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State of an innovation system: theoretical and empirical advance towards an innovation efficiency index

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Abstract

In Europe innovation is currently a cornerstone for economic development and to face the great challenges of human kind. Monitoring progress and measuring what drives innovation is crucial for policy development. Information infrastructures on innovation in Europe contain a number of indicators. Current performance indicators at the national or sector levels use frameworks based on an efficiency model of inputs and outputs. The Community Innovation Survey (CIS) has been a bastion of innovation policy research. Despite this, CIS has been criticised for not having an umbrella framework linking its different underpinnings to explain what drives innovation to actual innovation and economic outcomes. In this paper we propose a framework that enables the theoretical and empirical linkages between the drivers of innovation to innovation performance via the integration of core features determining innovative behaviour in to a single composite. This index enables to assess the total propensity of firms to innovate and assess the relative innovation performance at the sector and country level. The approach adopted here to create the index overcomes long standing theoretical and methodological issues related to the reduction of complexity in a meaningful form, scope, aggregation, normalisation and validation of innovation composites. The empirical testing uses CIS4 data and the results validate the theoretical structure and robustness of the proposed model. The model underlying the proposed index provides not only a depiction of the efficiency of the innovation system but also a link to economic performance and to the factors that determine relative performance.

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1 Introduction[1]

In Europe innovation is currently seen as a cornerstone not only for economic growth but also as an intrinsic human activity that could help to face the great challenges of human kind. Differences on innovation performance across sectors and countries give a varied landscape to the industrial structure and growth rates. Given the importance of innovation measuring progress but also monitoring what drives innovation becomes crucial for policy development. Currently the information infrastructures on Innovation in Europe contain a number of indicators. Most of the current indicators report over inputs to innovation (i.e., levels of investment in R&D, number of innovations to market) innovation activities (number of new products, processes, services, logistics, etc.), enablers of innovation (number of technicians, engineers, postgraduates, etc.) and outputs of innovation (number of patents, citations, turnover related to innovation, etc.) (See Hollanders and Cruysen, 2008; Schubert et al, 2011).

The integration of a single innovation indicator requires the compilation of a large number of individual indicators from different national statistical bureaus. Frequently, at the national level data on innovation is generated by surveying firms where managers' self-report diverse information related to the innovative behaviour of firms. The main instrument to gather this information in Europe is the Community Innovation Survey (CIS). During the last decade CIS has been a bastion of innovation research. Despite this, CIS has been criticised for not having an umbrella framework that unifies its different underpinnings to explain what drives innovation to actual innovation and economic outcomes (Beckenbach and Daskalakis, 2008; Bloch, 2007). The issue of scientific validity in science and technology indicators is a long standing problem. As will be noticed below, from the early works to recent ones on science and technology indicators many authors have pointed out deficiencies concerning how indicators are designed, deficiencies that remain to date.

For example, GAO (1979, pp. 50–51), pointed out that "It was natural that the initial Science Indicators (SI) reports would be based largely on an operational approach, deriving indicators from the readily available data on the basis of suspected importance. This approach, however, incorporated a limited view of science and technology, and led to the construction of a number of indicators whose underlying assumptions are tenuous or invalid". More recently it has been acknowledged that the underlying model of inputs and outputs is not sufficient to create a link between innovation investments and economic performance … "SI lacks any overall unifying model that makes sense of the connections between science, technology, economy and society" (Cozzens, 1991, p. 10). Furthermore, one of the latest tests on the robustness of innovation indicators at the European level still indicates the lack clear theoretical models to guide the selection and weighting of indicators (European Commission, 2003; Grupp and Thorbert, 2010).

In general, four challenges hinder the progress of innovation indicators, these challenges concern the scope, aggregation, normalisation and validation of indicators (Grupp and Mogee, 2004; Cherchye et al., 2004, 2008). The issue of *scope* refers to the underlying theory that guides the selection of variables that will integrate the composite. Traditionally there has been a lack of theories that enable the integration of disparate empirical

[1] **Acknowledgement**: To produce plots and tables we partially used data from the Community Innovation Survey (wave 2004). The data sets used in this paper were accessed during activities conducted in the Sector Innovation Watch Project (SIW) under the contract with the European Commission. Contract Number ENTR2007-11-[2]. Figures 5.1 and 5.2 as well as Tables 5.2 and 5.2 presented in this paper were sourced from the Europe INNOVA SIW Final Synthesis Report. The views and results presented in this paper do not represent the views or opinions of the European Commission.

insights from the literature of innovation towards the linkage of innovation drivers to innovation activities and to innovation and economic performances. Most composites are based in a simple input/output model with little possibility of hypothesis testing. The issue of *aggregation* regards two aspects. The first concerns the weight given to variables included in the model. That is, the respective weighing that each variable gets in a given scale. The second issue in aggregation refers to the bias caused by sample distribution, averages calculation and the weight given to data aggregated at the region, sector or national levels. The issue of *normalisation* concerns the transformation of variables with different measurement dimensions to enable aggregation or comparison in a meaningful fashion (Schubert and Braun, 1996). Last, construct *validity*, concerns the structure and contents of the theory supporting the construction of the composite. In the case of indicators, measurement implies the search for empirical structure by means of extensional, ordered, symmetrical and asymmetrical relations (Korzybsky, 1994). Thus, validation requires that the empirical structure in the data matches theoretical structure of the composite (Michell, 1997).

Recent advances in the fields of psychological economics and the economics of innovation have provided approaches that establish sound causality paths between innovation drivers and innovation performance (e.g., Ajzen 2005; Wehn 2003, Montalvo 2006, Beckenbach and Daskalakis, 2008, Zhang et al., 2012). In this paper, building on Montalvo (2006), we propose a framework that enables linkage between drivers of innovation to innovation performance via the integration of core features determining innovative behaviour into a single composite. The index enables the assessment of innovation propensity of firms and corresponding performance in terms of innovation intensity and innovation efficiency.[2] Once computed the index enables benchmarking sectors or countries with respect productivity, employment or GDP. The advantage is that indicator offers a graphic composite that displays at the first glance the inputs and outputs relative size and the throughput efficiency of an innovation system.

The paper is structured as follow: Section two presents the index concept and meaning of variation. Section three presents the theoretical underpinnings to estimate innovation propensity and innovation performance that enable the index scoping and its empirical weighing and validation. Section four conducts the empirical validation with three different data sets to assess stability and robustness. Section five applies the index to show innovation performance and system efficiency at the country and sector levels using CIS4 data. The last section discusses the contribution to the literature of innovation to overcome challenges of scope, aggregation and validation. In addition, it presents limitations of the proposed approach as well as further venues for research.

[2] The literature on innovation reports positive impacts of innovation intensity on economic performance, in (e.g., Cainelli et al., 2006). The empirical application of the index reveals that a sector or country could have high innovation intensity and still fail to profit from innovation activities.

2 Innovation System Efficiency index concept

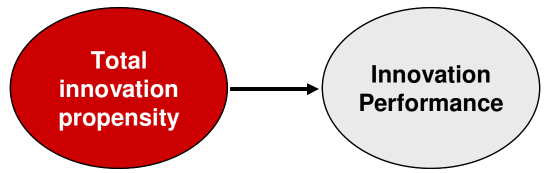
The notion of innovation system efficiency is implicitly present in the seminal works on innovation systems (Freeman, 1988, Nelson, 1993; Lundvall, 1992, Malerba, 2002). An overarching concern in policymakers is to make innovation systems efficient concerning the rate of transformation of inputs into outputs. The notion of innovation system holds a number of definition and methodological issues related with levels of analysis, system components and boundaries (for a revision see Carlson et al., 2002 and Coenen and Diaz-Lopez, 2010). Despite the many issues of innovation systems definitions recently there have been some attempts to measure efficiency following the classical definition of mechanic efficiency (Nasierowski and Arcelus, 2003; Kats, 2006; Guan and Chen, 2011). The latest innovation indicators aim to aggregate data at the national level or sector level and test whether investments made produce satisfactory returns. Despite overall agreement in the heuristics and analysis offered conclusions in general are spurious as there is no way to validate scores and results (Grupp and Mogee, 2004).

The index here proposed is complementary to previous attempts to assess innovation system efficiency as we take a micro approach, taking as primary unit of analysis the firm. While taking a supply side approach we emulate efficiency measurement of as it is done in physics and biology. In classical sciences any system analysed is composed by passive and active elements. A system has flows of energy and materials and rates of transformation. Despite that all components play a role in the system performance, generally efficiency measurement is done via throughput rates with respect to any of its components or any other overarching aim of the system (e.g., flow, pressure, potency, speed, acceleration, etc). Similarly, innovation system efficiency can be measured with respect to any of its elements (e.g., education, research, government, industry, etc.) and its throughput rates can be associated to employment, productivity, turnover, GDP, or broader aims like health, security, safety or environmental quality. Looking at how resources and framework conditions enabling or restricting innovation are accrued at the firm level we implicitly assess how well other components in the system support innovative behaviour.

The communication of complex, multidimensional phenomena in simple terms is a challenge in any scientific field. The aim of creating a composite innovation indicator is to summarize the big picture in relation to a complex issue with many dimensions (European Commission, 2003, p.70). Thus the index aims to summarise the interplay of innovation inputs, throughputs and outputs while maintaining visible issues of scale and rates of transformation. The rest of this section presents the index concept and the meaning of its variation. The overall concept regards an efficiency measure, thus we necessarily start with an input and output model, where we aim to know the transformation rate from inputs to outputs. So far the concept offered is not different to what is the state of the art in the literature. From here on the development of the index is based on behavioural science. In behavioural research it is known that most human social behaviour in specific situations is guided by goals. In turn goals are preceded by intent, a propensity to behave towards the accomplishment of the goal (Ajzen, 1985; Gollwitzer and Bargh, 1996).

Similarly, innovation activities, one type of behaviour in organizations, are generally guided by goals to fulfil and goals are guided by a strategic intent (Mintzberg, 1994). Innovation propensity is a summary of all conditions that predetermine engagement in innovation and to a large extent innovation performance. Metzelaar (1997) and Montalvo (2006) demonstrated empirically that the better the conditions to engage in innovation, the higher the propensity to innovate. In this sense, innovation propensity is meant to serve as a proxy measure of the social effort put into innovation in a given innovation system as experienced at the firm level.

Figure 2.1 Basic behavioural input/output measures



The assessment of both concepts - innovation propensity and innovation performance - is carried out at the firm level, and by aggregation, at the sector or country level. A data array of factors affecting innovation engagement and innovation activities conducted along a sector provide elements to calculate a total innovation propensity and corresponding innovation performance. Figure 2.1 shows the basic relationship between innovation propensity and innovation performance. Differences in propensity and performance across a population sample will produce varied rates of innovation efficiency.

