

TNO working paper series

Working paper 2011-002

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

or

**Walking between ridicule and praise: measuring
innovation systems efficiency with a single indicator**

Keywords:

*Innovation indicators, Innovation performance, innovation efficiency, innovation intensity,
theory of planned behaviour, CIS*

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ISSN 2211-0054

TNO Working Paper Series

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TNO Working Paper Series

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

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Working Paper No. 2011-02
28 October 2011

Abstract:

Innovation is currently seen as a cornerstone not only for economic development but also as an intrinsic human activity that could help to face the great challenges of human kind. Given the importance of innovation in the new European 2020 Strategy, measuring progress but also monitoring what drives innovation becomes crucial for policy development. Following upon this strategy the new European flag initiative “Innovation Union” called for a new “single” indicator on innovation. Currently the information infrastructure on innovation in Europe contains a number of indicators. Most of the current indicators at the national or sector levels use a performance theoretical framework based on an efficiency model of inputs and outputs. The last five editions of CIS have been a bastion of innovation policy research during the last decade. 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. 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 demonstration of the index was done using CIS4 data and the results validate the theoretical structure and robustness of the proposed model. This enables its replication for innovation policy analysis in different settings. 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.

JEL codes: O31, O32, N7, Q48

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ISSN 2211-0054

1 Introduction

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 in the new European 2020 Strategy, measuring progress but also monitoring what drives innovation becomes crucial for policy development. Following upon this strategy the new European flag initiative “Innovation Union” (European Commission, 2010), called for a new “single” indicator on innovation. 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 sets on innovation concerning the innovation system (supply side) are 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). The last five editions of CIS have been a bastion of innovation policy research during the last decade. 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 Mogege, 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 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, the calculation of averages and the weight given to data aggregated at the region, sector or national levels.¹ The issue of *normalisation* refers to the process of transformation of variables with different dimensions of measurement to enable aggregation or comparison in a meaningful fashion (Schubert and Braun, 1996). Last, construct *validity* is the hardest to achieve as this 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, the structure of the data should match the structure of the theory underpinning 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 based on behavioural science (e.g., Ajzen 2005; Wehn 2003, Montalvo 2006, Beckenbach and Daskalakis, 2008). In this working paper, following Montalvo (2006) we propose a framework that enables the theoretical and empirical linkage between drivers of innovation to innovation performance via the integration of core features determining innovative behaviour into a single composite. This index enables to assess the total propensity of firms to innovate and assess relative innovation performance in terms of innovation intensity and innovation efficiency.² Once computed the index is easy to handle enabling the benchmarking of different sectors or countries with respect to innovation performance, productivity, employment or GDP. The advantage is that indicator per country or sector is a graphic composite that displays at the first glance the relative throughput efficiency of an innovation system with easy to read graphics.

The paper is structured as follow, section two presents concept of the index and the meaning of its graphical representation. Section three presents the theoretical underpinnings that enable the scoping, weighing and validation of its contents and structure. Section four discusses issues of aggregation and weighing while conducting the empirical validation with three different data sets to assess stability and robustness. Section four seeks to apply and demonstrate the workings of the index showing innovation performance and system efficiency at the country and sector levels. The last section discusses the theoretical contribution of this paper to the literature of innovation studies with respect to overcoming of challenges regarding scoping, aggregation and validation. In addition, it presents salient limitations of the proposed approach to create the index to measure the state of a set of innovation systems as well as further venues for research.

¹ For country comparisons in the case of CIS series the issue has been removed by the allocation of country weights that compensate by the effects of sampling and country size. Sectors benchmarking using simple averaging will inherently be biased by country size and sample distribution. In this paper we have avoided this bias, see section 4.1 in this paper.

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 might have high innovation intensities while failing to profit from innovation activities.

2 Innovation System Efficiency index concept (*ISE*)

The notion of innovation system efficiency is implicitly present in the classical works on innovation systems (Freeman, 1988, Nelson, 1993; Lundvall, 1992). The aim of policy is to make the system more efficient regarding 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). Despite the many issues of innovation systems definitions recently there have been some attempts to explicitly measure efficiency at the innovation system level looking from a classical definition of mechanic efficiency (Nasierowski and Arcelus, 2003; Kats, 2006; Guan and Chen, 2011). The latest innovation indicators at hand aim to aggregate data collected at the national level or sector level and check at the macro level if investments made in the input side produce satisfactory returns. Despite that there is agreement in the overall heuristics of the analysis offered the conclusions in general are spurious as there is no way to validate scores and results (Grupp and Mogege, 2004).

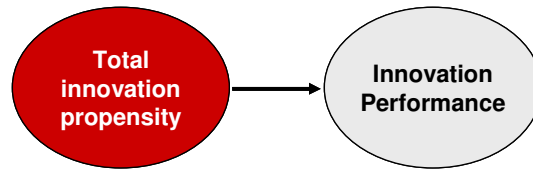
The index here proposed might result complementary to previous attempts to assess innovation system efficiency as we take a micro approach, taking as primary unit of analysis the firm. While taking a supply side approach we were emulating measurement of efficiency as it is done in physics and biology. 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 in the system play an important part in the system performance, generally any 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 different aspects of resources and framework conditions enabling or restricting innovation are accrued at the firm level we assess how well the other components in the system supports innovation behaviour.

