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Article

On the meaning of innovation performance: Is the synthetic indicator of the Innovation Union Scoreboard flawed?

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Abstract

The European Union (EU) annually publishes an Innovation Union Scoreboard (IUS) as a tool to measure the innovation performance of EU Member States by means of a composite index, called the Summary Innovation Index (SII). The SII is constituted by an average of 25 indicators. The SII is claimed to rank Member States according to their innovation performance. This means that the higher the average value of the 25 indicators, the better the innovation performance is said to be. The first purpose of this article is to assess whether the SII constitutes a meaningful measure of innovation performance. Our conclusion is that it does not. Our second purpose is to develop alternative, productivity or efficiency-based, measures of innovation system performance based on a simple index number, and complement it with advanced and robust nonparametric Data Envelopment Analysis techniques. By doing so, the article offers a critical review of the SII, and proposes to put more emphasis on the identification of and relation between input and output innovation indicators. The data provided by the 2014 and 2015 editions of the IUS are here used to analyze the innovation performance of all 28 EU national innovation systems. A theoretical background and reasons for selecting the indicators used are presented, and our new ranking of the innovation performance using bias-corrected efficiency scores of all EU countries is calculated. We find that the results differ substantially between the SII and the ranking based on our method, with significant consequences for the design of innovation policies.

Key words: innovation system; innovation policy; innovation performance; innovation indicators; input; output.

1. Introduction

The European Union (EU) has set ambitious objectives in five areas to be reached by 2020. In addition to climate and energy, education, employment, and social inclusion, innovation is one of the five pillars to form a so-called 'Innovation Union' (European Commission 2013). To support the establishment of the Innovation Union, the European Commission is using the Innovation Union Scoreboard (IUS).

The objective of the IUS is to provide a 'comparative assessment' of the 'innovation performance' of EU Member States (European Commission 2011: 3). To assess the 'innovation performance' of the Member States, a Summary Innovation Index (SII) is calculated by the IUS. The SII synthetizes the 25 indicators included in the IUS, through their arithmetic average, into a single measure. As a result, the SII ranks all EU Member States based on what is explicitly called 'EU Member States' Innovation Performance' (European Union 2014: 5).

The first aim of this article is to assess whether the SII constitutes a meaningful measure of innovation performance, as argued by the

IUS. Following Zabala-Iturriagagoitia et al. (2007a) or Nasierowski and Arcelus (2012), among others, the second aim is to develop alternative, productivity or efficiency-based, measures of innovation performance. By doing so, we provide a critical review of the SII, propose to place more emphasis on the identification of and relation between innovation input and output indicators, and on this basis we provide an alternative assessment and ranking of innovation performance.

When developing an alternative approach to the one used by IUS, we use exclusively and exactly the same data as provided by the IUS 2014 and 2015 to assess and compare the performance of all EU28 national innovation systems. We reexamine these data using our different approach, which relies on a productivity—or relative efficiency—rationale. We do not discuss the quality and accuracy of the IUS data. We simply use the existing data provided by the IUS but seen through a different (productivity) lens, with the purpose of increasing the breadth of sight of innovation policy makers and politicians.[1]

A similar efficiency approach has been used by the Global Innovation Index (GII). The 'Innovation Efficiency Ratio' provided by the GII is 'the ratio of the Output Sub-Index score over the Input Sub-Index score. It shows how much innovation output a given country is getting for its inputs' (Dutta et al. 2017). The GII aggregates 81 different indicators for 143 countries, using different sub-indices to aggregate them.

Following the theoretical bases used in productivity and efficiency measurement methods (Farrell 1957; Coelli et al. 2005), we single out a number of input ($N = 4$) and output ($M = 8$) innovation indicators from the 25 included in the IUS editions of 2014 and 2015. They are used to compare the innovation outputs with the innovation inputs of each of the EU28 countries, so as to get a measure of the performance of the innovation systems (i.e. the relationship between the innovation inputs and outputs).