2.1 *ISE* – definition and meaning of variation

The process to build the composite is the following: first the total innovation propensity (*TIP*) is estimated following equation (3.4); then the innovation performance (*IP*) is defined; the average scores in the population sample of *TIP* and *IP* obtained per country, region, sector or firm are scaled to take values that range in unit interval [0, 1], that is $0 \le TIP \le 1$, and $0 \le IP \le 1$.[3] Both constructs are to be scoped in section three of this paper.

The innovation efficiency is defined here as the innovation performance minus the total innovation propensity:

$$\eta = IP - TIP \qquad (2.1)^4.$$

The innovation system efficiency index, ***ISE***, is then defined to be an increasing, smooth and odd[5] function of the innovation efficiency,

$$ISE = g(\eta) \qquad (2.2).$$

With the range $\Re$ (i.e., $-\infty < ISE < \infty$).

2.2 Geometric representation

The graphical representation if the ***ISE*** index aims to summarise the interplay of innovation inputs, throughputs and outputs while maintaining visible issues of scale and

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[3] This is a process of normalisation where the dimensionality of disparate variables are standardised to make comparisons possible (see Nardo et al., 2005).

[4] Note that innovation efficiency η takes value in interval [-1, 1]. While the efficiency of an ideal innovation system is one, i.e. η=1. However, to maintain a perfectly ideal innovation system, the innovation performance should be 1 while the total innovation propensity being absolute zero, which is impossible to reach. Therefore, perfect innovation efficiency can never be achieved and consequently an actual innovation system's efficiency will always be less than one, (η<1). An innovation system with innovation efficiency η is called efficient of degree $|\eta|$ if $\eta \ge 0$, and (more or less) inefficient of degree $|\eta|$ if $\eta \le 0$.

[5] A real value function f with real domain called odd for every x in its domain we have that $f(-x)=-f(x)$. Geometrically, the graph of an odd function has rotational symmetry with respect to the origin, meaning that its graph remains unchanged after rotation of 180 degrees about the origin.This condition is needed to ensure that the signs of η and ***ISE*** are the same.

rates of transformation. Thus, innovation performance (*IP*) and total innovation propensity (*TIP*) are presented by circles $C(O_{IP}, R_{IP})$ and $C(O_{TIP}, R_{TIP})$ (where C denotes a circle with radius R and centre O) with areas *IP* and *TIP* respectively, i.e. :

$$R_{IP} = \sqrt{\frac{IP}{\pi}} \text{ and } R_{TIP} = \sqrt{\frac{TIP}{\pi}} \quad (2.3).$$

In order to represent ***ISE*** geometrically we use the trigonometric circle. We fix O_{TIP} at the origin and let O_{IP} be positioned on the trigonometric circle depending on *ISE*. To do that, we first specify the ***ISE*** function in 2.2 as follows:

$$ISE = g(\eta) = \tan(\frac{\pi}{2}\eta) \quad (2.4).$$

This is an odd and increasing function of innovation efficiency. Define

$$\alpha = \frac{\pi}{2} \cdot \eta .$$

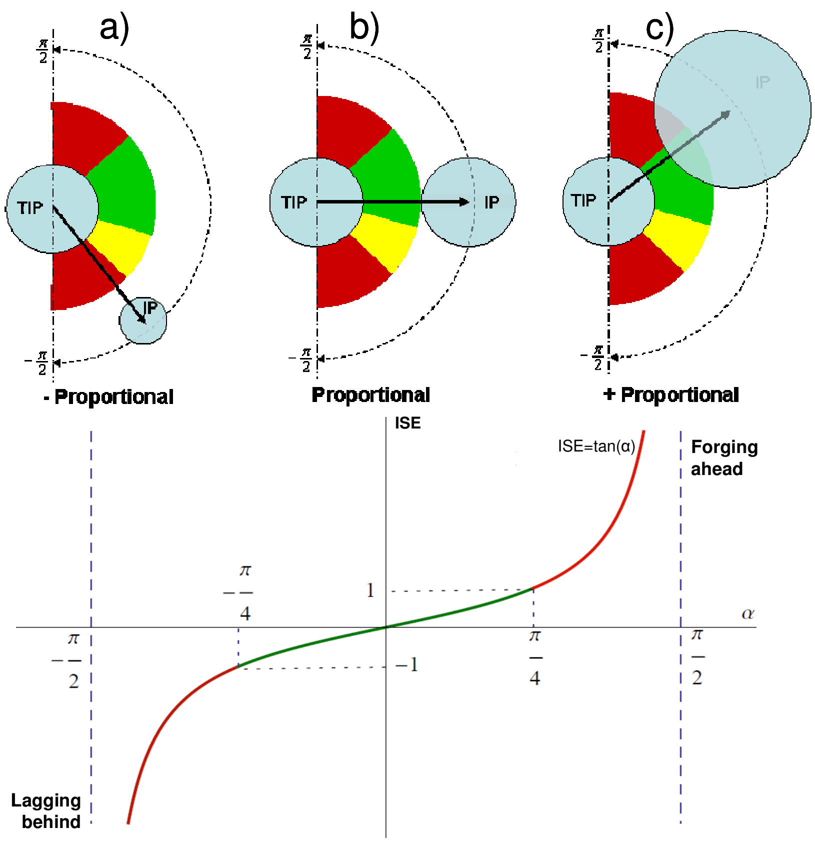
As $-1 \le \eta \le 1$, we have that $-\frac{\pi}{2} \le \alpha \le \frac{\pi}{2}$ and consequently $-\infty < ISE < +\infty$.

In this case, ***ISE*** is the slope of the line segment $O_{TIP}O_{IP}$. Given that O_{TIP} is fixed at the origin, ***ISE*** determines the geometric position of O_{IP} in the trigonometric circle. That is O_{IP} (the centre of the circle which represents *IP*) moves around the trigonometric circle from $-\pi/2$ to $\pi/2$ while ***ISE*** varies from $-\infty$ to ∞.

For policy analysis the above implies that the trajectory along which the results of function (2.4) vary describes the range of efficiency in the innovation system. The efficiency of a particular innovation system evolves along this trajectory ranging from infinite efficiency to infinite inefficiency. We can therefore broadly predict three situations of innovation performance and efficiency tendencies in firms, sectors and countries. These are: falling behind, punctuated equilibrium and forging ahead. The geometrical representation of ***ISE*** gives elements to assess the relative state and positioning of an innovation system across regions and countries with strong implications for policy design and assessment. These situations are illustrated in Figure 2.2 below, the upper side shows the index and the lower part shows the smoth function along which of the ***ISE*** index varies, which is in fact a classic efficiency curve.

The graphic representation of ***ISE*** shows in green tones cases where innovation performance ranges between proportional to more than proportional with repect to the total innovation propensity. The green range indicates that there is a confort zone where inputs, performace and efficiency could be considered ideal. The yellow zone indicates a tendency of falling behind. Red zones indicate undesirable innovation efficiency. The arrow indicates the rate of efficiency in the innovation system.

Figure 2.2 Innovation system efficiency index – meaning of variation



Tendency one: This case includes innovation performances that are less than proportional to the propensity displayed. This include sets of firms (by aggregation sectors or countries) that have relative good support and framework conditions for innovation (TIP) and still have a less than proportional innovation performance (IP) (see figure 2.2a). The trajectory along the smoth function indicates at the end of yellow area that there is a threshold where firms, sectors our countries with persistent low efficiency rates have large shortfall on innovation investment to a point where the risk of lagging behind and sinking. Extreme decressing returns make difficult for firms to get out of the sink due to insufficient investments or lack of returns on innovation. Risk of extreme lack of innovative and absorptive capacities and stagnation. The potential variation in this tendency spans within the interval $(-\pi/2,\ \pi/4)$, figure 2.2a shows innovation performance just below the negative threshold at $-\pi/2$ while $\boldsymbol{ISE}$ shows asymptotic decreasing efficiency tending to $-\infty$.

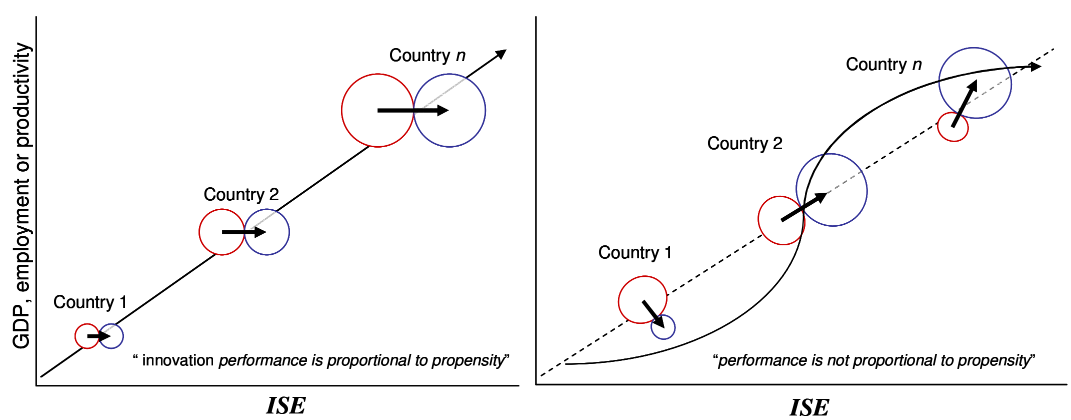
Tendency two: refers to innovation performances that are proportional to the propensity displayed (see figure 2.2b). That is, sets of firms where investments and social support for innovation (TIP) produce a proportional or near to proportional innovation performance (IP). This could be conceptualised as a “confort zone” with a highly desirable puctuated equilibrium. Here timelags in structural change allow for timely adjustmets in labour supply and capital flows. The variation interval in this tendency spans within the interval $(-\pi/4,\ \pi/4)$, figure 2.2b shows the middle point with optimal efficiency at the middle of the graph.

Tendency three: concerns innovation performances that are more than proportional to the propensity displayed (see figure 2.2c red area). That is, sets of firms that in general produce more innovation with relatively less inputs (TIP), in some cases firms could face a less favourable social support for innovation and still show a more than proportional innovation performance (IP). Although this tendency in some cases is highly desirable and all firms aim to achieve high returns, this tendency shows also a threshold of extreme returns on innovation investments. Extreme innovation efficiency at the sector level bares the risk of churning, overheating, fast structural change, unbalances in labour supply and capital markets favouring investments in a fast growing sectors with the potential of creating finacial bubbles. The variation interval in this tendency spans within the interval ($\pi/4$, $\pi/2$), figure 2.2c shows innovation performance very close to the positive threshold at $\pi/2$ while ISE shows increasing asymptotic efficiency tending to $+\infty$.

