Figure 6 shows the IPI's dimensions of the Lombardy region and of the three provinces

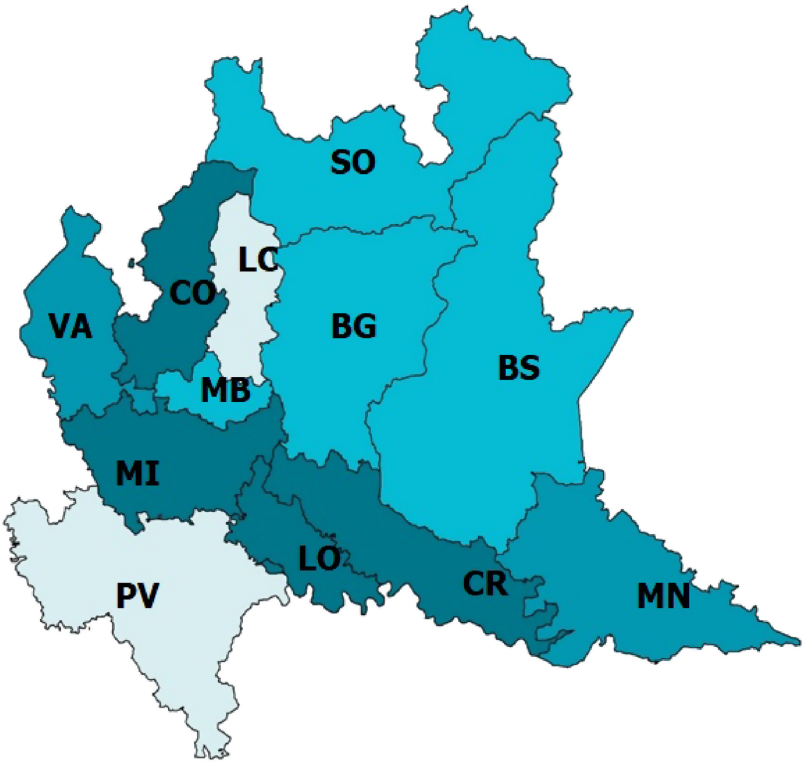


Figure 3.
IPI rank

Varese, Milan and Lodi in three different periods. The green line represents the dimensions before the crisis (2000–2006), the pink line during the crisis (2007–2011) and the black line after the crisis (2012–2017). Figure 6a shows that all the indicators except quality decrease after the crisis. This means that after the crisis there are fewer patents but with better quality. During the crisis, the time spent in developing the patent, i.e. the resources spent on it, seems longer than the period before the crisis.

In addition, the IPI's dimensions of each province is evaluated in different periods. Figures 6b, 6c, and 6d show the different IPI dimensions in different time periods for the province of Varese, Milan and Lodi, respectively. Each province has its own peculiarity but also for the provinces the IPI dimensions after the crisis are smaller than the ones before the crisis. Summarizing the results of case (a), Tables 3–5 report for each province the values of the indicators and the IPI in the three periods, before, during and after crisis, respectively. For example, we can notice how the territory of Milan clearly stands out in terms of efficiency, while other territories such as Como, smaller than Milan, grow in terms of diversification and time.

5.2 IPI and AMAPLAST (case (b))

The IPI measure was used to measure the innovation performance of firms belonging to the AMAPLAST [6] association. For privacy reasons the paper does not report the innovation performance of each firm, but the behavior of the five indicators of IPI for small, medium and large firms. Small means that firms have less than 50 employees, medium means that firms