We conclude that the SII does not constitute a meaningful measure of innovation performance and that this indicator is not useful from the point of view of innovation policy design. Our alternative approach results in a radically different ranking of EU Member States' innovation performance. Our performance and ranking results, however, lead to counterintuitive conclusions, which we discuss and evaluate. This means that the analysis has to be refined and developed in future research.

The rest of the article is organized as follows. Section 2 discusses the concept of innovation performance and presents the rationale for the approach we have chosen. In Section 3 we present the index number and DEA methods and discuss the selection of output and input indicators. The empirical analysis is presented in Section 4. There, we use the normalized IUS scores for each of the selected indicators, provide the rankings for both innovation inputs and outputs, and calculate the efficiency of all 28 innovation systems by relating the innovation outputs and inputs to each other through the index number and robust DEA scores. Section 5 provides a discussion of the main findings and its relevance for the practice of innovation policy making, and also makes some proposals for future research.

2. Theoretical background

During the past decade an increasing literature has dealt with the development and use of indicators to improve the measurement and characterization of innovation systems (e.g. Archibugi, Denni, and Filippetti 2009). The European Commission has been one of the most active agents in this sense, with the development of the European Innovation Scoreboard (since 2011, IUS) and the implementation of the Community Innovation Surveys.

As indicated in Section 1, the IUS claims that the SII calculated is measuring innovation performance of EU Member States. But what is then meant by 'innovation performance'? Let us discuss this concept by a metaphor. Let us imagine that two countries are trying to send a rocket to the moon, and both succeed. However, the first required \$1 billion to achieve that goal, while the second required \$1. If only outputs are considered, both countries would have achieved the same level of 'performance'. However, it can be strongly argued that the second country might have achieved a remarkably higher performance, since the amount of resources used in the two cases is so unalike. This approach is also shared by Carayannis and Grigoroudis (2014) and Liu, Lu, and Ho (2014: 318) who consider that the measurement of the performance of an innovation system should be accomplished through 'a linear process-oriented approach, whereby a nation's innovation system is treated as a process in which certain output factors... are seen as products produced from a set of input resources'.

This means that if we are to compare performance in a meaningful way the achievement (e.g. landing on the moon) must be related to the resources used (e.g. a budget constraint). In other words, outputs must be related to inputs in some way. In economics, productivity is defined as the value of output produced per unit of input, e.g. labor productivity is total production divided by employment. This is similar to measuring performance of innovation systems in terms of productivity or efficiency.

From the policy evaluation literature we have learned that (innovation) policies must be context specific. These policies will define the goals of the innovation policy, identify the problems in the innovation system, and specify or develop and implement the instruments to mitigate the problems and thereby achieve the objectives (Edquist 2018). In other words, the policy must define where to go and how to get there. However, if we do not know where we are, how can we get anywhere? Indeed, it is in fact very difficult to improve what cannot be measured.

It is not possible to say whether certain innovation intensities are high or low in a specific system if there is no comparison with those in other systems (Edquist 2011). This has to do with the fact that we cannot identify optimal or ideal innovation intensities (just as we cannot specify an optimal innovation system). There appears to be general support 'to the premise that all performance evaluations involve comparisons' (Mersha 1989: 163). Hence the measurement of innovation performance must be comparative between existing systems (Zabala-Iturriagagoitia et al. 2007b). Only then can they be helpful to policy design by identifying problems to be solved or mitigated by the implementation of policy instruments.

In spite of the flags often raised in the literature as to the misuse of synthetic indicators in policy making spheres (e.g. Grupp and Schubert 2010), composite indicators are repeatedly used for the design of innovation policies (Saltelli 2007). One of the risks of using synthetic indicators is that, once they are used and accepted, their abuse makes them become policy targets, and hence, loose their meaning as a tool to explain certain realities. Saltelli refers to the work by Nardo et al. (2005) when discussing the steps required before creating a composite indicator.[2] The SII falls short in meeting several of those steps.