In general, detours from the "confort zone" depicted in figure (2b) above, should be seen as natural structural anomalies where a far less than proportional performance would indicate problems of inefficiency in the use of social resources for innovation. A deviation too far into more than proportional returns could indicate hiden subsidies or overheating of the innovation system. Both cases in the long run are not economically and socially desirable.

Once computed the index can be used to benchmark the relative performce of sectors or countries. Figure 2.3 below provides an example of typical plottings. The circles red and blue represent respectively the normalised measures of total innovation propensity (TIP) and (IP). The left side shows countries with efficient systems of innovation but with different overall size. This side holds the *moto* that innovation performance is proportional to propensity. That is, there is proportionality between the social investments made on innovation and corresponding innovation performance. The rigth side of the figure shows situations that are closed to what happens in reality. That is, that there are different innovation efficiency rates where some sectors or countries perform at different levels. It will be shown in the empirical application (section 5) that although most sectors and countries have less than proportional performances, there are some cases where sectors or countries do more with less. A common feature in both sides of the plot is that the higher the innovation efficiency of the country the higher the levels on employment, productivity and GDP could be expected. This is an empirical issue tested in the empirical part of this paper.

Figure 2.3 Typical plotting ISE_i vs. GDP, employment or productivity



3 *ISE* elements definition and scoping

The issue of how and what integrates innovation indicators has been widely discussed in the literature of innovation (e.g., Kleinknecht et al., 2002; Godin, 2003; Mairesse and Hohnen, 2008). In this section we define and construct the model to assess the total innovation propensity and innovation performance. Here we address the issues of scope and weighing, that is, how and what variables are included in the composite and how their importance and weight is given in the index.

3.1 Total innovation propensity – elements scoping

The theory used to build the single innovation indicator to assess and monitor the state of an innovation system here proposed is based in a behavioral model designed to explain and predict human innovative behaviour in specific situations and contexts. Under the framework proposed behaviour is explained once its determinants have been traced to the underlying belief system motivating action (Ajzen, 1991, 2012). The model has been widely tested and used to explain human social behaviour in multiple settings (for a review see Armitage and Conner 2001, Ajzen 2005).[6] Recently the model has been applied to assess the propensity of firms to engage on innovation and tested empirically in diverse innovation setttings. The explainded variance on behaviural innovation ranged form 0.62 to 0.86 of the total variance in the data (Montalvo 2002, Wehn 2003, Montalvo 2006, Sartorious, 2008). More recently the approach has been applied in surveys at a European level producing satisfactory results in sectors like industy, transport, agriculture and energy (Montalvo et al., 2007). The basic rationale of the model to guide the integration of and innovation efficiency index is presented below.

Ajzen (1985) demonstrated that the behavioural intent of people could be explained in terms of three constructs: the attitude towards the behaviour, the social norm pushing pro or against the behaviour, and the degree of control exerted upon behavioural performance. An equivalent structure with three constructs to organise behavioural drivers was proposed by Guttman (1973). Guttman's structure includes a cognitive component (attitude), an affective-normative component (social norm) and an instrumental component (control over behaviour). Each of these constructs is formed by a number of latent variables (salient beliefs held by people, by decision makers in the case of firms). The beliefs can arise from expectancies, current or long past experience. Following Guttman (1973), Ajzen (1991) and Montalvo (2006) here is proposed that the belief system held by decision makers in firms concerning innovation engagement, i.e., the drivers of innovation, can be captured via these three components. Thus, the concatenation of these three components enables the creation of a multi-dimensional construct, construct that here is denoted as total innovation propensity (***TIP***).

The relationships between the three constructs and the respective paths between different drivers generating and moderating innovation propensity and innovation performance is depicted in Figure 3.1 below.[7]

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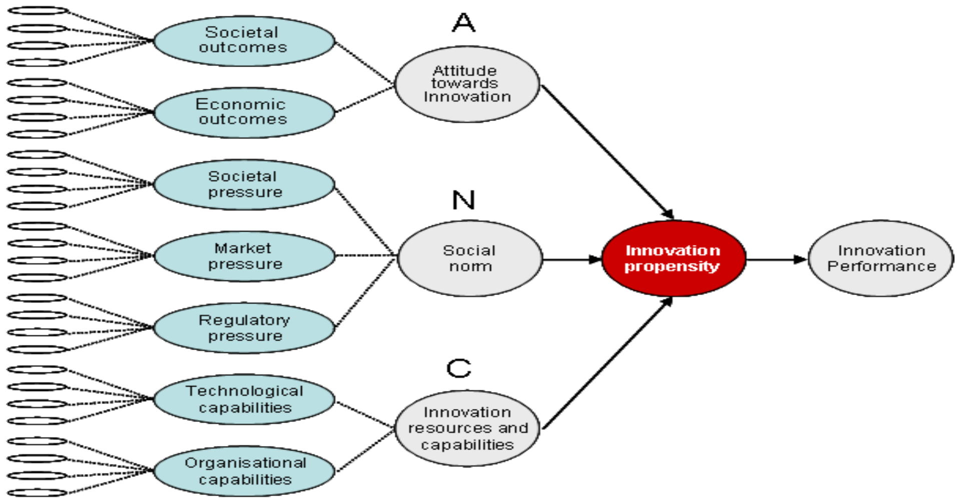
[6] An indication of its wide use is given by the number of citations found in Google Scholar, 13208 citations in 8 October 2011. For applications in different behavioural domains see http://people.umass.edu/aizen/tpbrefs.html

[7] The path of causality is depicted here for matters of stylised presentation, the relationships between contructs are limited to those to the lines indicated. Empirical evidence indicates that there are also correlations between constructs other that those indicated in the diagram. See for example Chian et al, (2012) and Wehn, 2003.

Figure 3.1 Determinants of innovation propensity and innovation performance



Source: Modified from Montalvo (2002).

The first component, a cognitive component of innovative behaviour (A) is captured through an index of predisposition towards innovation. (A) is obtained as shown in equation (3.1). The evaluation of each factor regarding potential outcomes of innovation engagement (a_i) is done by a differential semantic that combines the subjective evaluation of each belief attributed to innovation and the strength of that belief. The resulting ratings across a scale (A) are summed over the I salient beliefs.

$$A \propto \sum_{i=1}^{I} a_i \qquad (3.1).$$

Where,

A is a firm's evaluation toward the engagement in innovative activities;
a_i is the belief that the engagement in innovation is related to outcome i;
Σ is the sum of the I salient outcomes arising from innovation activities.[8]

In general, $\boldsymbol{A}$ aims to capture the perception of the business environment as well as the societal and economic outcomes arising from innovation. A factor affecting innovation engagement will be included in this component if and only if it holds a connotative load pertaining to potential or experienced outcomes arising from innovation activities.

The second component, a normative component of innovative behaviour, is captured through the subjective social norm (N). The dominant social norm concerning innovation engagement is estimated with a differential semantic for each normative belief with the firms' perceived pressure or perceived necessity to comply with or follow the referent in question (n_j). The social norm is hypothesised to be directly proportional to the sum the J salient beliefs concerning referents, as shown in equation (3.2).

[8] The usage of this type of scale for all three components of the innovation total propensity is preceded by the empirical validation of the scale. That is, the internal cohesiveness of all items composing the scale is be demonstrated. If the reliability test is not satisfactory the computation of the index should not be conducted. This is contingent on a satisfactory value of Crombach α test for each of the scales generated. This validation will be shown in the empirical part of this paper.

$$N \propto \sum_{j=1}^{J} n_j \quad (3.2).$$

Where,

- N is the perceived social norm;
- n_i is the organisation's motivation to comply with, follow or anticipate to the preferences of the referent j, and
- Σ is the sum of the J salient normative beliefs to produce an index of the overall perception of social pressure and the need to engage in innovation.

In general, N aims to capture the role and influence of institutions in fostering or hampering innovation. A factor affecting innovation engagement will be included in this normative component only if it holds a connotative load pertaining to social pressures pro or against innovation activities.

The third component, an instrumental component of innovative behaviour (C) is captured through the estimation of the perceived control and power over the innovation process. (C) is estimated by assessing the control beliefs (c_k) upon of the specific factor that facilitates or inhibits performance of innovation. The resulting ranking for each factor affecting control over innovation is summed across the K salient beliefs as shown in equation (3.3).

$$C \propto \sum_{k=1}^{K} c_k \quad (3.3)$$

Where,

- C is the perceived control over the innovative activity,
- c_k is the perceived capacity or control over factors that facilitate or inhibit the performance of innovation,
- Σ is the sum of the K salient control beliefs to produce an index of the overall perception of control over the innovation process.

This component aims to gather the perceived capabilities held by the firms to actually to conduct specific innovations. A factor affecting innovation engagement will be included in this component if and only if it holds a connotative load pertaining to the capacity, available resources and impediments to carry out innovation activities.

Finally, following Montalvo (2006), in order to integrate the above components equation (3.4) indicates that the innovation propensity of the firm is a function of the three components presented above, i.e., $TIP = f(A, N, C)$.[9] The function f is assumed to be an increasing and concave function in each of its variables, A, N, and C and is defined as

$$TIP = f(A, N, C) = A^{\alpha_1} \cdot N^{\alpha_2} \cdot C^{\alpha_3}, \quad (3.4),$$

with $\alpha_1 + \alpha_2 + \alpha_3 = 1$ and $0 \leq \alpha_i \leq 1, \forall i$. Where,

$TIP \geq 0$ is the target population's total innovation propensity to engage in a

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[9] Note that Function F is increasing in A, N and C. Moreover, F is concave in its variables, that is for low values of a variable, e.g. A, the marginal return to TIP as a result of an increase in the variable is relatively high, however, this marginal return decreases for the higher values of the variable.

specific innovative activity;

$A \geq 0$ is the firm's attitudinal predisposition to engage on innovative activities;

$N \geq 0$ is the firm's experienced social pressure concerning the engagement on innovation;

$C \geq 0$ is the firm's degree of control over the innovation process;

$0 \leq \alpha_i \leq 1$ is the weight of the component, this weight is given by the percentage of the variance explained by each of the components in the model.[10]

Note that the parameters α_i measure the responsiveness of *TIP* to a change in levels of either *A*, *N*, or *C*. The assumption that $\alpha_1 + \alpha_2 + \alpha_3 = 1$, means that the function has constant returns to scale. That is, if *A*, *N*, and *C* are each increased by 5%, *TIP* increases by 5%. The aggregation of diverse propensities across a population sample will generate an estimate of the total innovation propensity at the region, sector or country level.