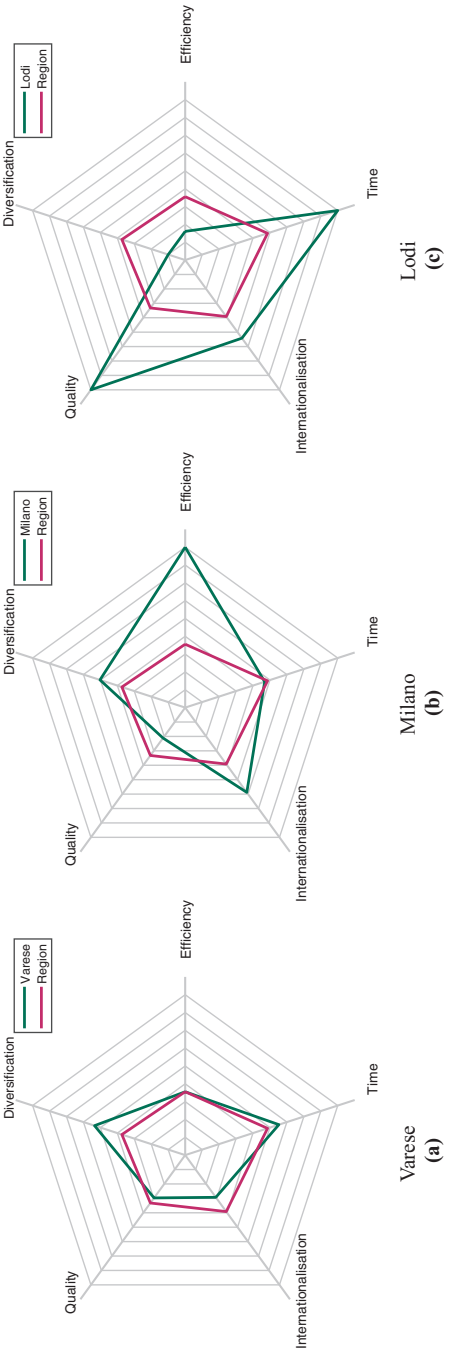


Figure 4.
IPI dimensions in the period after crisis

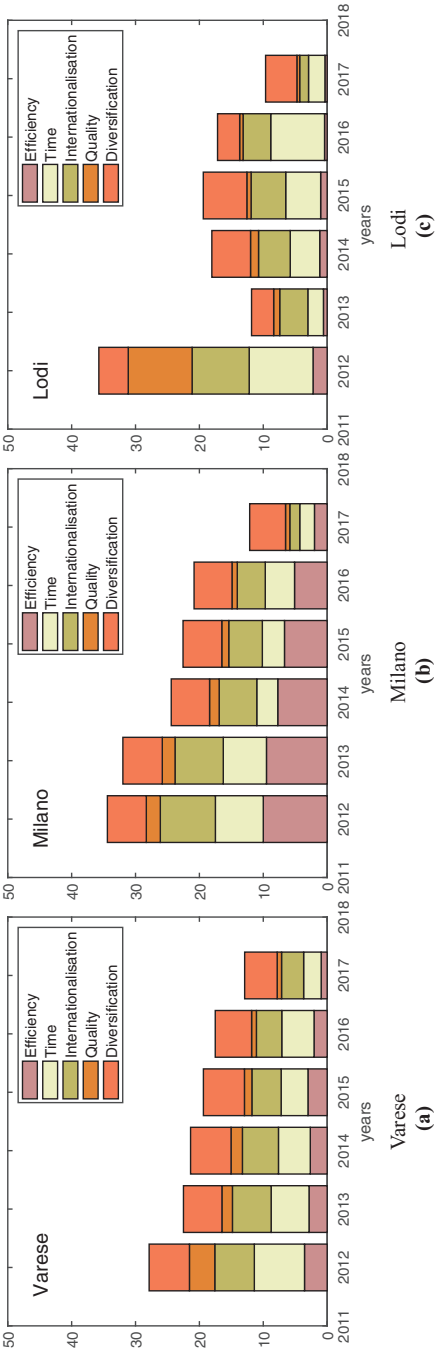


Figure 5.
IPI dimensions in the period after crisis year by year

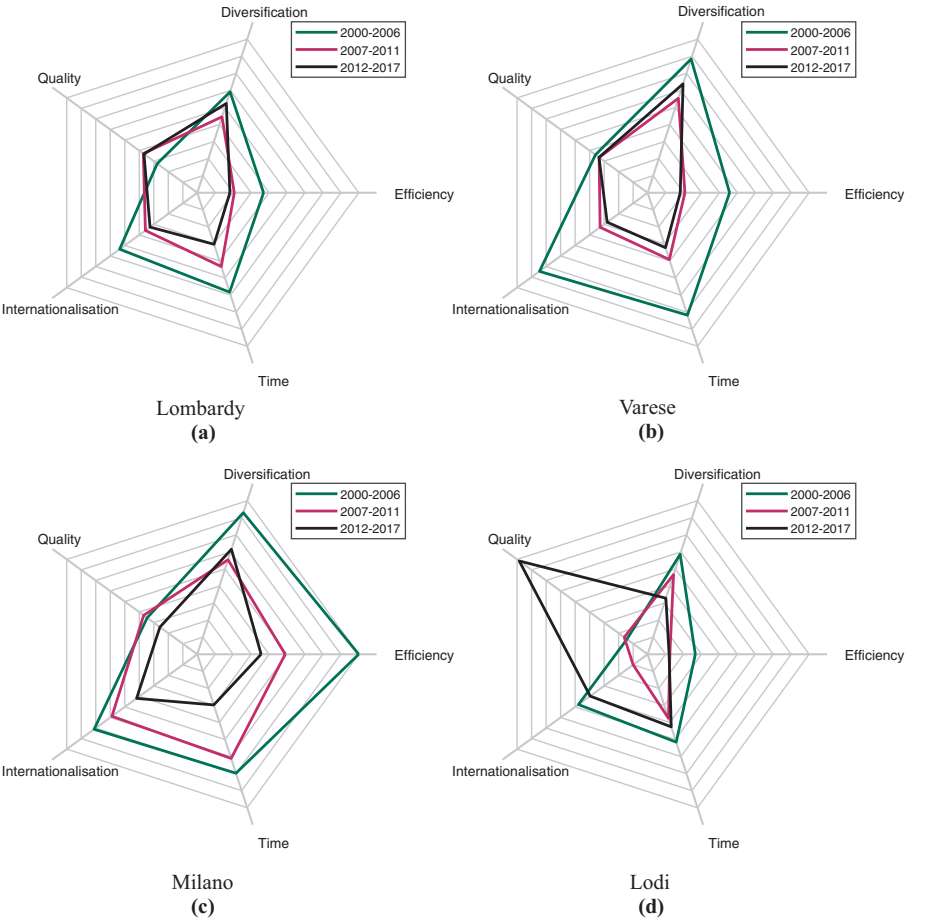


Figure 6.
The green line represent the dimensions before the crisis (2000–2006), the pink line during the crisis (2007–2011) and the black line after the crisis (2012–2017)

Table 3.
Dimension indicators and IPI before crisis 2000–2006

Provinces	Efficiency	Time	Internationalization	Quality	Diversification	IPI
Varese	4.462	7.722	8.072	3.248	8.555	6.412
Bergamo	3.322	4.596	3.541	1.968	4.206	3.526
Milano	10.000	7.469	7.643	3.070	9.126	7.462
Brescia	2.556	3.574	3.508	2.071	4.138	3.169
Monza Brianza	0.035	10.000	3.339	3.324	10.000	5.340
Como	4.656	7.230	10.000	3.531	8.417	6.767
Pavia	2.585	7.303	5.509	1.392	6.977	4.753
Mantova	3.964	6.176	6.268	3.033	6.036	5.095
Cremona	2.869	6.561	5.929	2.693	6.268	4.864
Lecco	3.584	4.752	6.083	1.570	3.973	3.992
Sondrio	0.299	1.869	0.677	0.000	0.000	0.569
Lodi	2.072	5.192	4.713	0.536	6.080	3.719

Provinces	Efficiency	Time	Internationalization	Quality	Diversification	IPI
Varese	1.347	3.646	2.847	2.930	5.672	3.288
Bergamo	1.308	4.359	3.293	3.233	3.818	3.202