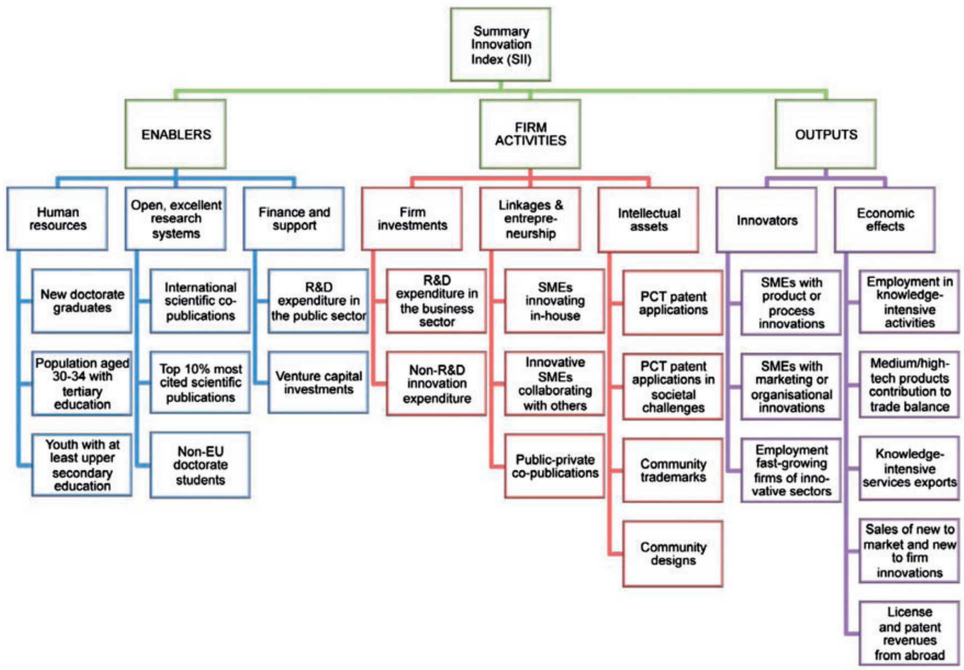

Figure 1. Measurement framework of the IUS.

Source: European Union (2014: 8).

We claim that to assess the innovation performance of any system, the performance measure should be based on a productivity relation, defined as a ratio of aggregate innovation outputs (numerator) to aggregate innovation inputs (denominator). The most simple way of doing so is to classify indicators as either inputs or outputs, combine them using an aggregator function (e.g. the arithmetic average), and then relate one to another by using a simple fraction. A more advanced method relies on robust nonparametric data envelopment analysis (DEA) techniques to calculate a productivity index for each country using individual—most favorable—aggregating functions, which also allow accounting for the nature of returns to scale (increasing, constant, or decreasing). In this article we use both methods.

An important difference between the simple aggregate productivity index and its DEA associate is that the former, being a basic index number, can be easily calculated with low effort and high immediacy (e.g. using a spreadsheet), while the latter relays on linear programing techniques that require solver optimization with bootstrapping. But, in return, the latter yields relevant information about the innovation processes that are evaluated (benchmark peers for inefficient observations, nature of returns to scale, etc.) as well as the statistical significance of the productivity estimates.

3. Methodology and relevant indicators

The IUS identifies ι_l, $l = 1, \ldots, 25$, indicators, which are divided into three categories and eight dimensions (see Fig. 1). The three categories considered are *Enablers*, *Firm activities*, and *Outputs*. According to the IUS, the *enablers* 'capture the main drivers of innovation performance external to the firm' (European Union 2014: 4) and cover three innovation dimensions: human resources, open, excellent and attractive research systems, and finance and support. *Firm activities* 'capture the innovation efforts at the level of the firm' (ibid) and are also grouped in three innovation dimensions: firm investments, linkages and entrepreneurship, and intellectual assets. Finally, *outputs* cover 'the effects of firms' innovation activities' (ibid) in two innovation dimensions: innovators and economic effects.