In summary, the total innovation propensity (*TIP*) of a firm arises from internal and external framework conditions within which an array of firms operate. While innovating a firm experiences either the availability or the lack of resources and capacity to innovate. This innovative capacity to a great extent is embedded in and generated by the social context within which the firm operates (e.g., provision and access to finance, provision and availability of skills and knowledge resources, technological opportunities, national patterns of technological specialisation, etc.). The social norm to innovate is a reflection of the social pressures for and against innovation (competitive pressures, regulation, IPR regime, demand for innovation, overall national policies, etc.). To a large extent this is conceptualised as the institutional regime where the firms operate. Last, the predisposition to innovate is the result of the societal value given to expected innovation benefits as well as potential risks for business opportunities incurred to the firm arising from innovation activities (e.g., competitiveness, societal and environmental benefits, brand image, profitability, etc.). In conclusion, the total innovation propensity can be conceptualised to consist of the concatenation of social investment capacity and framework conditions that give support to innovation as experienced by entrepreneurs and firms. An array of propensities across sectors or countries represents an estimate of their respective susceptibility to innovate.

3.2 Innovation performance - elements scoping

Innovation has been defined as the introduction of inventions to the markets (Freeman and Soete, 1997). Given the importance of innovation for economic performance, the measurement of innovation performance has received a great deal of attention over the last decades. Despite that there is agreement in this narrow definition of innovation several indicators that are not directly linked to commercialisation and market performance have been used to indicate innovation performance. Amongst the most popular we can include R&D inputs, patent counts, patent citations and new product announcements. Their nature is revealed following Hagedoorn and Cloodt (2003) whereby R&D is a good input measure of inventive effort, patents are a good output indicator of inventive effort, patent citations are a good indicator of the quality of inventions and new product announcement are a good indicator of product innovation levels. More recently multidimensional aggregated measures have been popularised.

[10] The weight of each component is calculated via a test of principal components. This test also serves to test the robustness of the model for a particular application (for an in depth discussion see Montalvo 2002, pp.198-220). If the empirical structure (i.e., data set) fits the model proposed (i.e., most of the variance is explained with three components) the model can be considered valid. See section 4.2 in this paper.

Examples of multidimensional measures include the European Commission with its Innovation Scoreboard (Hollanders and Cruysen, 2008), the INSEAD global innovation index (Dutta, 2011) and the German Innovation Indikator (Schubert et al., 2011). These composites integrate a large number of individual variables to produce country rankings. For extensive reviews on innovation performance indicators see Hagedoorn and Cloodt (2003), Grupp and Schubert (2010) and OECD (2011).

In order to create a reliable measure of innovation performance that follows closely the notion of market introduction and economic performance at the firm level, we follow the most recent definition of innovation activities provided by the Oslo Manual (OECD/Eurostat, 2005). The Oslo Manual in its third edition defines that "…innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations" (OECD/Eurostat, 2005). This broad definition of an innovation encompasses a wide range of possible innovations. Building upon this definition innovation is defined in terms of a number of innovation activities where change occurs at the firm level. The innovation activities typology listed below includes technical and non technical change.

- Products;
- Services;
- Manufacturing methods;
- Logistics, delivery or distribution methods for inputs, goods or services;
- Supporting activities for your process, such as maintenance systems or operations for purchasing, accounting or computing;
- Management systems;
- Layout changes of production organisation;
- Relations with other firms or public institutions (through alliances, partnerships, subcontracting, etc.);
- Design (or packaging or presentation) of a good or service (exclude routine or seasonal changes);
- Sales or distribution methods (e.g. introduction of internet sales, franchising, licensing, etc.).

In order to operate innovation performance we define two terms: Innovation intensity and innovation efficacy. Here we differentiate between innovation intensity ($\boldsymbol{IP_I}$) and innovation efficacy ($\boldsymbol{IP_E}$). Innovation intensity will be given by the number of innovation activities conducted by the firm in a given period, depicted in equation 3.5. In turn, innovation efficacy is the value of innovation intensity moderated by the imputed turnover to the innovation activities conducted at the firm level, depicted in equation 3.6. Innovation efficacy is a better indication of market value attributed to the innovation effort.

$$IP_I \propto \sum_{i=1}^{n} IA_i \tag{3.5}$$,

and

$$IP_E \propto (\sum_{i=1}^{n} IA_i) \cdot IT_i \tag{3.6}$$.

Where,

$\boldsymbol{IP_I}$ is innovation intensity,
$\boldsymbol{IP_E}$ is innovation efficacy,
IA_i is the innovation activity i,

IT_i is the imputed market value to innovation activities conducted in a given period,

Σ is the sum of the n innovation activities.

These definitions follow closely the definition of innovation as provided by Freeman and Soete (1997) that implied market value and economic performance derived from innovation.

3.3 Variables and aggregated composite elements weighing

The construction of indicators requires the selection of variables to be included in the composite and attribution of weights to each variable included, whereby the number of variables included and the weights imputed are not easily deducted from innovation theory (Grupp and Schubert, 2010: p. 68). The section above gave a rationale for the inclusion of variables in each of the components that integrate the index. The weighing of the variables in each of the components is done in the following manner. First, each variable is rated in a interval (0-3, -3,3, or 1,7), where all variables in the component are geared to measure a dimension of innovation propensity in firms as defined in section 3.1. The difference in the relevance of each variable in a component is given by the expectancy-value reported by each respondent that participates in the data survey. The expectancy-value model ensures that each variable has independent probability to contribute to the overall weight of each of the three components in *TIP*.[11]

The variables considered for inclusion in the model are dependent on insights derived from the literature on innovation and from empirical reseach aiming to elicit factors affecting innovation in firms via direct interviews with managers in firms. The number of variables in the composite is not set at the outset of the composite design. This depends on two aspects. First whether the variable belongs to the domain that is intended to assess, i.e., it follows the ratione of one of the constructs in the model and its internal cohesiveness is high. Second, inclusion is also contingent upon the variance explained in the data when an additional variable is included.

[11] In the expectancy-value model (EV) the probability of each item within a component is independent while in the subjective utility model (SU) all items in a component must add to one. The later approach to decision making analysis presents problems in the allocation of variables weights while the former the weight of each item is given by its statistical distribution in empirical data.

4 Empirical validation

4.1 Empirical validation – Total Innovation Propensity

The empirical validation of the ***ISE*** index structure was done in two instances. The first used a limited data set that strictly followed Montalvo's (2002) approach, gathering data to fit the model with a dedicated questionnaire and respective survey. This exercise used the ideal type of data needed to test the model. The later in terms of scales intervals and questionnaire wording for data collection. The second instance used an existent data set, the Community Innovation Survey (CIS4), where variables included in the analysis were selected and aggregated following the euhristics described in section 3.1 and 3.2. The conceptual match between the ***ISE*** index components and variables present in CIS4 data set are shown in Figure 4.1 below.

Figure 4.1 ***ISE*** and Community Innovation Survey (wave 4) – *conceptual match*

INNOVATION DRIVERS

BUSINESS ENVIRONMENT (0-3)
(Atitudes)

EMAR	Increased market share
EFLEX	Increased flexibility
ECAP	Increased production capacity
EMAT	Reduced material energy
HDEM	Uncertain demand for innovation
EENV	Reduced environmental impact

INSTITUTIONAL SETTING
Subjective NORMS (0-3)

ESTD	Meeting regulation and standards
HDOM	Market dominated by dominant enterprises
HMAR	No demand for innovation (consumers)

INNOVATION CAPABILITY (0-3)
(Behavioural control)

RDENG	R&D engagemen level (1= Continous 2=Esporadic)
CO	Cooperation activities
HFENT	Lack of funds internally
HFOUT	Lack of funds externally
HPER	Lack of qualified personnel
HTEC	Lack of information on technologies
HINF	Lack of information on market
HPAR	Difficulty finding partners for cooperation

INNOVATION PERFORMANCE

INPDGD	Product
INPDSV	Service
INPSPD	Process
INPSLG	Logistics
INPSSU	Supporting activities
ORGSYS	Management systems
ORGSTR	Layout production organisation
ORGREL	Industrial relations
MKTDES	Design
MKTMET	Marketing
TURN	Turnover
TURNMAR	Innovation turnover

The European Community Innovation Survey (version CIS4) provides relatively good possibilities to apply and test the theoretical framework proposed in Section 3. The conceptual match is relatively good, the left side in Figure 4.1 displays different innovation drivers pertaining to the three domains mentioned at the outset of this paper: cognitve – conating outcomes of innovation; norms – conating social pressures and instrumental aspects – conating the control over innovation. It is clear that there is an underrepresentation of aspects related to the social norm (institutional factors). Only three items where found that match the criteria set in section 3.1. The insufficient attention given in CIS to normative aspects arising from regulation, market competition, standards, community demand, and other international standards that are known to affect innovation have been pointed out in the literature (Blind 2007; Montalvo, 2007; Montalvo, 2011). Despite the small conceptual mistmatch with CIS the results are highly satisfactory. The clustering done following the model of innovation propensity here provided renders a good fit to the data. Figure 5.2 below shows empirical results with three different data sets.

Figure 4.2 Structural validity – robustness in different data sets and samples

a)

Environmental technology

64% of explained variance

	Component		
	1	2	3
evr1 Enviromental risk	-,003	,437	,636
er Economic risk	,017	-,448	,684
mp Market pressure	,257	,652	-,014
cp Community pressure	,243	,769	,017
rp Regulatory pressure	,039	,716	,059
tc1_ Technological capability	,550	,172	,461
l Learning capability	,723	,331	,080
al Strategic alliances	,823	,117	-,031
nk Networks of collaboration	,849	,052	,003

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in 4 iterations.

Data source Montalvo 2002,
N=97 observations

b)

Spain

51% of explained variance

Rotated Component Matrix[a]

	Component		
	1	2	3
EMar	,075	,538	,082
EFlex	,134	,663	-,066
ECap	,021	,795	,058
EMat	,024	,772	,168
Hdem	,587	-,103	,236
EStd	,069	,576	,040
Hdom	,591	,050	,150
HMar	,368	-,092	,196
EEnv	,010	,744	,075
RdEng	,025	-,170	,050
Co	,006	,013	,159
Hfent	,241	,082	,818
Hfout	,200	,044	,848
Hper	,689	,143	-,057
Htec	,730	,128	-,005
HInf	,727	,070	,031
Hpar	,696	,070	,124

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 4 iterations.