Milano	4.877	6.386	6.105	3.369	5.675	5.282
Brescia	1.695	5.398	5.408	4.281	1.902	3.737
Monza Brianza	0.090	4.618	0.438	2.645	5.612	2.681
Como	1.439	3.616	3.973	3.638	3.277	3.189
Pavia	0.942	4.590	2.666	2.391	5.251	3.168
Mantova	1.473	4.940	6.188	10.000	2.056	4.931
Cremona	1.240	5.635	4.618	2.283	4.567	3.669
Lecco	1.134	3.285	0.717	1.589	2.617	1.868
Sondrio	0.083	0.000	2.426	3.676	6.748	2.587
Lodi	0.297	3.447	0.000	0.766	4.588	1.820

Table 4. Dimension indicators and IPI during crisis 2007–2011

Provinces	Efficiency	Time	Internationalization	Quality	Diversification	IPI
Varese	1.021	2.777	2.240	2.945	6.730	3.142
Bergamo	1.107	1.862	1.779	2.506	4.990	2.449
Milano	3.198	2.464	3.982	1.970	6.444	3.612
Brescia	1.370	2.651	3.031	2.148	3.712	2.582
Monza Brianza	0.403	2.948	3.140	1.102	5.297	2.578
Como	1.369	3.171	3.896	5.335	4.615	3.677
Pavia	0.304	1.088	1.222	0.701	6.840	2.031
Mantova	1.075	2.226	2.436	7.576	3.425	3.348
Cremona	1.153	3.390	5.818	2.592	4.679	3.526
Lecco	1.016	1.678	1.104	1.554	3.961	1.863
Sondrio	0.000	2.004	1.530	1.917	9.983	3.087
Lodi	0.244	4.071	3.707	9.815	2.859	4.139

Table 5. Dimension indicators and IPI after crisis 2012–2017

have between 51 and 250 employees and large means that firms have more than 251 employees.