From a numerical perspective, to adjust the values of each indicator observed in country i in period t to a notionally common scale, the IUS normalizes each series so their values belong to the following range: $\hat{\imath}_{li}^t \in [0,1]$.[3] Subsequently, the IUS calculates the SII using the arithmetic mean as aggregating function, in which all indicators are given the same weight υ_l:

$$SII_i^t = \sum_{l=1}^{25} \bar{\upsilon}_l \hat{\imath}_{li}^t, \quad \bar{\upsilon}_l = 1/25,\ \hat{\imath}_{li}^t \in [0,1]. \qquad (1)$$

Note that the SII_i^t index does not necessarily yield a distribution whose maximum value is equal to 1, thereby identifying the most productive innovation system with such value. To ensure this desirable property that is helpful to highlight best performance, and rank innovation systems against a single scalar—and that is shared with the forthcoming productivity indices, we normalize SII_i^t by dividing by the maximum observed value across the set of $j = 1, \ldots, J$ countries:

$$\widehat{SII}_i^t = \frac{\sum_{l=1}^{25} \bar{\upsilon}_l \hat{\imath}_{li}^t}{\max_j \left(SII_j^t\right)}, \quad \bar{\upsilon}_l = 1/25,\ j = 1, \ldots J,\ \widehat{SII}_i^t \in [0,1]. \qquad (2)$$

The IUS draws the conclusion that the country with the highest SII_i^t- or $\widehat{SII}_i^t$-is also the best innovation performer regardless of whether the indicators used measure the input or output side of innovation or something else. In addition, the IUS provides no explicit definition of innovation performance, which is quite surprising, since this is the most central concept in the scoreboard reports. However, implicitly and in practice, the SII score can be said to be the IUS definition of innovation performance. On this basis, EU Member States are ranked according to the SII in the following groups: *innovation leaders* (more than 20% above EU average), *innovation followers* (less than 20% above, or more than 90% of the EU average), *moderate innovators* (relative performance rates between 50 and 90% of the EU average), and *modest innovators* (less than 50% of the EU average) (European Union 2014: 11).

3.1 Identification of input and output indicators

We have argued that innovation performance must be measured as a ratio between a numerator and a denominator. Our way of doing so is to classify indicators as either inputs or outputs and then relate them to one another. We will now discern which of the 25 IUS indicators in Fig. 1 can be qualified as inputs, as outputs, or as something else (e.g. indicators measuring intermediate phenomena, or consequences of innovations). Following the guidelines provided by the Oslo Manual (OECD/Eurostat 2005), we define input and output indicators as follows:

Innovation input indicators *refer to the resources (human, material, and financial; private as well as governmental) used not only to create innovations but also to bring them to the market.*

Innovation output indicators *refer to new products and processes, new designs, and community trademarks, as well as marketing and organizational innovations, which are connected to the market, and which can either be new to the world, new to the industry, and/or new to the firm.*

We classify eight IUS indicators as measuring innovation output and four as measuring innovation input. The remaining 13 indicators from the IUS are certainly not irrelevant. In fact, many of these indicators can be regarded as determinants of innovation processes. However, further research is needed on the factors influencing (fostering or hindering) the development and the diffusion of innovations (see Edquist 2005). When more evidence is available about these determinants, the view on what indicators can be regarded as inputs or outputs will certainly have to be adapted. Below we provide our reasons to include some indicators and not others in these categories. Below we list the eight output indicators considered in this article.[4]

- 2.2.1: Small and medium-sized enterprises (SMEs) innovating in-house (% of SMEs)
- 2.3.3: Community trademarks per billion gross domestic product (GDP) (in Purchasing Parity Power (PPP)€)
- 2.3.4: Community designs per billion GDP (in PPP€)
- 3.1.1: SMEs introducing product or process innovations (% of SMEs)
- 3.1.2: SMEs introducing marketing or organizational innovations (% of SMEs)
- 3.2.2: Contribution of medium and high-tech products exports to the trade balance
- 3.2.3: Knowledge-intensive services exports (as % of total service exports)
- 3.2.4: Sales of new-to-market and new-to-firm innovations (as % of turnover)

The notion of *innovation output*, according to our definition, is partly different than the IUS category of ‘outputs’, which is defined as ‘the effects of firms’ innovation activities’ (European Union 2014: 4).[5] We contend that indicators 2.2.1, 2.3.3, and 2.3.4 should be categorized as output indicators, despite they are classified in the IUS as ‘firm activities’ rather than ‘outputs’. For example, the indicator 2.2.1, ‘SMEs innovating in-house’, refers to the SMEs that have succeeded in the introduction of new or significantly improved products and/or processes, and which may have been innovated inside the company. Therefore, this indicator is in fact capturing an output of an innovation system.