Data source Eurostat CIS4,
N=1865 observations

c)

Europe

54% of explained variance

Rotated Component Matrix[a]

	Component		
	1	2	3
emar	,170	,530	,352
eflex	,085	,734	,136
ecap	,106	,766	,128
emat	,166	,747	,030
hdem	,738	,100	,044
eenv	,129	,755	-,010
estd	,122	,700	-,035
hdom	,716	,147	,032
hmar	,250	-,035	-,483
rdeng	,118	,106	,738
co	,172	,083	,704
hfent	,695	,085	,107
hfout	,683	,090	,054
hper	,752	,146	,038
htec	,788	,149	-,035
hinf	,809	,124	-,005
hpar	,732	,142	-,030

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Data source Eurostat CIS4,
N=63917 observations

Figure 4.2a displays the results of a small data set where the data was collected with questionnaire and survey dedicated to test the model. This implies ideal wording and better balance in the scope of the variables included to test the model. In this case the survey was conducted on innovation drivers and innovation performance four sectors innovating in environmental technologies. Here there is a good match in all three components of the model. Figure 4.1b and 4.1c display results from two data sets with the same questionnaire and survey where the questionnaire and scope was not primarily designed to test the model here proposed. To select the variables for each of the components in the index we followed the heuristics proposed in section 3.

Figure 4.1b shows the test of the structure and contents with a moderate size population sample. The fit to the model is good in two components and and less favourable in one. Figure 4.1c shows results in a very large data sample, this result is remarkably stable model structure in relation to what is shown in figures 4.1 and 4.2. The fit achieved in the usage of the second data set is due to the not sufficient representation of normative variables in the dataset used. In addition, the loading of the variables included in the normative component is caused by the poor wording of the items in the questionnaire. In these two cases the items include two target concepts, thus rendering a poor reliability of the questions used to generate data on regulation and standards in the CIS4 questionnaire.

The results from the principal components analysis support the validity of the structure and contents proposed for the creation of the input composite “total innovation propensity” (***TIP***). This validity stems from the basic definition of measurement validity in social sciences (see Morgenthaler, 2001; Montalvo, 2002, Appendix A). The composite captures a large proportion of the variance in three different datasets. In addition, its theoretical structure remains to a large extent valid over the three samples. The stability and robustness of the structure has the benefit of generating robust weights for each of the components in the model as indicated in equation (0.8) in section 3.1.

4.2 Empirical validation – Innovation Performance

The validity test for the innovation performance construct is relatively simpler than ***TIP***. This stems from the high agreement on the scale of innovation activities at the firm level present in the literature of innovation studies. The reliability of this scale is highly satisfactory; its Crombach Alfa reliability test resulted above 0.79. According to normal practice in self-report questionnaire design the reliability of a scale above 0.60 is considered acceptable (Crombach, 1994). This means that the internal cohesiveness and meaning of the latent variable ‘innovation performance’ is well covered by the typology proposed by OECD/Eurostat (2005). Table 4.1 shows the inter-correlations between innovation types. All innovations types are highly inter-correlated.

Table 4.1 Correlations between innovation types – CIS4 data

	Products	**Services**	**Manufacturing**	**Logistics**	**Supporting activities**	**Management systems**	**Layout production changes**	**Relations with others**	**Designs**	**Sales or distribution**
Products	1.000									
Services	0.5521*	1.000								
Manufacturing	0.3519*	0.3524*	1.000							
Logistics	0.3219*	0.3684*	0.4661*	1.000						
Supporting	0.2854*	0.3434*	0.3979*	0.4956*	1.000					
Mgmt. systems	0.2318*	0.2494*	0.2462*	0.3175*	0.3461*	1.000				
Production layout	0.2325*	0.2324*	0.2491*	0.2901*	0.3126*	0.5640*	1.000			
Relations w others	0.2118*	0.2252*	0.1791*	0.2314*	0.2198*	0.3621*	0.4149*	1.000		
Designs	0.3024*	0.2697*	0.2799*	0.2718*	0.2275*	0.3127*	0.3139*	0.2767*	1.000	
Sales or distribution	0.2540*	0.2726*	0.2549*	0.3151*	0.2323*	0.3461*	0.3521*	0.3188*	0.4463*	1.000

Data source: EUROSTAT CIS4 data, Automotive sector, N=1865 observations, Similar patterns of inter-correlations of innovation were found across all sectors in CIS4.

Given that both measures proposed to calculate and integrate the composite ***ISE*** are validated concerning their structure and content we apply the ***ISE*** index to a CIS data set at the sector and country level. This is done to test whether the ***ISE*** index ranking results confirm current innovation ranking trends for countries in Europe (i.e., Innovation Union Scoreboard). The rationale is to show that some countires could be ranking relatively lower than innovaiton leaders and still show healthy and efficient innovation systems. The algorithm to calculate the ***ISE*** index is presented in Appendix 1.

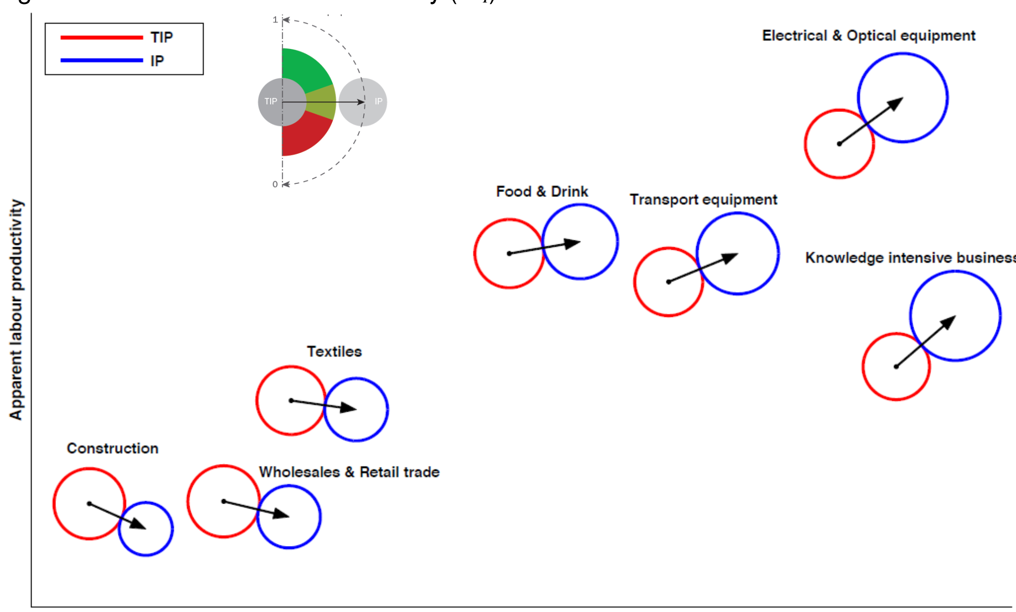
5 State of an innovation system

The empirical demonstration of this index is conducted for the sectors of transport (automotive and aviation), construction, food and beverages, optial and electical equipment, knowledge intensive businesses, textiles, and wholesales and retail trade. The estimation of ***ISE*** is done with CIS4 data including 63917 observations. The response distribution weighting follows Eurostat (2004) norm.[12] The landscape of innovation performance is presented for sectors and countries. The results presented to a large extent match what other innovation performance measures indicate concerning the relative ranking of countries. The difference concerns the multi-dimensional character of the indicator that allows gauge in a simple picture the social effort gone in to innovation and the rate of returns.

5.1 Sectors innovation efficiency

Figure 5.1 below shows the performance athe sector level in terms of innovation intensity. The arrows show the rate fo efficiency in the innovation system. In general, systems with higher efficiencies will be found in the right side of the plottings.

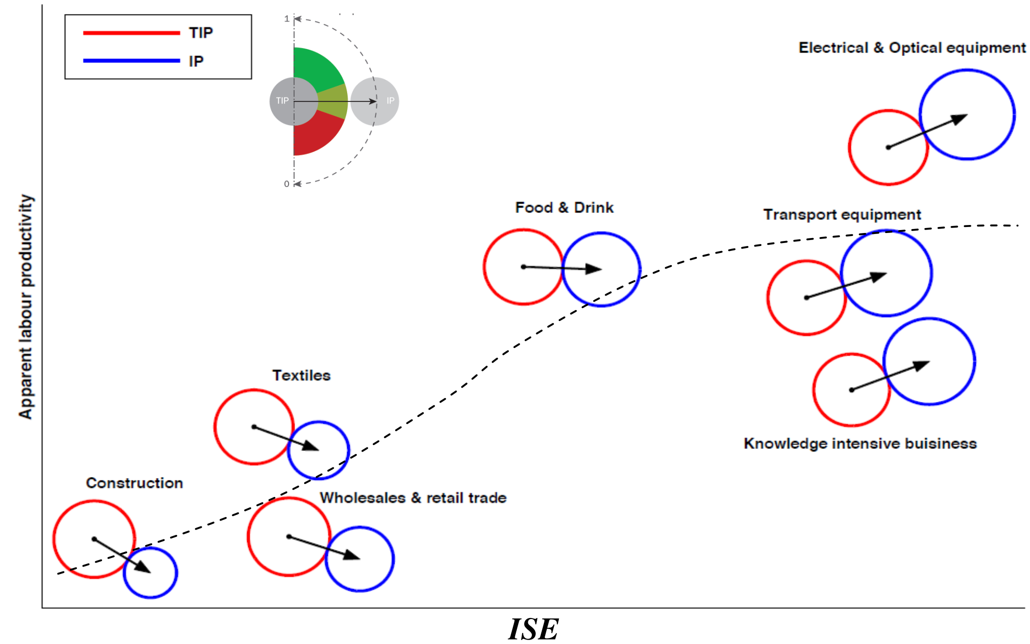
Figure 5.1 Sectors innovation intensity (IP_I)



The picture shows two groups of sectors where the right side of the plot indicate sectors with relative higher innovation intensity. The top ranking sector is the knowledge intensive sector and the sector lagging behind is the construction sector. The sectors in the right side show more than proportional returns to the innovation effort compared to those in the left side. Figure 5.2 shows the same picture with the imputed value to innovation in the turnover of firms. The overall positioning of the sectors now in terms of innovation efficacy does not change drastically. In general, those sectors with higher innovation intensity profit more from innovation.

[12] For the sector-level aggregation of each of the variables aggregated in the composites '*A*', '*N*', '*C*', and '*IP*' the weighted average is used. The weighting factors in CIS dataset ('WEIGHT ' or 'WEIGHTNR') are based on shares between the numbers of enterprises in the realised sample and the total number of enterprises in each stratum of the frame population (Eurostat, 2004, p. 7). . To avoid sampling bias generated by county size and response levels we conducted stepwise averaging. First, we calculate average for sectors within a country and then proceed to calculate average at the EU level.

Figure 5.2 Sectors innovation efficiency (***IP***$_E$)



On average firms in the electrical and optical equipment sector profit the most of innovation and show the highest innovation system efficiency. The transport equipment and knowledge intensive sectors follow closely. The food and drinks sector present a situation where the overall propensty to innovate match the returns on innovation. The sectors wholesale and retail, textiles and clothing and construction resulted lagging behind in the innovation efficacy ranking. In average their innovation systems produce lower returns compared to their own innovation effort. Here it is worth to be noticed that the rough shape of the efficiency function describing the relatioship of the ***ISE*** index with labour productivity match the meaning of the index variation depicted in figure 2.2. This is an empirical result that should be investigated further as this would confirm the index prediction power as was described in section 2.2.