Figure 7a shows a radar plot of the five indicators composing IPI for all the companies who patent and, that belong to the AMAPLAST organization. It is worth remarking that in this graph only the 67 firms that have patented in the period of observation are plotted. In general companies have different performances if the five indicators are considered separately. There are no companies where all the indicators are very high. For example, one company may have a very high efficiency indicator but a very low diversification indicator. This shows further the importance and completeness of the IPI measure, which is able to identify the areas of weakness on which the companies must work even if the total value of the index is high. Moreover, Figure 7b shows the radar plot for AMAPLAST firms divided into small, medium and large companies. It is worth noting that IPI also gives information to sets of companies. For example, Figure 7b shows that all the three sets (small, medium and large companies) consider all the five indicators in the same way, but in more detail it is possible to observe how the set of large firms, in black, has a high quality indicator compared to the set of small and medium firms but a low efficiency indicator. Information here for managers is that large firms are more interested in having few patents but with high quality whereas for small firms, even if they give importance to the quality dimension, the efficiency, i.e. number of patents, is more important. Finally, these results show how IPI can be applied to measure the innovation performance of firms or territories, giving information both at company and territory level.

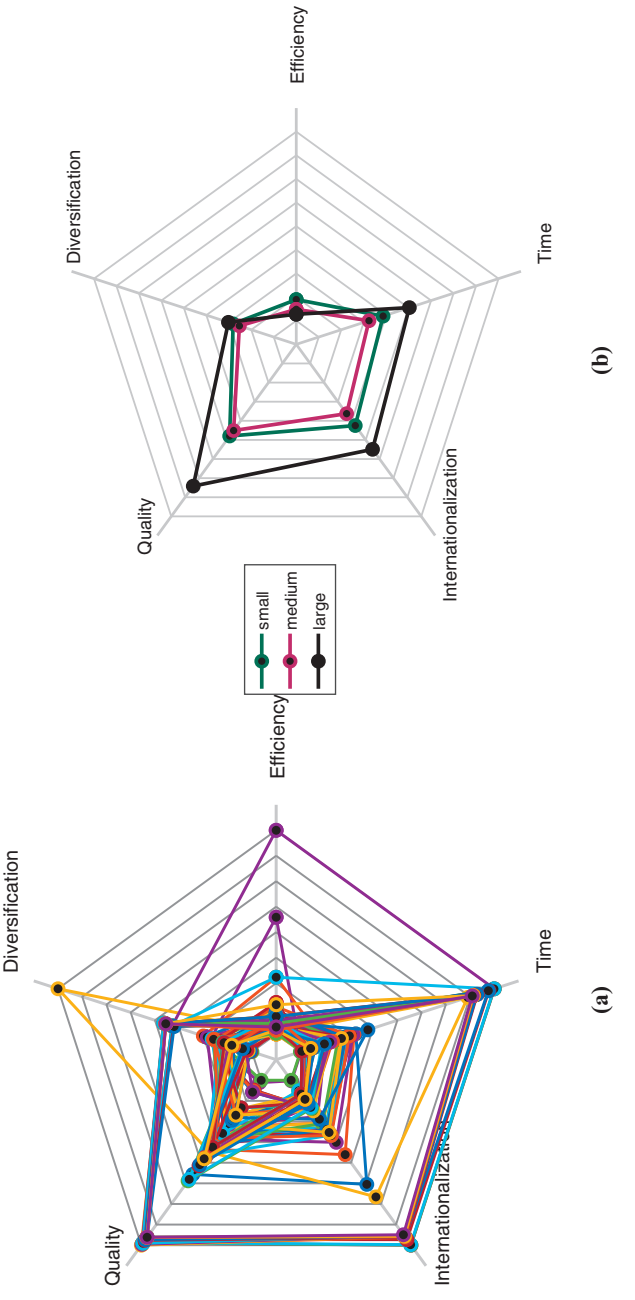


Figure 7.
(a) The five dimensions of IPI for all the companies belonging to AMAPLAST association that have patent in the period 2000–2017. (b)The five dimensions of IPI for the companies belonging to AMAPLAST association divided in small, medium and large

From a managerial point of view, IPI gives each firm or territory not only a rank but also information about the innovation performance profile. In fact, with the information included in the IPI dimension indicators it is possible to identify the strengths and weaknesses of innovation performance.