The rest of this section presents a conceptual demonstration of the workings of the index. The overall concept regards an efficiency measure, thus we necessarily start with an input and output model, where we are interested in measuring the rate of transformation from inputs to outputs. So far the concept offered is not different to what is the state of the art in the literature as described in section one. 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.

The assessment of both concepts - innovation propensity and innovation performance - can be 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 intends to show 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. The validity of both constructs used for the creation of an innovation system efficiency (*ISE*) composite will be demonstrated in sections three and four below. In the following, we present the definition, a graphical representation of the index and the meaning of its variation.

Figure 2.1 Basic behavioural input/output measures



2.1 *ISE* index – definition, graphical representation and meaning of variation

The process to build the composite is the following: first the total innovation propensity (*TIP*) is estimated following the definition in 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 $0 \leq TIP \leq 1$, and $0 \leq IP \leq 1$.³

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

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

The innovation system efficiency index, *ISE*, is then defined to be an increasing, smooth and odd⁵ function of the innovation efficiency,

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

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

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. $\eta=1$. 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, ($\eta < 1$). An innovation system with innovation efficiency η is called efficient of degree $|\eta|$ if $\eta \geq 0$, and (more or less) inefficient of degree $|\eta|$ if $\eta \leq 0$.

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.

2.2 Geometric representation

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 graphical representation is to summarise the interplay of innovation inputs, throughputs and outputs while maintaining visible issues of scale and rates of transformation.

The 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. :

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

In order to represent ISE geometrically, the trigonometric circle is used. 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:

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

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

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

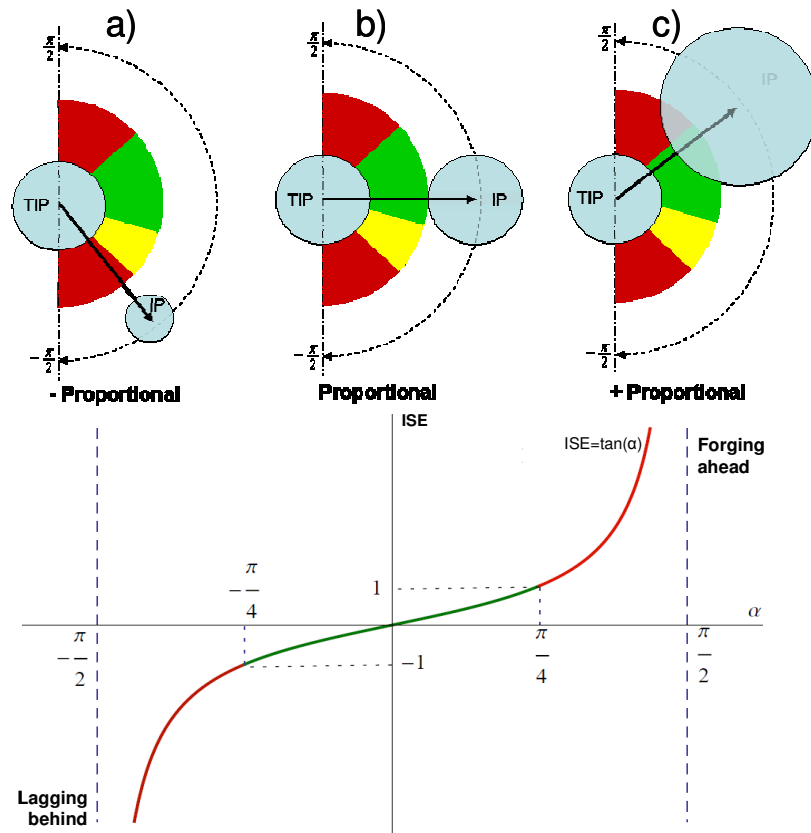
As $-1 \leq \eta \leq 1$, we have that $-\frac{\pi}{2} \leq \alpha \leq \frac{\pi}{2}$ and consequently $-\infty < ISE < +\infty$.

In this case, the geometric representation of 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, this implies that the trajectory along which the results of function (2.4) vary describes the range of efficiency in innovation systems. The efficiency of a particular innovation system will be placed along this trajectory which ranges from infinite efficiency to infinite inefficiency. We can therefore broadly depict three categories 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 state of an innovation system with strong implications for policy design and assessment. In graphical terms these situations are illustrated in Figure 2.2 below. The top part of Figure 2 shows the graphic representation of the index and the lower part shows the shape and trajectory of the smooth function along which the graphic representation of ISE varies.