5.2 Sectors innovation performance – countries specificities

Section 3.1 mentions that available composite innovation indicators tend to hide the weaknesses and strengths of an innovation system. In this regard, the index here proposed is meant not only to link to factors determiing innovation performance but also allow easy to follow differentiation in sectoral innovation efficiencies. The plots in previous section described the overall positions of sectors innovation efficiencies with and without the imputation of turnover value to innovation. The relative overall innovation intensity (***IP***$_I$) and innovation efficacy (***IP***$_E$) ranking across sectors per country is shown in tables 5.1 and 5.2 respectively.

Table 5.1 Sectors innovation *intensity* (IP_I) ranking[13]

Sectors	NO	SK	BG	HU	LT	RO	SI	ES	BE	CZ	PT	DE	GR	Score
Knowledge Intensive Bussines	-0,13035	-0,1556	-0,33715	-0,22375	-0,1813	-0,15265	-0,1121	-0,03155	-0,019	0,1627	0,2788	0,1982	0,5781	-0,12565
Electrical and optical equipment	-0,0521	-0,2546	-0,238	-0,1882	-0,1018	-0,2292	-0,0012	-0,0297	0,1108	0,1414	0,1975	0,1533	0,3553	-0,1365
Food & beverages	-0,2891	-0,1494	-0,5319	-0,2148	0,1067	-0,2151	-0,1527	-0,1401	0,0073	0,1025	0,1346	0,0747	0,1145	-1,1528
Automotive & AS	-0,2622	-0,2005	-0,4957	-0,299	-0,388	-0,2661	0,0609	0,0015	-0,0089	0,1745	0,159	0,1777	-0,1671	-1,5139
Textiles and clothing	-0,2425	-0,2889	-0,2095	-0,2931	-0,4229	-0,3206	-0,0914	-0,1242	-0,0531	0,0478	-0,0402	0,233	0,0948	-1,7108
Wholesale & Retal Trade	-0,5313	-0,7984	-0,2299	-0,3965	-0,3488	-0,3948	-0,330767	-0,173867	-0,2496	0,0113	0,12755	0,135	0,1906	-2,989483
Construction	-0,7628	-0,4254	-0,194	-0,5679	-0,2917		-0,4516	-0,1881	-0,41	0,0057	0,1025			-3,1833
score	-2,27035	-2,2728	-2,23615	-2,18325	-1,6278	-1,57845	-1,078867	-0,686017	-0,6225	0,6459	0,95975	0,9719	1,1662	

Table 5.2 Sectors innovation *efficacy* (IP_E) ranking

Sectors	NO	LT	SK	HU	BE	RO	BG	SI	GR	ES	PT	CZ	DE	Score
Automotive & AS	-0,394	-0,1723	1,4662	-0,6198	0,1735	-0,3814	0,3051	-0,1023	-0,4312	1,0695	-0,0349	0,5824	1,3224	2,7832
Electrical and Optical Equipment	0,5569	-0,1714	-0,5393	0,2474	0,3723	-0,1876	-0,0999	0,1164	-0,2095	-0,06	0,2552	0,1955	-0,2234	0,2526
Knowledge Intensive Bussines	-0,271	-0,47395	-0,47305	-0,3738	-0,34245	-0,4252	-0,3139	-0,253	0,40215	-0,2476	0,0542	-0,14625	-0,242	-3,10585
Textiles and Clothing	-0,4469	-0,4832	-0,4342	0,268	-0,3083	-0,4803	-0,2973	0,1629	-0,3627	-0,2413	-0,195	-0,1288	-0,2396	-3,1867
Food & Beverages	-0,2971	-0,0152	-0,3597	-0,3676	-0,2794	-0,3469	-0,5743	-0,1913	-0,3225	-0,2847	-0,1557	-0,124	-0,244	-3,5624
Construction	-0,8383	-0,3778	-0,5693	-0,3351	-0,5228		-0,4189	-0,5522		-0,3523	-0,1219	-0,109		-4,1976
Wholesale & Retal Trade	-0,6337	-0,3652	-1,0295	-0,41635	-0,611967	0,3384	-0,0569	-0,595433	-0,1904	-0,440233	-0,15135	-0,131433	-0,1823	-4,466367
score	-2,3241	-2,05905	-1,93885	-1,59725	-1,519117	-1,483	-1,4561	-1,414933	-1,11415	-0,556633	-0,34945	0,138417	0,1911	

[13] The ranking done here per country with inputs at the sector level has the advantage of eliminating the data bias issue concerning relative country or sample sizes.

The tabulations show the differences in innovation intensity and innovation efficacy in each of the sectors analysed in this paper. The scoring tables should be read vertically and horizontally. The vertical tabulation shows the performance of sectors, where those sectors doing better are placed at the top of the table. This tabulation shows how each sector contributes to the position of each country in the overall ranking. The horizontal tabulation shows the scores achieved per country. Those countries located at the extreme right are those forging ahead on innovation, thus performing better.

Table 5.1 shows scores and positions on innovation intensity **(IP_I)** for sectors and countries. Concerning the amount of innovation activities in different types of innovation, table 5.1 shows a good to excellent performance for more than half of the countries included in the analysis. The performance position for some sectors and countries as displayed in table 5.1 changes when the percentage of turnover due to innovation is imputed to the innovation intensity, i.e., the monetary value imputed to the amount and type of innovation activities conducted over the last three years prior to the survey date. These changes are displayed in Table 5.2, one of the most extreme country repositioning concerns Grece. In the innovation intensity ranking where many countries show relative good performances Grece resulted top. After recalculation with the imputation of monetary value to innovation, it falls back to fifth position with two sectors with critical innovation systems inefficiencies in two sectors. Belgium falls back three positions and Spain is promoted one position. The imputation of value to innovation activities shows that two sectors in Spain are failing to profit from their innovation activities. Countries like Norway, Hungary, Lituania, Slovakia and Belgium with lower efficiency and innovation performance show little variation in their positions before and after turnover imputation to innovation. These countries show several sectors with strong inefficiencies in their innovation systems.

5.3 State of the innovation system in European countries

The figures 5.3 and 5.4 below show the innovation intensity and innovation efficacy for several european countries. Simlarly to what is shown for sectors, countries in the right side of the plots show higher system efficiencies. In general countries showing lower efficiency rates report relatively similar in total innovation propensities with low innovation performance, that is lower turnover imputed to innovation. In agreement with what was presented at the sector level those countries showing higher innovation intensities show also higher innovation efficacy. The tendency here is that sectors and countries with higher innovation intensity also profit relatively more from innovation. Countries like Germany, the Zchek Republic, and Portugal are the best performers.

Figure 5.3 Countries innovation intensity landscape (**IP_I**)

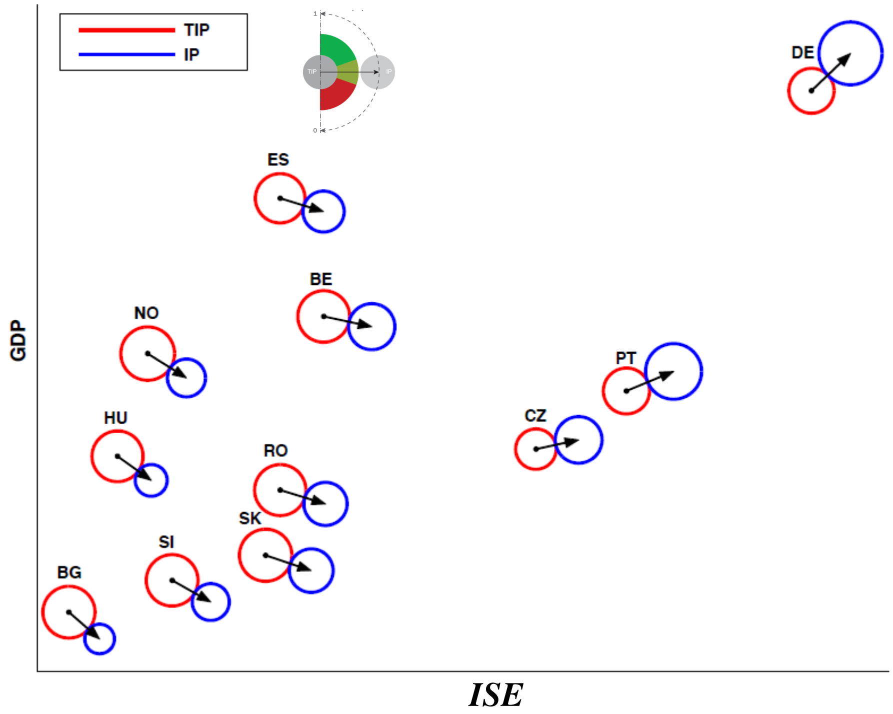
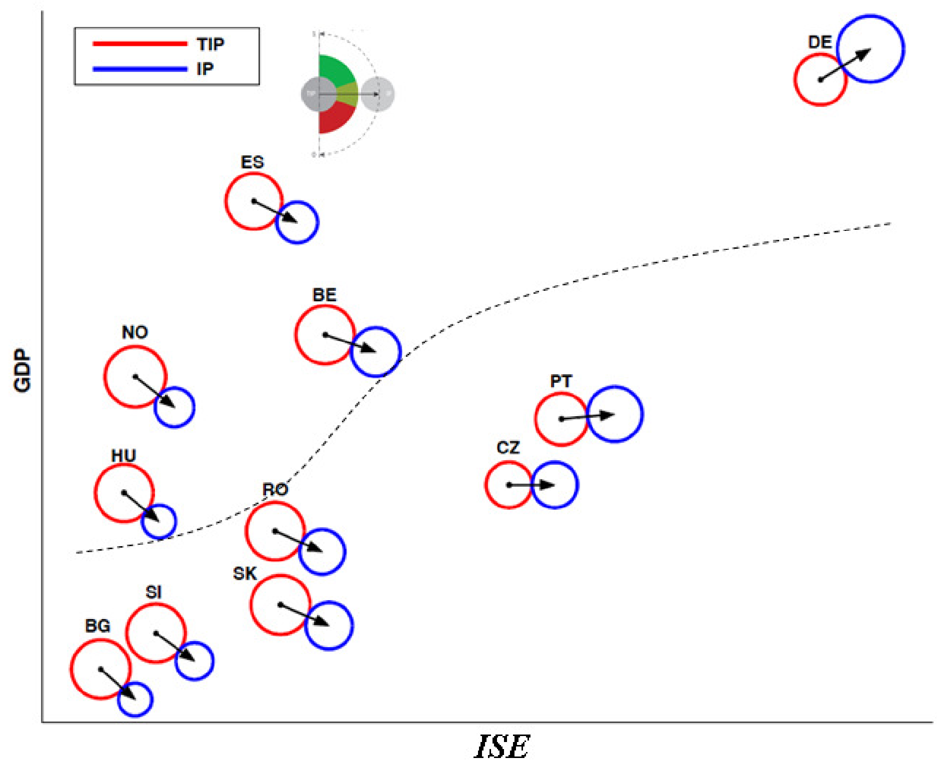


Figure 5.4 Countries innovation througput efficiency landscape (**IP_E**)



6 Conclusion

In some policy circles innovation is seen as one of the main instruments to promote growth and employment while helping to face the great human challenges. Monitoring progress across different countries innovation systems has become crucial for policy design and assessment. Progress in composite innovations indicators that capture the complexity of the innovation system has been slow. In this paper, we have proposed a new approach to build an innovation index that overcomes issues of scope, aggregation, normalisation and validity. The index was validated with three data sets, the test revealed stability and robustness across datasets. In the following we highligh the theoretical contribution, innovation efficiency monitoring applicability issues in sectors and countries, limitations identified and issues requiring further research.