6. Discussion

The study shows an attempt to find an innovation performance measurement that overcomes the limits of previous studies. Over the years, researchers search for the definition of indicators to measure the company innovation process that is one of the most important determinants of the firm performance (Janssen *et al.*, 2011; Hou *et al.*, 2019). Nevertheless, studies are searching for developing a complete and comprehensive understanding of innovative performance systems and an appropriate set of indicators. The definition of appropriate innovation measures contributes to enhance the innovation performance, to spread the innovation culture, to benchmark companies against each other and to provide information also to institutional bodies, who can monitor and take decisions according to the performance of firms or groups of them. As suggested by Lanjouw and Schankerman (2004), the study proposes an index, i.e., the IPI. It is a novel approach and follows the main guidelines provided in the literature (Dewangan and Godse, 2014) and it is applicable in different contexts (Nuruzzaman *et al.*, 2019; Gaur *et al.*, 2019; Bahl *et al.*, 2020; Hanifah *et al.*, 2019; Saunila, 2016). The IPI is a composite indicator (Harhoff *et al.*, 2003; Lazzarotti *et al.*, 2011) that uses multiple information set out in patents. Moreover, it offers the possibility to use multiple indicators in prompt. Most of the previous innovation performance systems use primary sources to address the multiple perspective requirements. However, it is often difficult to collect this kind of information. Differently secondary sources data, such as those of patents are generally widely available, but they are not immediately accessible nor do they provide a multiple perspective. Most of the previous indicators to build a performance measurement system were based on the patent count or the number of patents forward citations (Dziallas and Blind, 2019). However, the use of patent count alone does not allow managers to have a multiple view. On the other hand, the use of forward citations limits the prompt use of the innovation performance measurement. Indeed, forward citations are accessible only after some time. With the identification of the patent forward citations predictors, that can be combined with the count of a firm's number of patents, the IPI is both a multiple-composite and prompt system of performance measurement. Moreover, it addresses the guidelines provided in the literature providing scholars a possible convergence on the wide range of perspectives on measurement, specifically using patent data. In particular, the IPI can be used at several different level. It is not only a project or technological level measure but, as shown in the application, it allows evaluations at project, firm and regional levels (Scalera *et al.*, 2014; Gaur *et al.*, 2019). Moreover, it provides a benchmark with other actors or contexts (Liu *et al.*, 2015; Soosay and Chapman, 2006). The indicators should include throughput measures of innovation (Hagedoorn and Cloodt, 2003). It makes possible to address different perspectives and multiple stakeholder's goals, for example including learning aspects (measured with the backward citations), marketing aspects (measured with the internationalization citations). The scheme is also easy to implement and use because it only the extraction of patent information and the calculation of the indicators.

In addition, the use of public and secondary data, i.e. patent data, permits to avoid also the ethics issues due to the use of artificial intelligence and machine learning approaches (Siau and Wang, 2020; Makarius *et al.*, 2020). In fact, data security, privacy, transparency, autonomy, intentionality, responsibility, human and social rights challenges do not come up. Even if the IPI is based on results of machine learning analyses, privacy issues do not emerge

because IPI do not use personal data. Transparency, autonomy, intentionality, and responsibility concerns do not arise because the IPI is easily interpretable and it is not used to take decision that are not under the control of managers. Finally, human and social rights are respected because the use of the IPI should not influence for example ethical standards but only provide managers a decision tool that permits to better decide firms' R&D investments and enhance firms' innovation performance.

6.1 Theoretical implications

The study aims to contribute to the innovation performance measurement literature. In particular, it provides a step forward in the innovation stream of literature that seeks to measure R&D performance using secondary data. Thus, it takes advantage of the use of secondary data opening up to several uses, measures and analyses that can be done with patents in order to measure the innovation performance. From a methodological standpoint, it shows the usefulness of applying machine learning approaches also in the innovation field for decision making purposes. Indeed, machine learning approaches and artificial intelligence are still barely used in innovation fields, in particular when trying to measure and forecast performance and take decisions out of these results. In addition, the IPI is an instrument that can be used not only at a firm level but also at a regional level. For this reason, it could be an instrument useful also in innovation macroeconomic and regional studies and it can provide a contribution in this stream of literature. Finally, the IPI shows also a new way to combine current and future data, thanks to highly accurate techniques of forecasting such as the machine learning ones.