The graphic representation of the ISE indicates those cases in green tones where the performance ranges between being proportional or more than proportional to the total innovation propensity. The upper middle green range in the indicators that there is a comfort zone where inputs, performance 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 includes 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 smooth function indicates at the end of yellow area that there is a threshold where firms, sectors or countries with persistent low efficiency rates have large shortfall on innovation investment to a point where the risk of lagging behind and sinking. Extreme decreasing returns make it difficult for firms to get out of the sink. Insufficient investments or lack of returns on innovation. Risk of extreme lack of innovative and absorptive capacities and stagnation. The variation interval 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 *ISE* shows asymptotic decreasing efficiency tending to $-\infty$.

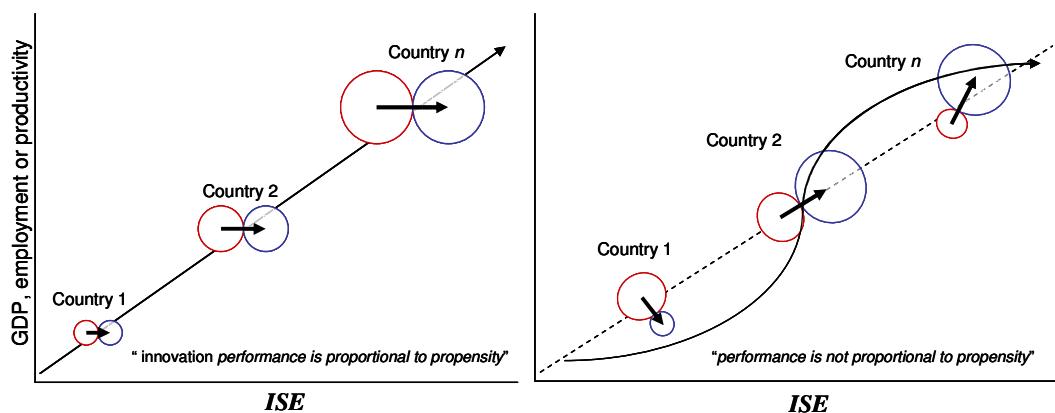
Tendency two: refers to innovation performances that are proportional to the propensity displayed (see figure 2.2b). That is, sets of firms where investments and social support for innovation (*TIP*) produce a proportional or near to proportional innovation performance (*IP*). This could be conceptualised as a “comfort zone” with a highly desirable punctuated equilibrium. Here timelags in structural change allow for timely adjustments 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 financial 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 hidden 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 performance 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 right 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 test (section 5) that although most sectors and countries have less than proportional performances, there are some cases 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 settings. The explained variance on behavioural innovation ranged from 0.62 to 0.86 of the total variance in the data (Montalvo 2002, Wehn 2003, Montalvo 2006, Sartorius, 2008). More recently the approach has been applied in surveys at a European level producing satisfactory results in sectors like industry, transport, agriculture and energy (Montalvo et al., 2007). The basic rationale of the model to guide the integration of an innovation efficiency index is presented below.

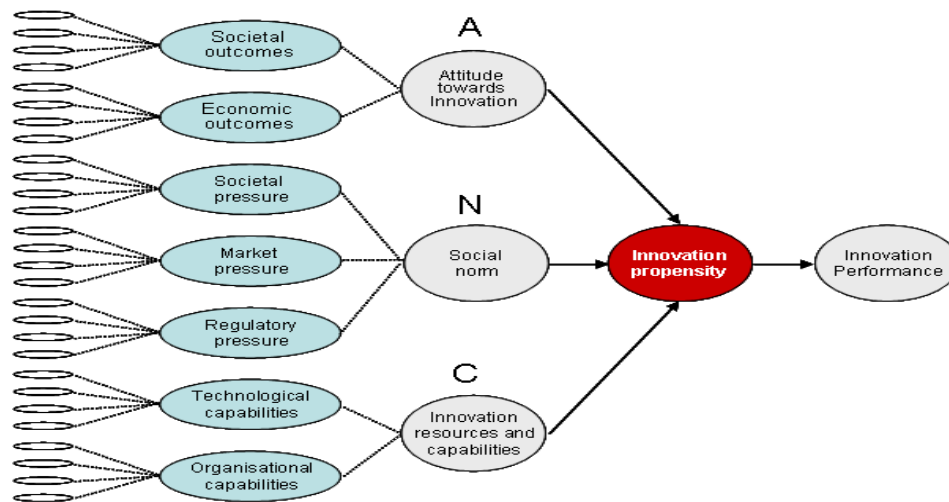
Ajzen (1985) demonstrated that the behavioural intent of people could be explained in terms of three constructs: the attitude towards the behaviour, the social norm pushing pro or against the behaviour, and the degree of control exerted upon behavioural performance. An equivalent structure with three 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

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/ajzen/tbrefs.html>

⁷ The path of causality is depicted here for matters of stylised presentation, the relationships between constructs are limited to those to the lines indicated. Empirical evidence indicates that there are also correlations between constructs other than those indicated in the diagram. See Montalvo (2006).

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.

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

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, 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 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 Cronbach 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

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. A firm while innovating 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, 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.). 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 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 still several single 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 Cloudt (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. Examples of multidimensional measures include the European Commission with its Innovation Scoreboard (Hollanders and Cruysen, 2008), the INSEAD global innovation

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.