6.1 Theoretical contribution

In contrast with current innovation indictors available underpinned only by an input-output model, the index here proposed is based on behavioural science that has been successfully applied in diverse areas of human activity. Perhaps the stronger theoretical contribution of the paper is the application of a model to reduce complexity on innovation drivers in a meaningful way. The sheer number of potential drivers of innovation performance is reduced to a three simple concepts very much amenable to policy intervention. These are the social pressures to innovate, the capabilities to actually conduct innovation and perceived results of innovation accrued in the firm and the society at large. That is, the main constructs of the total innovation propensity in firms, sectors or countries. The high reliability and validity of the constructs proposed enable the focusing and prioritisation of the policy effort with a higher degree of certainty based on normal science.

The second contribution is the assessment of the innovation system in a graphical fashion and the possibility of assessing where a given innovation system is situated in tendencies like falling behind, equilibrium or forging ahead. The later bears the possibility of assessing stagnation or overheating at the sector level. This is an aspect that requires further research via the application of the model to longitudinal data.

The third theoretical contribution regards the underlying rationales for scoping and validation of the index. Previous efforts to create a single index that explain performance and efficiency in innovation systems lacked a theory to justify the inclusion and scoping of the index components. The model used here has been widely tested to predict human behaviour in very many settings of human activity.

The fourth theoretical contribution regards the robust design of ISE to ensure stability across time. Stability is one of the most critical problems indicators, i.e., what comes in and what comes out of the indexes. This frequently makes comparison across time invalid. Benefits of the type of scaling and standardisation introduced in section 2.1 and the three components definition in sections 3.1 and 3.2 have the additional benefit of providing flexibility while still ensuring stability to ISE across time. Regarding *flexibility* of each of the index components, the internal design of each component can vary across time depending on new insights about framework conditions and determinants of innovation. Concerning *stability*, the total size of the effect of each component will still be determined by its statistical relevance in the explanation of variance in the sample. Finally, the main constructs in the index, i.e., TIP and IP are scaled to take values that range from zero to one, the later remains independent of the variations that could occur in the respective internal components.

6.2 Empirical application

The empirical testing validated the structure and contents of the index proposed. The data analysis shows an empirical structure matches closely the conceptual structure of the index. In general, with some exceptions, the sectors and countries that showed higher innovation intensities also showed higher innovation efficacy, thus profiting from innovation activities reported. In addition, those countries and sectors that showed higher innovation intensities also resulted with higher labour productivity. The tabulation of sectors' innovation efficiency across countries enabled the identification of what sectors are more efficient and best contributing to the overall ranking of countries. The tabulation presented in tables 5.1 and 5.2 identifies not only countries but blocks of sectors that require policy intervention to support innovation.

The possibility of identifying weights for each of the components that integrate the total innovation propensity makes possible to identify more specific areas of policy intervention. In the European case used as example, the overall degree of innovation capabilities account for 27 % of the variance in propensity, while the outcomes derived from innovation account for 18% and norms account for 8% (see Table 7.2 in Appendix 1). This indicates that those sectors that have stronger innovation capability perform better.

In the three data sets used to test the index the three components play a role in explaining the variance in the sample and thus influencing innovation performance. This implies that policy mixes need to address the issues that pertain to innovation outcomes as perceived by innovators, the normative and market framework and the conditions enabling innovation at the sector level. Thus policy mixes failing to address one of the components will be predisposed to underperform by design. Thus, a strong implication of this finding is that policies improving general framework conditions for innovation are by design doomed to have limited success, a strong policy focus is required. The challenge here for policy makers is to deliver the "cure" to a specific targeted population in a coordinated manner.

6.3 Limitations and future research

Over several decades, we witnessed the appearance of many science and technology indicators. Their permanence over time relies heavily on the availability of data. Indeed, as mentioned in the introduction of this paper, most indicators available in the literature of innovation were designed upon the limitation of what data is more broadly and readily available. This is a strong limitation for any new index with different underpinnings departing from those found traditionally in the literature of science and technology indicators. Concerning the ***ISE*** index proposed here, the limited data availability on drivers of innovation at the firm level across countries beyond Europe's limits the possibility of broader international benchmarking.

Previous research in innovation studies highlighted the relevance of regulation and policy to set favourable framework conditions for innovation to flourish. The level of variance explained by the model could be improved when data infrastructures like CIS include a more representative set of indicators of regulation. Currently the amount of variance in the model explained by regulation is low. Previous research indicates that this is very likely due to an under-representation of regulation issues in the instruments to gather data. This is an issue that deserves attention from statistical authorities to enable the modification of the CIS questionnaire.

The application of the index has been done with panel data. Longitudinal analyses should be conducted to reveal the full potential of the proposed model. Longitudinal analyses will enable efficiency evolution monitoring at the country and sector levels and identification of salient factors amenable to intervention.

The model proposed is static and addresses one element of the innovation system, the firm. There are other actors with an important role in the overall system efficiency. A truly comprehensive evaluation model should include other actors in the system. Given the realities over the last decades of generating databases at national or European levels for one actor (i.e., the firm), we can expect that the challenge of creating a European or even a Global Multi-actor database will remain open for the foreseeable future.

As a last remark, the proposed innovation index could be used as many others that are available, just to rank sectors or countries, as done for soccer league type ranking. Its true potential extends far beyond this. The theoretical underpinnings of the index proposed offer a refined approach based on behavioural research. The possibility of defining the target variables considering specific innovation behaviour, time and context allows the sharpening of the monitoring into specific desired innovative behaviour in industry at the sector or theme level (i.e., environment, health, safety, etc.). The underlying model has been used to understand and predict many types of behaviour. This is a stock of knowledge that has not been tapped into by innovation research. This fact has relevance for reorientation of innovation policy towards the great human challenges. Challenges like environmental sustainability, healthy aging, energy saving, safety and resources efficiency require a reorientation of existing national or sector innovation systems. Thus, in summary the proposed index could be seen as a general framework to explain, predict and monitor social behavioural change and innovation.

References

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior, in J. Kuhl and J. Beckmann (eds). *Action-control: From cognition to behavior*, Heilderberg: Springer, pp. 11-39.

Ajzen, I. (2005), Laws of human behavior: Symmetry, compatibility, and attitude- behavior correspondence. In A. Beauducel, B. Biehl, M. Bosniak, W. Conrad, G. Schönberger, & D. Wagener (Eds.), *Multivariate research strategies* (pp. 3-19). Aachen, Germany: Shaker Verlag.

Ajzen, I., 1991. The theory of planned behavior. *Organizational Behavior and Human Decision Process*, 50, 179–211.

Ajzen, I. (2012). The theory of planned behavior. In P. A. M. Lange, A. W. Kruglanski & E. T. Higgins (Eds.), Handbook of theories of social psychology (Vol. 1, pp. 438-459). London, UK: Sage.

Armitage, C.J. and M. Conner (2001), Efficacy of the theory of planned behaviour: A meta-analytic review, *British Journal of Social Psychology* 40, 471–499.

Beckenbach F. and M. Daskalakis (2008), Behavioural foundations of innovation surveys *International Journal of Foresight and Innovation Policy*, Vol. 4, Nos. 3/4, 181-199.

Blind, K. (2007), Innovation and regulation, Editorial Special Issue, International Joural of Public Policy, Vol. 2, Nos. 1/2.

Bloch, C. (2007), Assessing recent developments in innovation measurement: the third edition of the Oslo Manual, Science and Public Policy, 34, 1, 23–34.

Cainelli, G., R. Evangelista and M. Savona (2006), Innovation and economic performance in services: a firm-level analysis, Cambridge Journal of Economics, 30, 3, 435-458.

Carlsson, B., S. Jacobsson, M. Holmén and A. Rickne (2002), Innovation systems: analytical and methodological issues, Research Policy, 31, 233–245.

Cherchye, L., Moesen, W., Rogge, N., van Puyenbroeck, T., Saisana, M., Saltelli, A., Liska, R., Tarantola, S., (2008). Creating composite indicators with DEA and robustness analysis: the case of the Technology Achievement Index. Journal of the Operational Research Society 59, 239–251.

Cherchye, L., Moesen, W., van Puyenbroeck, T., (2004). Legitimately diverse, yet comparable: on synthesizing social inclusion performance in the EU. Journal of Common Market Studies 42, 919–955.

Coenen, L. and F.J., Díaz-López (2010) Comparing systems approaches to innovation and technological change for sustainable and competitive economies: an explorative study into conceptual commonalities, differences and complementarities Journal of Cleaner Production, 18, 12, 1149-1160.

Cozzens, S. (1991). Science indicators: description or prescription? Washington: Office of Technology Assessment.

Cronbach, T. (1994), Essential of Psychological Testing, London: Hamper and Row.

De Haan, J. (2010), Towards transition thoery, Doctoral Thesis, Rotterdam: Erasmus Univarsity Rotterdam.

Dutta, S. (Ed.)(2011), The Global Innovation Index 2011: Accelerating Growth and Development, Fontainebleau: INSEAD.

European Commission (Ed.), 2003. Third European Report on Science & Technology Indicators 2003. EUR 20025 EN, Brussels

European Commossion (2010), Europe 2020 Flagship Initiative: Innovation Union, Communication from the Commission to the European Parliament, The Council, the European Economic and Social Committee and the Committee of the Regions, COM(2010) Brussels, 6.10.2010, 546 final, SEC(2010) 1161.

Eurostat (2004) The Fourth Community Innovation Survey (CIS 4): Methodological recommendations, Luxemburg: EUROSTAT.