6.2 Practical implications

For managers and those in business the IPI may provide several implications and suggestions. As mentioned above, IPI can be calculated at a firm level, providing an indication not only on the performance of the single project but more in general on the innovation area. In this way R&D managers may take decisions on the full portfolio and not only "correct" the single project. In addition, the information included in the IPI provides a nuanced overview of R&D, suggesting in which areas to invest promptly (Park and LiPuma, 2020). The dimensions allow for identifying the strengths and weaknesses of innovation performance in their companies. It makes possible to position the company with respect to competitors and suggests the dimensions/areas that should be improved by the managers in order to increase innovation performance. The fact of having a multiple perspective and indicators that refer to different firms' areas and skills may foster the culture of innovation and all the department could be involved to enhance the innovation process of the organization (Hanifah *et al.*, 2019). This is even truer considering the usability and flexibility of the instrument. That flexibility may be of particular importance in terms of improving the responsiveness and achieving better performance (Kumar and Singh, 2019; Kindström *et al.*, 2013).

For policy-makers, it is worth noting that IPI can be applied in different contexts, such as companies that belong to the same geographic area, to the same industrial sector, to the same technological area, with the same dimension, with the same governance, etc. This shows the high flexibility of the tool and gives policy-makers the possibility to quickly compare different sectors and territories and take decisions as a result (Kumar and Singh, 2019; Kindström *et al.*, 2013). For financiers, the IPI may support their decision, suggesting which companies that perform better, and what their strengths and weaknesses are.

For patent experts, IPI provides some suggestions on how to write the patent. It indicates the most important features to look at in order to increase the number of forward citations and consequently the technology performance.

7. Conclusion, limitations and future research

The paper has presented a new measure of Innovation Performance, called Innovation Patent Index (IPI) based on secondary data, i.e. the patent database. The IPI is defined by means of five indicators that represent the five most relevant dimensions, which are efficiency, time, diversification, quality and internationalization. These dimensions have been identified according to the literature (Lee *et al.*, 2018) and applying three different machine learning algorithms, i.e. RLS, the DNNs and the DTs to the patent database.

The IPI has been applied to a territory and an industrial sector. Results have shown that IPI is an immediate tool of measurement. In fact, it is able to overcome the limits of measures based on primary data and, through an analysis of the indicators, it gives information about the reasons for a good or poor innovation performance. Compared to existing indicators, generally not widely used because of their complexity or their limited ability to predict, the IPI is a simple and at the same time forward-looking tool of innovation performance measurement (Lee *et al.*, 2018). Moreover, IPI overcomes limits of other, widely used measures based on secondary data, such as, patent counts and forward citations (Park and Park, 2006; Aristodemou and Tietze, 2018). In fact, the number of patents does not seem to be fully representative of the innovation performance and the use of other indicators provides a better understanding of innovation performance. Concerning the forward citations, they are considered a better indicator than the patent counts (Hall *et al.*, 2005), however, they can be known only after a long period of time (Brinn *et al.*, 2003). The IPI, on the other hand, merges the patent count with forward citation predictors, i.e. the other patents' features already included in the patent when issued, overcoming the limitations of the other measures. In fact it enriches the number of patents measure and overcomes the time issues of the forward citation measure. IPI gives each firm or territory information not only about the level of IP (the rank) but also the IP profile that can be used by managers, businessmen, policymakers, organizations, patent experts and financiers to evaluate and plan future activities, to enhance the innovation performance and capability, to find financing and to support and improve innovation.

This work is not without limitations. Despite most of companies extensively apply for patents, in some sector they are not widely used. Thus, a specific innovation index could be developed for the sectors that do not largely apply for patents. In addition, the IPI is based only on the pure number of forward citations to have a forward looking perspective. In further studies, other patent features could be used, as for example forward citations indexes (Aristodemou and Tietze, 2018).

Notes

1. Likert Scale is a type of rating scale used to measure attitudes or opinions. With this scale, respondents are asked to rate items on a level of agreement. For example: Strongly agree, Agree, Neutral, Disagree, Strongly disagree.
2. https://ec.europa.eu/eurostat/web/microdata/community-innovation-survey.
3. www.questel.com.
4. Italian plastics and rubber processing machinery, ancillary equipment and moulds manufacturer's association.
5. www.questel.com.
6. www.amaplast.org.

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Appendix

Results for all Lombardy provinces

This appendix shows all the figure for the provinces of the Lombardy region. Figure A1 shows the IPI dimensions in the period after crisis for the provinces not shown in the paper, i.e. Bergamo, Brescia, Monza Brianza, Como, Pavia, Mantova, Cremona, Lecco and Sondrio. Figure A2 shows, year by year, the five dimensions of IPI for the provinces not shown in the paper, i.e. Bergamo, Brescia, Monza Brianza, Como, Pavia, Mantova, Cremona, Lecco and Sondrio. Figure A3 shows the IPI's dimensions of the provinces not shown in the paper, i.e. Bergamo, Brescia, Monza Brianza, Como, Pavia, Mantova, Cremona, Lecco and Sondrio evaluated in different time ranges.