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 (IP_I) and innovation efficacy (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.

$$IP_I \propto \sum_{i=1}^n IA_i \quad (3.5),$$

and

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

Where,

- IP_I is innovation intensity,
- 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 operate closely the definition of innovation as provided by Freeman and Soete (1997), definition that implies market value and economic performance. The reliability of the innovation intensity construct will be tested in the next section. In section five the empirical application of the index reveals that those countries and sectors with higher innovation intensities and better conditions to innovate are not necessarily those profiting more effectively from innovation.

4 Empirical validation

In this section we demonstrate the empirical validation of the composite proposed. First we briefly discuss how the individual variables in the composite are weighed and how the three components integrating the total innovation propensity obtain their respective weight. Then we proceed then to show the validation of the two major components of the *ISE* index proposed.

4.1 Variables and aggregated composite elements weighing

The construction of indicators according Grupp and Schubert requires the selection of variables to be included in the composite and of weights attributed to each variable included. The selection and number of variables and the respective 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 of item (or variable) is rated in an interval scale (0-3, -3,3, or 1,7) where all items in the component are geared to measure a dimension of innovative behaviour in firms (along the three components: cognitive, normative and instrumental) as defined in section 3.1 above. The difference in the relevance of each item in a component is given by the expectancy-value held and reported by each respondent that participated in the data survey. The expectancy-value model ensures that each item holds probability independence to contribute to the overall weight of each of the respective components.¹¹ Each component is tested regarding the reliability of measurement of every item that is included (Crombach test). Items that do not contribute to the measurement of the component are not included for further analysis. Then the variables are aggregated as part of one of the three components that integrate the model. Three dimensions integrate the more general model *TIP*, thus the model includes three scales.

The number of variables to be considered for inclusion in the model is dependent on insights derived from the literature on innovation and from empirical research 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 rationale of one of the constructs in the model and its internal cohesiveness is high. Second, it will be also contingent upon the amount of variance explained in the sample when an additional variable is included in one of the components. It is desirable to continue including variables in the model for as long as a higher percentage of explained variance in the sample is obtained. Here is necessary to pool a large number of variables to be considered for aggregation. It can be expected that, at the end of the pooling process, few variables will remain in the model when applied to specific cases. Empirical evidence indicates that few factors affect and drive behaviour in specific settings and time. This is not a minor issue and should not be neglected in future applications of this model, as we could expect that the importance of a set of factors will vary across time and settings. No general rule exists that indicate that a factor will remain important across time.

The weighing of variables within in each of the components and the weighing of components themselves are determined by the random rating given by each participant

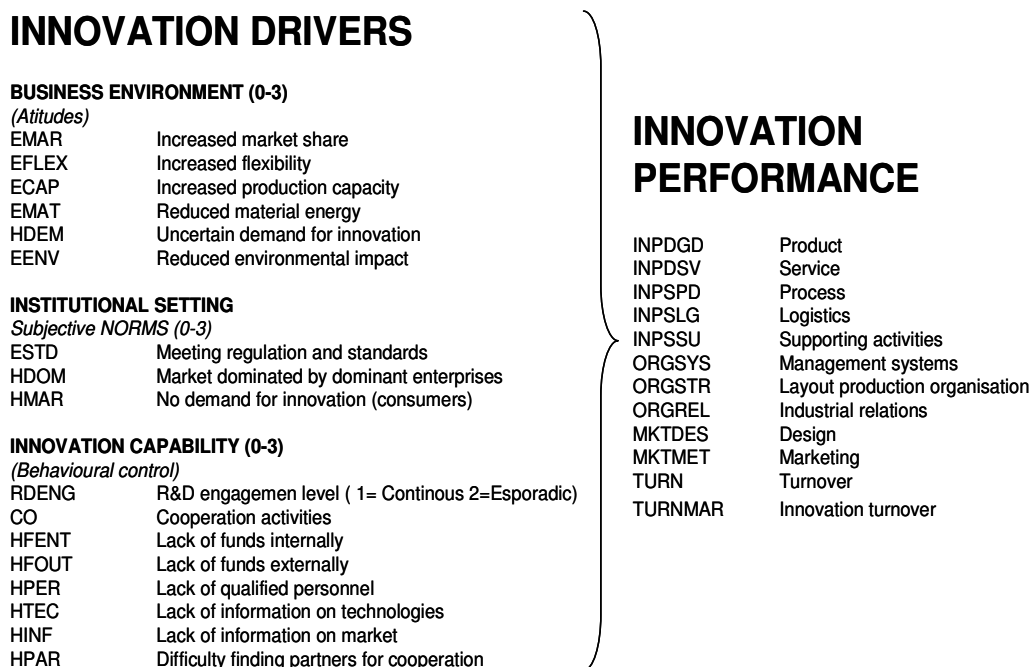
¹¹ In the expectancy-value model (EV) the probability of each item within a component is independent while in the subjective utility model (SU) all items in a component must add to one. The later approach to decision making analysis presents problems in the allocation of variables weights while the former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