Similar arguments hold for indicators 2.3.3 ‘Community trademarks per billion GDP’ and 2.3.4 ‘Community designs per billion GDP’. We consider that community trademarks and designs are significant aspects of actual product innovations, as they signal intellectual property rights related to a specific new product that is connected to the market (see also Mendonça, Santos Pereira, and Mira Godinho 2004).

Indicators 3.1.1 through 3.2.5 are considered to be ‘outputs’ by the IUS. However, a conceptual difference exists between the label ‘outputs’ as used in the IUS and the concept of innovation output used in this article. It is for this reason that we do not classify as innovation outputs the following three indicators referred to in the IUS as ‘outputs’: 3.1.3, ‘Employment in fast-growing firms of innovative sectors’; 3.2.1, ‘Employment in knowledge-intensive activities’; and 3.2.5, ’License and patent revenues from abroad’. Indicators 3.1.3 and 3.2.1 measure employment. Employment may be a consequence of innovations or the result of other economic forces rather than an innovation as such—just as with economic growth. As to the indicator 3.2.5, licenses and patent revenues, it refers to sales of intellectual property rights, and cannot be considered an indicator of innovation output according to the previous definition.[6]

Classifications of individual indicators in a certain category (outputs here) can certainly be questioned and discussed. We therefore carried out a sensitivity analysis, which is reported in Section 4.1, in which we classified 12 indicators instead of 8 as innovation outputs.[7]

Looking further at the measurement framework of the IUS (Fig. 1), it becomes clear that while one of the main categories is considered to be a measure of innovation *Outputs*, there is no category explicitly referring to innovation inputs, or providing a clear specification of what such inputs could be. We consider four indicators to fulfill the requirements for being classified as innovation inputs—see below. Two of these indicators are categorized in the IUS as ‘enablers’ and two as ‘firm activities’. Two measure R&D expenditures from the public and private sector, which are both important determinants of innovation.[8] Venture capital, which is important ‘for the relative dynamism of new business creation’ (European Union 2014: 87), is especially needed for risk and cost-intensive innovation and is also required to enhance innovation through commercialization of R&D results. In addition to R&D-intensive investments, companies need to invest in non-R&D innovation expenditures as well. Below we list the four input indicators considered.

- 1.3.1: R&D expenditure in the public sector (% of GDP)
- 1.3.2: Venture capital (% of GDP)
- 2.1.1: R&D expenditure in the business sector (% of GDP)
- 2.1.2: Non-R&D innovation expenditures (% of turnover)

We carried out a sensitivity analysis also for the inputs (see Section 4.2), in which we classified seven indicators instead of four as input indicators.[9] The four input indicators proposed above are linked to innovation activities and are undertaken to enhance innovation, at least in part, as the Oslo Manual highlights.

There are, of course, other determinants of innovation processes. Ideally we should include *all such determinants* as input indicators. However, we would then need a fully articulated systemic and holistic approach in which all determinants of innovation processes, the feedback loops among them, and in which the relative importance of the different determinants of innovation processes are accounted for (Edquist 2014a, 2014c, 2018). That we do not have (yet). Admittedly, this is unsatisfactory, but a fact.

For example, in the IUS (and in this article) no account is taken of determinants of innovation processes operating from the demand side (see Edquist et al. 2015). If all innovation input and all innovation output indicators were included, we would be able to calculate something corresponding to total factor productivity (or multifactor productivity) in the field of innovation. As indicated, we will be satisfied here with a limited number of indicators on both sides (i.e. we will only be able to provide a partial measure of innovation performance).