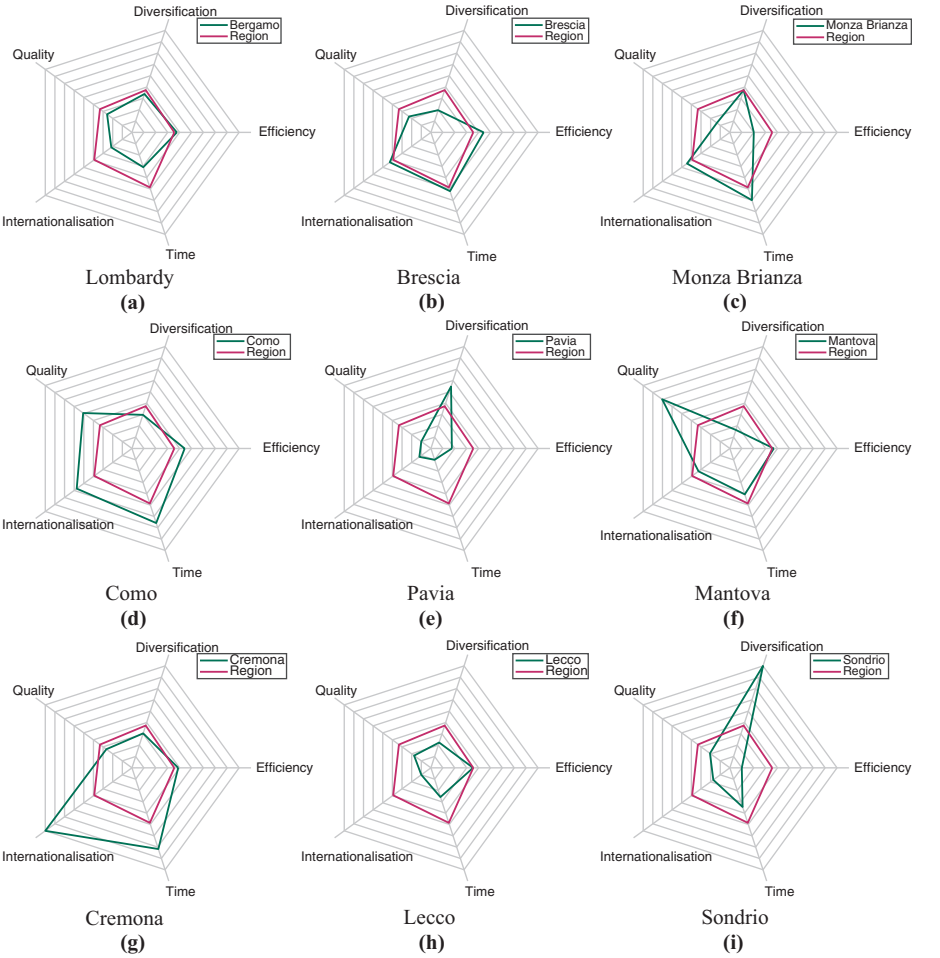

Figure A1.
IPI dimensions in the period after crisis

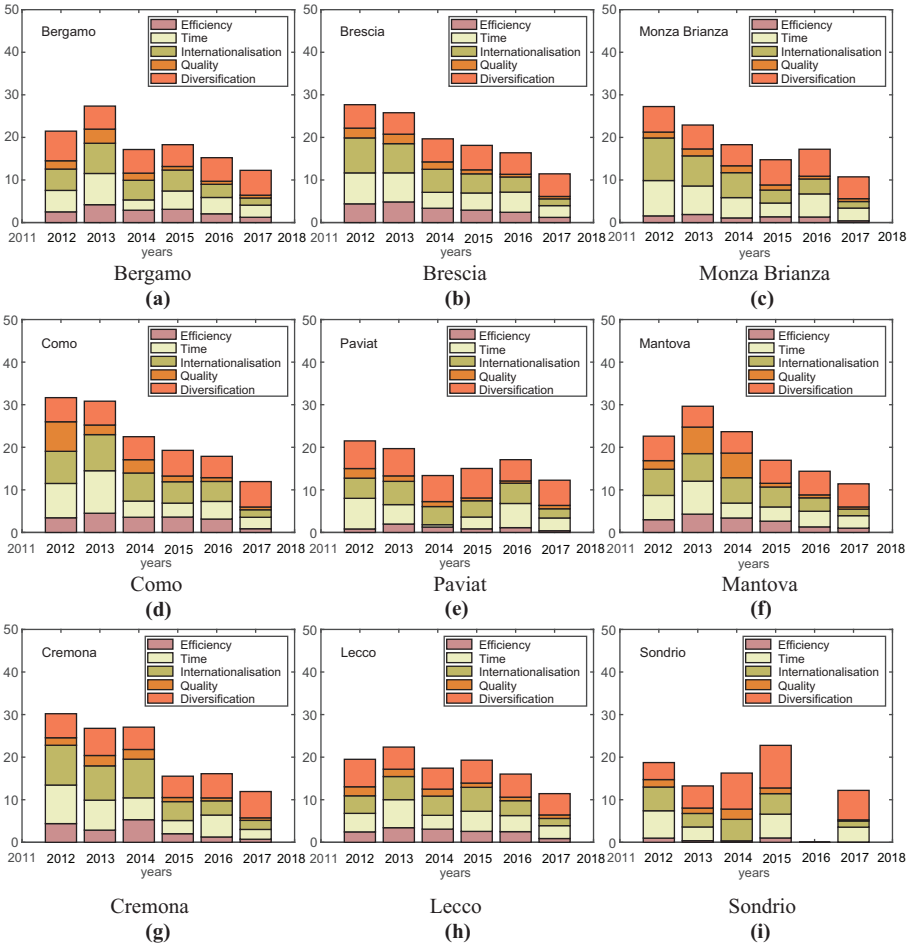

Figure A2.
IPI dimensions in the period after crisis year by year