in the survey and the theoretical properties of the model proposed. In this case equal weighing, that is, using the same item scale across all variables renders a rule that is used as measuring device to find differences amongst firms, sectors or countries. The explanatory properties, that is, the relative weight of each component are tested by OLS and PCA tests. The model differs further more from what is available in the innovation literature once we relate the value of *TIP* to a scale of innovation activities (*IP*) with and without imputed turnover over an efficiency function. Each country is given an efficiency rate and that efficiency rate is plotted against employment, GDP or productivity. The model underlying the index proposed provides not only a picture of the innovation system efficiency but also a link to economic performance and to the factors that determine the relative performance.

4.2 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 (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 ranging and questions wording in the questionnaire applied during the data collection. The second instance includes the usage of an existent data set, the Community Innovation Survey (CIS4), where the variables contained in the data set were classified and aggregated following the euhristics described in section 3.1 and 3.2. The conceptual match of between *ISE* components and CIS4 variables included in the statistical validity testing and index calculation in section five of this paper are shown in Figure 4.1 below.

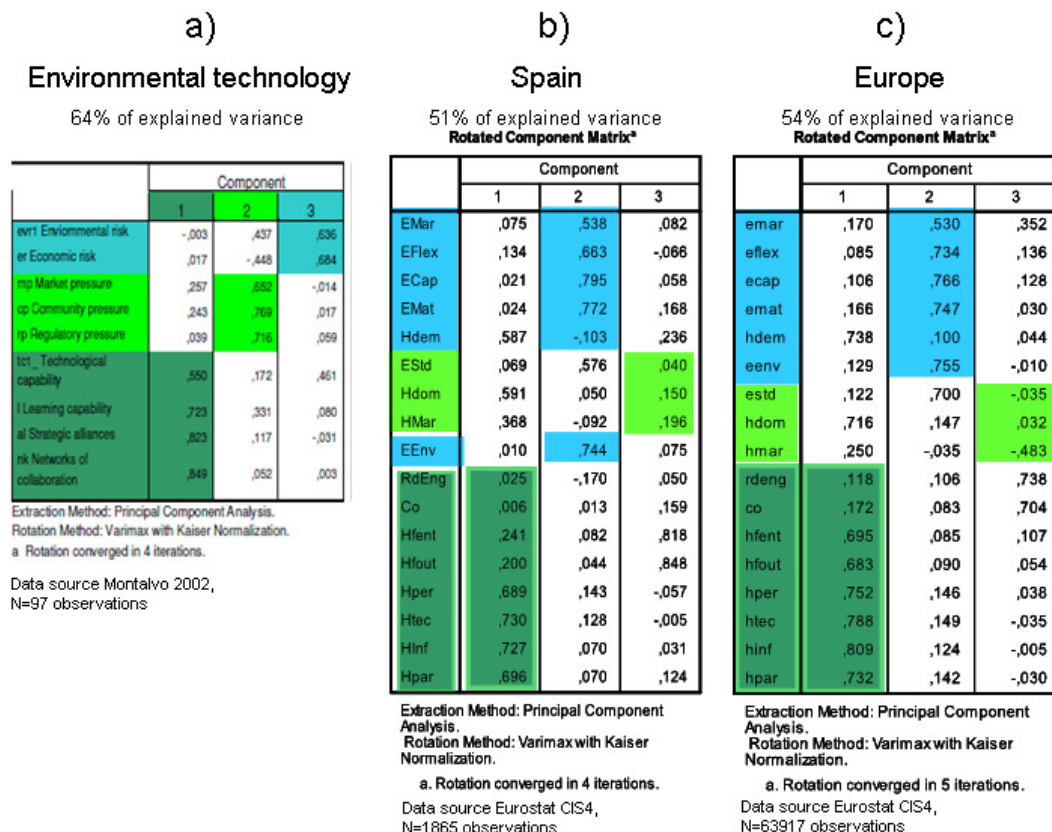
Figure 4.1 *ISE* and Community Innovation Survey – conceptual match



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: cognitive – 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. Only three items were found that match the criteria set in section 3.1. The insufficient attention given 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 mismatch with CIS the results are highly satisfactory. The clustering done following the model of propensity here provided renders a good fit to the data, thus, explaining a large proportion of the variance in the sample. Figure 5.2 below shows empirical results with three different data sets.

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



The results presented in Figure 4.1 strongly support the validity of the structure proposed for the creation of the input composite “total innovation propensity” (*TIP*). 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.

Figure 4.2a display 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 very 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 with a moderate size population sample. The fit to the model is very good in two components and not so good 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 less perfect fit in the usage of the second data set is due to the not sufficient representation of normative variables in the dataset used. In addition, poor 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 in the questionnaire set. Taking into account the results presented in the above we can consider the structure and content of the total innovation propensity construct proposed here a valid measure. This validity stems from the basic definition of measurement validity in social sciences (see Morgenthaler, 2001; Montalvo, 2002, Appendix A).