Freeman, C. (1988), Japan: a new national system of innovation. In: Dosi, et al. (Eds.), Technical Change and Economic Theory, London: Francis Pinter, pp. 330–348.

Freeman, C. and L. Soete (1997). The Economics of industrial inovation. Pinter, London.

GAO, (1979). Science Indicators: Improvements needed in design, construction, and interpretation. Washington.

Godin , B. (2003), The emergence of S&T indicators: why did governments supplement statistics with indicators? Research Policy, 32, 679–691

Gollwitzer, P.M., and Bargh, J.A. (eds) (1996). *The psychology of action: Linking cognition and motivation to behavior.* New York: The Guilford Press.

Guan J. and K Chen (2011) Modeling the relative efficiency of national innovation systems, Research Policy (in press available on line)

Guttman, R. in Gratch, H., (Ed.). (1973). Twenty years of social research in Israel. Jerusalem: Jerusalem Academic Press.

Hagedoorn, J. and M. Cloodt (2003), Measuring innovative performance: is there an advantage in using multiple indicators? Research Policy, 32, 1365–1379.

Hollanders H. and A. van Cruysen (2008). Rethinking the European Innovation Scoreboard: A New Methodology for 2008-2010, Report to Pro-INNO, European Commission DG Enterprise and Industry.

Katz, J. S. (2006), Indicators for complex innovation systems, Research Policy 35 893–909.

Kleinknecht, A., Van Monfort, K and E. Brouwer (2002), The non-trivial coice between innovation indicators, Economics of Innovation and New Technologies, 11, 2, 109-121.

Korzybsky, A. (1994), Science and Sanity: An Introduction to Non-Aristotelian Systems and General Semantics, 5th edn, Englewood, N.J: Institute of General Semantics.

Lundvall, B.-Å. (Ed.), (1992), National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning, London, Pinter Publishers.

Mairesse, M. and P. Hohnen (2008), *Innovation surveys and innovation policy*, paper presented at the conference “En route vers Lisbonne” Luxembourg: 4-5 December 2008.

Michell, J. (1997), ‘Quantitative science and the definition of measurement in psychology’, British Journal of Psychology, 88, 355–83.

Mintzberg, H. (1994), The rise and fall of strategic planning. New York: The Free Press.

Malerba, F. (2002) Sectoral systems of innovation and production, Research Policy; 31(2).

Montalvo C. (2002), *Environmental policy and technological innovation: Why do firms adopt or reject new technologies*? Cheltenham, UK and Northampton, MA.: Edward Elgar, pp. 300.

Montalvo, C. (2006), What triggers change and innovation, *Technovation*, 26(3): 312-323.

Montalvo, C. (2007), Explaining and predicting the impact of regulation on innovation: towards a dynamic model, International Joural of Public Policy, Vol. 2, Nos. 1/2, 5-31.

Montalvo, C. (2011), Analysis of market and regulatory factors influencing sectoral innovation patterns. Interim report to the Sector Innovation Watch. Europe INNOVA initiative, Brussels: European Commission Directorate General Enterprise and Industry.

Montalvo, C., P. ten Brink, C. Sartorious, M. Sotoudeh, D. Stromberg, C. Bowyer, M. Fergusson, J. Anderson, F. Sprei, A. Alhback, J. Nassén, R. Nemeskeri, P. Bodo, S. Schilder, F. Heil, G. Angerer, O. Wolf, L. Delgado, M. van Dijk, and F. Lippman (2007). *Policy pathways to promote eco-innovations – Scientific summary report*. European Sixth Framework Program, Contract no. 502487, Project “Policy pathways to promote the development and adoption of cleaner technologies (POPA-CTDA)”, Delft: TNO - The Netherlands Organisation for Applied Scientific Research.

Morgenthaler, S. (2001), Robustness in Statistics, International Encyclopedia of the Social & Behavioral Sciences, 13379-13385.

Nardo, M., M. Saisana, A. Saltelli and S. Tarantola (2005), Tools for Composite Indicators Building, Ispra: DG Joint Research Centre Institute for the Protection and Security of the Citizen, Econometrics and Statistical Support to Antifraud Unit

Nasierowski, W. and F.J. Arcelus (2003), On the efficiency of national innovation systems, Socio-Economic Planning Sciences 37, 215–234.

Nelson, R.R. (Ed.), (1993), National Systems of Innovation. A Comparative Analysis, Oxford: .Oxford University Press.
OECD (2011), OECD science, technology and industry scoreboard 2011, Paris: OECD Publising.
OECD/Eurostat (2005), Guidelines for Collecting and Interpreting Innovation Data — The Oslo Manual, 3rd edn. Paris: OECD.
Sartorious, C. (2008), Promotion of stationary fuel cells on the basis of subjectively perceived barriers and drivers, Special Issue on Diffusion of cleaner technologies: Modeling, case studies and policy Journal of Cleaner Production, 16, 1, Supplement 1, S171-S180.
Schubert T., P. Neuhäusler, R. Frietsch, C. Rammer and H. Hollanders (2011), Innovation indicator - Methodology Report, Bonn: Deutsche Telekom Stiftung
Weissenberger-Eibl, M.A., R. Frietsch, H. Hollanders, P. Neuhäusler, C. Rammer, T. Schubert (2011), BDI – Innovation indicator report 2011, Bohn: Deutsche Telekom Stiftung.
Wehn de M., U. (2003), Mapping the determinants of spatial data sharing, Ashgate.
Zhang, B., S., Yang and J. Bi (2012 in press), Enterprises' willingness to adopt/develop cleaner production technologies: an empirical study in Changshu, China, Journal of Cleaner Production, 20 1-9.

7 Appendix

7.1 Appendix 1 – *ISE* Index calculation with CIS4 data

The following the process was conducted to build $\boldsymbol{ISE_i}$ with CIS4 data. This algorithm is based on the general framework discussed in sections 3.1 and 3.2. Let sectors in CIS4 are denoted by S_i and firms within a sector S_i by $j \in S_i$.

First A_j, N_j, and C_j for a firm j in a sector S_i are estimated. Where,

$A_j = average\ [emar_j + eflex_j + ecap_j + emat_j + (3 - hdem_j) + eenv_j]$, where $0 \leq A_j \leq 3$;

$N_j = average\ [(3 - estd_j) + (3 - hdom_j) + (3 - hmar_j)]$, where $0 \leq N_j \leq 3$;

$C_j = average\ [(3 - rdeng_j) + \mathrm{co}_j + (3 - hfent_j) + (3 - hfout_j) + (3 - hper_j)$
$+ (3 - htec_j) + (3 - hinf_j) + (3 - hpar_j)]$, where $0 \leq C_j \leq 3$;

$IP_j^1 = average\ [inpdgd_j + inpdsv_j + inpslg_j + inpssu_j + orgsys_j + orgstr_j$
$+ orgrel_j + mktdes_j + mktmet_j]$, where $0 \leq IP_j^1 \leq 1$;

and

$IP_j^2 = turnmar_j(tunrover_j)$

The next step is to aggregate A_j, N_j, C_j over all firms in sector S_i (j's in S_i) so that A_{S_i}, N_{S_i}, and C_{S_i} are estimated in such a way that these variables take values in unit interval $[0,1]$. To do that the average over all firms within the sector is calculated and scaled as follows:

$$A_{S_i} = \frac{\underset{j \in S_i}{average}(A_j)}{3}, \ 0 \leq A_{S_i} \leq 1$$

$$N_{S_i} = \frac{\underset{j \in S_i}{average}(N_j)}{3}, \ 0 \leq N_{S_i} \leq 1$$

$$C_{S_i} = \frac{\underset{j \in S_i}{average}(C_j)}{3}, \ 0 \leq C_{S_i} \leq 1$$

Finally we estimate the total innovation propensity for a sector S_i, TIP_i, following the definition given in equation 0.8 in section 3.1 and the innovation performance based on the definitions of innovation intensity (equation 0.9) and innovation efficiency (equation 0.10) given in section 3.2. Then the innovation performance (***IP***) per sector is defined by:

$$IP_{S_i}^1 = \underset{j \in S_i}{average}(P_j^1), \ 0 \le IP_{S_i}^1 \le 1$$

$$IP_{S_i}^2 = \frac{\sum_{j \in S_i} P_j^2}{\sum_i \sum_{j \in S_i} P_j^2}, \ 0 \le IP_{S_i}^2 \le 1$$

Finally $\boldsymbol{ISE_i}$ index for each sector can be calculated and geometrically presented based on the methods which are developed in section 2.1. The same aggregation method is used to obtain $\boldsymbol{ISE_i}$ for a sector, region or country. [14]

[14] To avoid sampling bias generated by county size and response levels we conducted stepwise averaging. First country sectors averages are calculated and later do averages the EU level. This has a significant flattening effect. This is specially the case with CIS data where many of the ranking used ranges in the interval [0, 3]. Great improvements in discrimination and averages calculation will be obtained with a simple change to a broader range, i.e., [1, 7], for example.

7.2 Appendix 2 – Principal component analysis of CIS4 data set

Table 7.1 Spain

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,707	21,808	21,808	3,707	21,808	21,808	2,978	17,518	17,518
2	2,552	15,011	36,819	2,552	15,011	36,819	2,951	17,357	34,875
3	1,271	7,479	44,299	1,271	7,479	44,299	1,602	9,424	44,299
4	1,223	7,196	51,495						
5	1,187	6,982	58,477						
6	,922	5,423	63,900						
7	,861	5,063	68,963						
8	,821	4,830	73,792						
9	,705	4,149	77,941						
10	,666	3,917	81,858						
11	,590	3,468	85,326						
12	,552	3,246	88,572						
13	,508	2,989	91,562						
14	,421	2,477	94,039						
15	,362	2,131	96,170						
16	,346	2,034	98,204						
17	,305	1,796	100,000						

Extraction Method: Principal Component Analysis.

Table 7.2 Europe

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5,431	31,948	31,948	5,431	31,948	31,948	4,596	27,036	27,036
2	2,493	14,666	46,614	2,493	14,666	46,614	3,168	18,633	45,669
3	1,295	7,618	54,232	1,295	7,618	54,232	1,456	8,563	54,232
4	1,023	6,020	60,252						
5	,913	5,372	65,624						
6	,816	4,797	70,421						
7	,720	4,236	74,657						
8	,670	3,938	78,596						
9	,603	3,546	82,142						
10	,549	3,227	85,368						
11	,504	2,963	88,331						
12	,387	2,277	90,608						
13	,366	2,155	92,764						
14	,358	2,107	94,870						
15	,337	1,980	96,850						
16	,278	1,635	98,486						
17	,257	1,514	100,000						

Extraction Method: Principal Component Analysis.