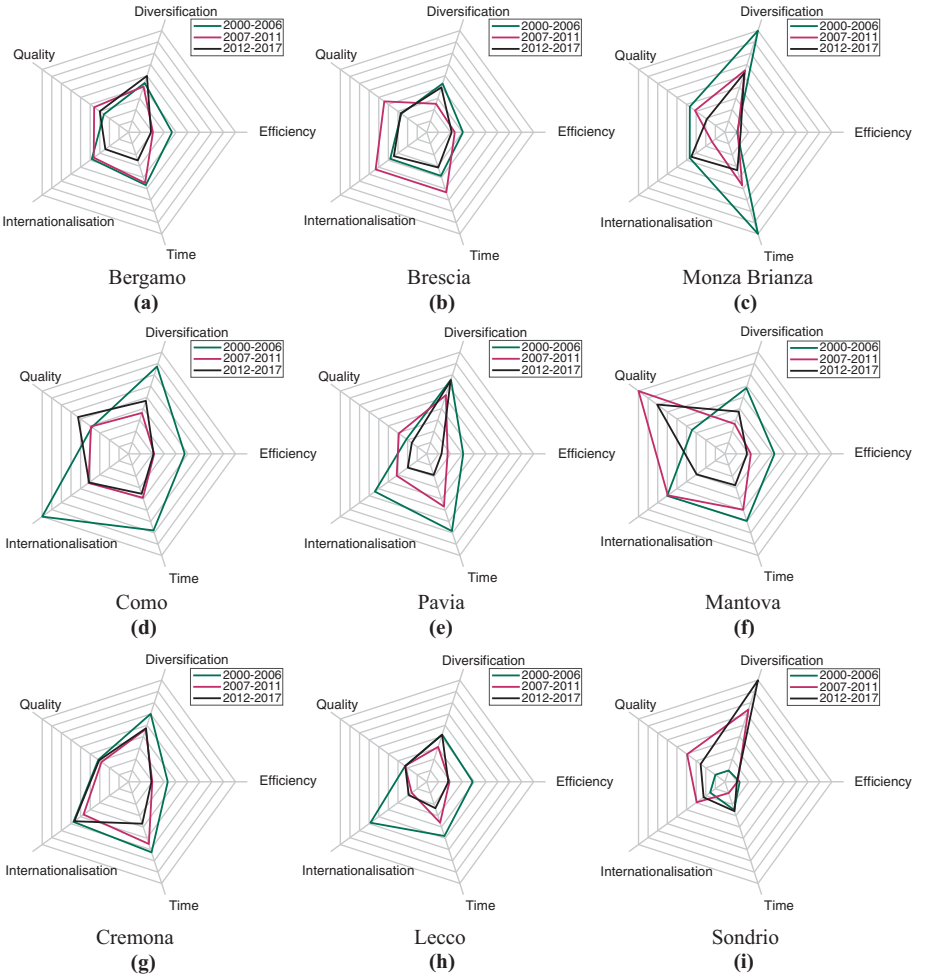

Figure A3.
IPI dimensions in the three periods for each province not reported in the paper

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