4.3 Empirical validation – Innovation Performance

The validity of the innovation performance construct is relatively simpler than *TIP*. This stems from the relative 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 Cronbach 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 (Cronbach, 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 *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 analyse levels of innovation performance and efficiency with different underpinnings to what is currently available in the literature of innovation. In addiiton, this is done to test whether the *ISE* index ranking results provide confirm current innovation ranking trends for countries in Europe. The rationale is to show that some countires could be ranking relatively lower than innovaiton leaders and still show healthy and efficient innovation systems.

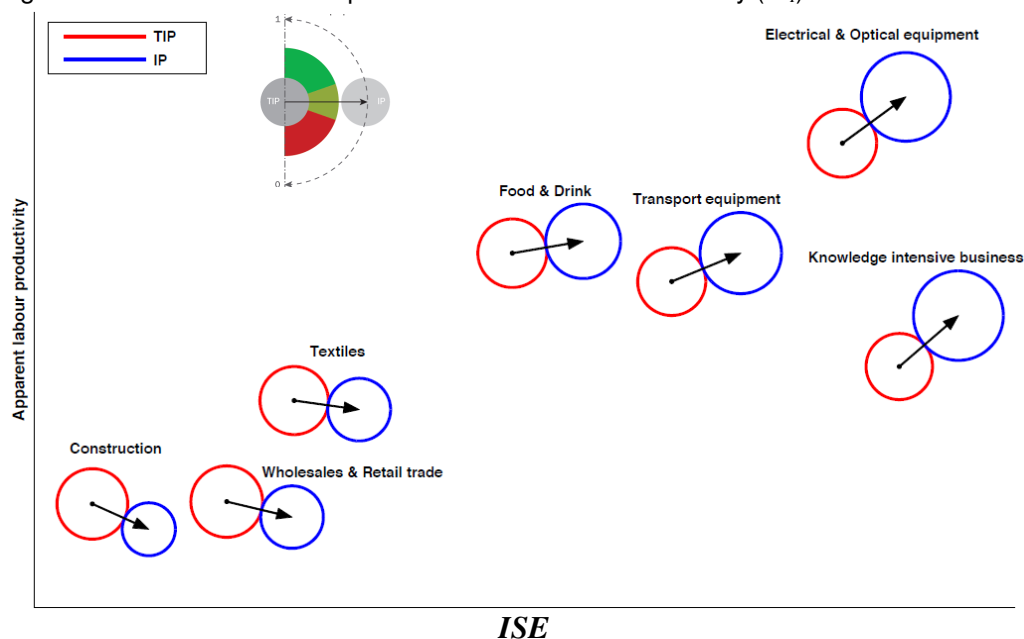
5 State of an innovation system

This section offers examples of the application of the innovation efficiency index introduced above. The empirical demonstration of this index is conducted for the sectors of transport (automotive and aviation), construction, food and beverages, optical and electrical equipment, knowledge intensive businesses, textiles, and wholesales and retail trade. In this section results of the index demonstration is done with CIS4 data including 63917 observations. The weighting of response distribution was done according to the regulation provided by Eurostat (2004).¹² The algorithm used to calculate the *ISE* with CIS4 data is provided in Appendix 1 of this paper. 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 as will be noted below concern 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 at the sector level in terms of innovation intensity. The arrows show the rate to efficiency in the innovation system. In general, systems with higher efficiencies will be found in the right side of the plottings.

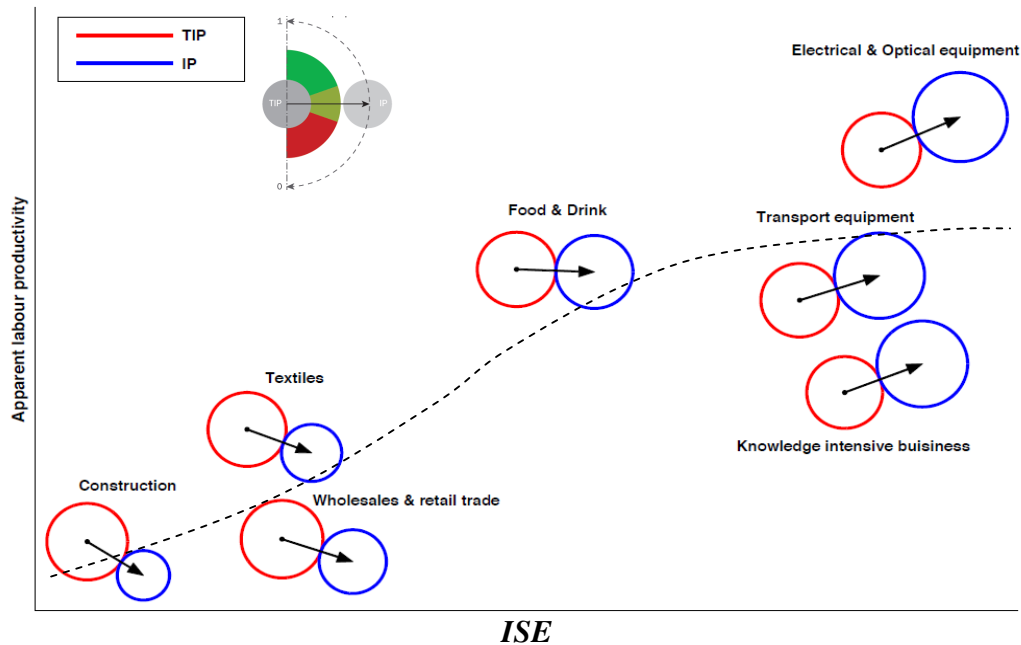
Figure 5.1 Sectors innovation performance – innovation intensity (IP_i)



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. Note that, the variable WEIGHT is the original weighting or grossing factor to be used for grossing up purposes. In cases for which no non-response survey done (i.e. the response rate was sufficiently high) then no correction for non-response bias has been made. If there was a correction to the weights for bias from the non-response survey, then this is recorded as WEIGHTNR in CIS data. For a detailed info see the attached document (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. This has a significant flattening effect. This is specially the case with CIS data where many of the ratings used range in the interval [0, 3]. Great improvements in discriminatory power and averages calculation will be obtained with a simple change to a broader range in items rating, i.e., [1, 7].

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.

Figure 5.2 Sectors innovation performance – 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 propensity 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 relationship of the ISE index with labour productivity match the meaning of the index variation. 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 determining 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) ranking¹³

| 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 & Retail 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 & Retail 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 (IP_E). These changes are displayed in Table 5.2, one of the most extreme country repositioning concerns Greece. In the innovation intensity ranking where many countries show relative good performances Greece 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, Lithuania, Slovakia and Belgium with low 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 Countries innovation system efficiencies

The figures 5.3 and 5.4 below show the innovation intensity and innovation efficacy for several European countries. Similarly 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 Czech Republic, and Portugal are the best performers.

Figure 5.3 Countries innovation intensity landscape

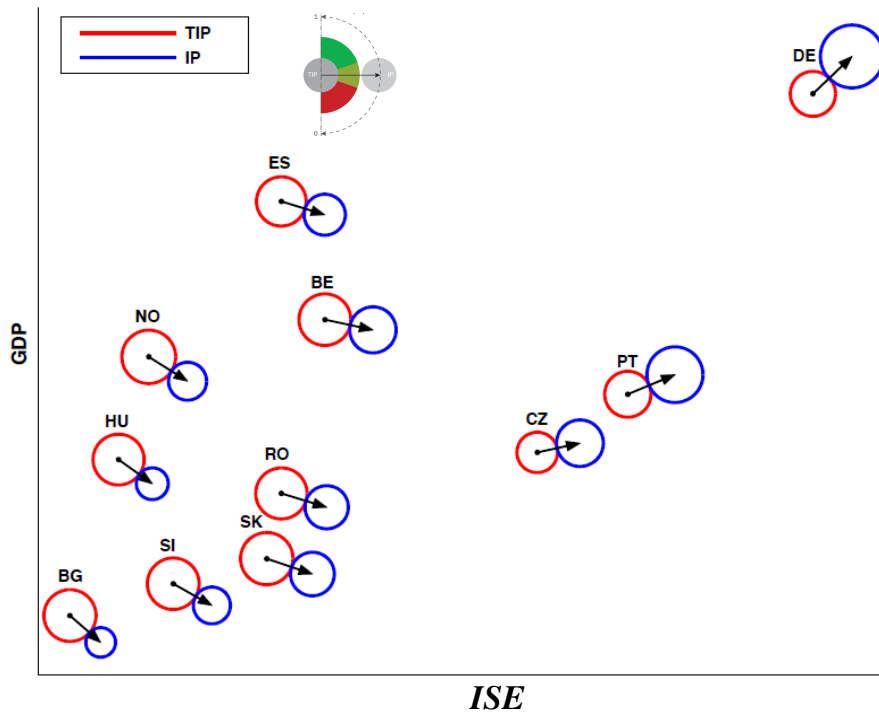
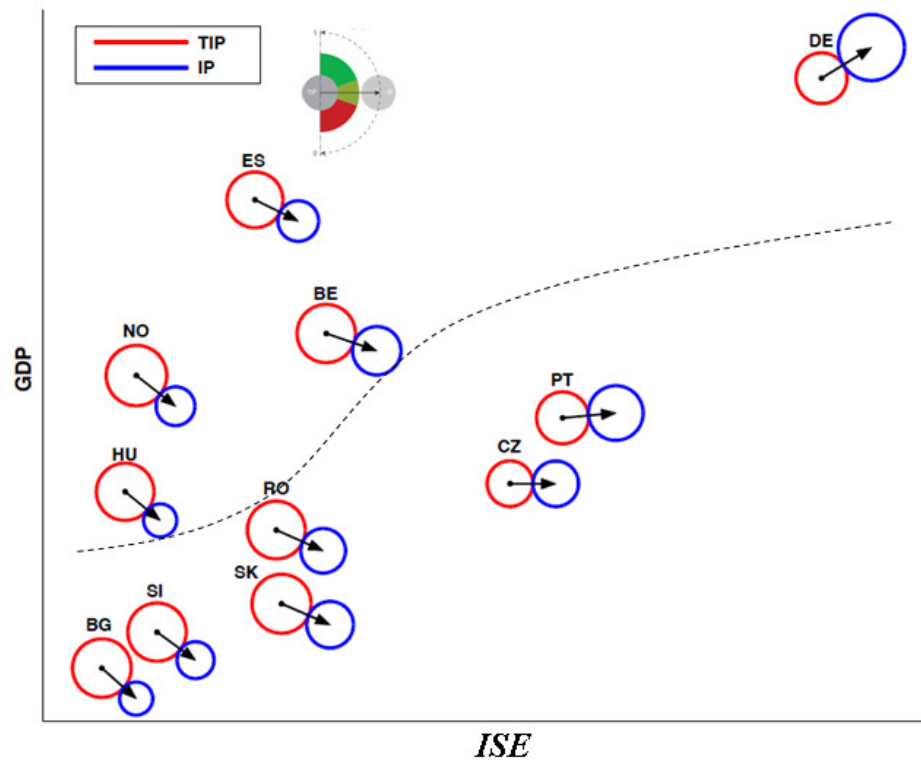


Figure 5.4 Countries innovation throughput efficiency landscape



6 Conclusion and final remarks

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 different data sets rendering good properties in stability and robustness across datasets. In this concluding section we address the issues of theoretical contribution done, salient aspects of its application to innovation efficiency monitoring in sectors and countries, limitations identified so far and some aspects that deserve to be further researched.

6.1 Theoretical contribution

In contrast with current innovation indicators 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 application of the index validated the structure and contents of the index proposed. The empirical structure of the data 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 have 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 have been 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 the European Community limits the possibility of a 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 so far for data sets at one point in time. Longitudinal analyses should be conducted to reveal the full potential of the proposed model to build the indicator. Longitudinal analyses will enable not only to monitor the evolution of efficiency at the country and sector levels, but also to test which are the most salient factors amenable to policy intervention.

The model proposed is static and addresses one element of the innovation system, the firm. There are clearly other elements in the system with an important role in the overall system efficiency. A truly comprehensive evaluation model should include other actors in the system. This presents two challenges, the first regards the theoretical model that describes and enables the conceptual and mathematical modelling of the interactive dynamics of several actors in the innovation system. To a large extent, this challenge has been resolved with the works of Kleinwoolthuis et al. (2005), Montalvo (2007), Suurs (2009) and De Haan (2010). These works presented elements to design a quantitative framework to assess the overall dynamics of an innovation system, with behavioural science underpinnings. The second challenge concerns data availability. Given the realities of generating databases for one actor in the system (i.e., the firm) over the last decades, 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 here offer a refined approach based on human behavioural change 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 behavioural change and innovation.

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7 Appendix

7.1 Appendix 1 – Index calculation with CIS4 data

The following the process was conducted to build 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,

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

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

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

$$IP_j^1 = \text{average} [inpdgd_j + inpds_v_j + inpslg_j + inpsu_j + orgsys_j + orgstr_j + orgrel_j + mktdes_j + mktmet_j], \quad \text{where } 0 \leq IP_j^1 \leq 1;$$

and

$$IP_j^2 = \text{turnmar}_j(\text{turnover}_j)$$

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:

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

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

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

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:

$$IP_{S_i}^1 = \text{average}(P_j^1), \quad 0 \leq IP_{S_i}^1 \leq 1$$

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

Finally 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 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

| Component | Total Variance Explained | | | | | | | | |
|-----------|--------------------------|---------------|--------------|-------------------------------------|---------------|--------------|-----------------------------------|---------------|--------------|
| | 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

| Component | Total Variance Explained | | | | | | | | |
|-----------|--------------------------|---------------|--------------|-------------------------------------|---------------|--------------|-----------------------------------|---------------|--------------|
| | 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.

Vitae

Carlos Montalvo works as Senior Scientist on Industrial and Innovation Policy at TNO. With 23 years of professional experience, he has extensive practice as engineer in project and R&D management and in multidisciplinary and international policy research. Previous to joining TNO he held a number of engineering and management positions in industry and international organisations. His research output gives support to European Commission in several key RTD and innovation actions and policy. Since 2001 he is Subject Editor on innovation and environment for the Journal of Cleaner Production. His work on Behavioural Innovation Economics has been recently recognised as pioneering in the literature of innovation studies. Dr. Montalvo current activities and research interest spread across: evaluation of innovation and RTD policy; sectoral R&D and structural change; innovation and the environment, innovation and regulation, technology adoption and diffusion analyses, and in the application of behavioural dynamic models to explore the interaction between actors influencing innovation and change.

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