3.2 Productivity measures based on simple index numbers and robust DEA

Once the indicators that we deem most relevant for the purposes of this article have been selected, we gather all the data from the IUS 2014 and 2015, to calculate both the conventional and normalized productivity measures for all EU28 countries. As a subset of the previous $\hat{\imath}^t_{li}$ normalized indicators in (1), and following the preceding discussion, we denote innovation input indicators of country i in period t by $\hat{x}^t_i = (\hat{x}^t_{1i}, \ldots, \hat{x}^t_{Ni}) \in \mathbb{R}^N_+$, while the innovation outputs indicators are represented by the vector $\hat{y}^t_i = (\hat{y}^t_{1i}, \ldots, \hat{y}^t_{Mi}) \in \mathbb{R}^M_+$—in the selected model, N = 4 and $M = 8$.

Relying on the simplest index number definition, the Productivity Innovation Index (PII) is calculated as the relation (i.e. ratio) between the normalized input and output indicators-$\hat{y}^t_{mi} \in [0,1]$, $\hat{x}^t_{ni} \in [0,1]$, using once again the arithmetic mean as aggregating function; i.e.

$$PII^t_i = \frac{\sum_{m=1}^{M} \bar{\mu}_m \hat{y}^t_{mi}}{\sum_{n=1}^{N} \bar{\nu}_n \hat{x}^t_{ni}}, \quad \bar{\mu}_m = 1/M,\ \bar{\nu}_n = 1/N, \tag{3}$$

where $\bar{\nu}_n$ and $\bar{\mu}_m$ are the input and output weights. As its SII^t_i counterpart, (3) must be normalized by the maximum observed value across all J countries, so its value is bounded above by 1.

$$\widehat{PII}^t_i = \frac{PII^t_i}{\max_j \left(PII^t_j\right)}, \quad j = 1, \ldots, J,\ \widehat{PII}^t_i \in [0,1]. \tag{4}$$

When compared to (2), a high score for the input indicators in the denominator means that a great deal of effort and resources has been devoted to stimulating innovation. Similarly, a high score for the output indicators in the numerator shows a high production of innovations. However, if the input side is, relatively speaking, much larger than the output side, the performance of the system as a whole is low (i.e. note the moon project). This implies that the efforts to produce or stimulate innovation have not led to a corresponding actual production of innovations. The different interpretations of $\widehat{SII}^t_i$ in (2) as an average measure of indiscriminate innovation indicators and the productivity measure $\widehat{PII}^t_i$ above, should now be clear.

The properties of $\widehat{PII}^t_i$ can be easily determined by resorting to index number theory. Balk (2008) discusses the desirable properties that a productivity index should fulfill from the so-called axiomatic or test approach (monotonicity, homogeneity, identity, proportionality, etc.). Nevertheless, we are aware of the potential limits that using a deterministic formulation like (4) entails for the evaluation of innovation performance. Potential problems are the existence of sampling variation and measurement errors that may polarize results and bias the productivity values and associated rankings. For this reason we propose the use of an alternative approach that allows addressing the bias emanating from the above issues. This approach extends with bootstrapping statistical techniques the nonparametric DEA methods for assessing efficiency already used by Zabala-Iturriagagoitia et al. (2007a).

Bootstrapped DEA constitutes a sophisticated method to estimate innovation productivity, differing from the simple index number aggregate in a subtle and fundamental way. Through mathematical programming, in each run the input and output weights ν_n and μ_m are now the result of the optimization process that maximizes a country's productivity relative to its counterparts.

We can rely on the seminal contribution by Charnes, Cooper, and Rhodes (1978) to illustrate the productivity interpretation of DEA. Indeed, based on the normalized indicators, their original ratio-form formulation, known as CCR, computes the productivity of country's i innovation system in the following way:[10]

$$\max_{\nu^t_m, \mu^t_m} \frac{\sum_{m=1}^{M} \mu^t_m \hat{y}^t_{mi}}{\sum_{n=1}^{N} \nu^t_n \hat{x}^t_{ni}} = \widehat{EII}^t_i \in (0,1], \tag{5}$$

s.t.

$$\frac{\sum_{m=1}^{M} \mu^t_m \hat{y}^t_{mj}}{\sum_{n=1}^{N} \nu^t_n \hat{x}^t_{nj}} \leq 1, \quad j = 1, \ldots, J,$$

$$\mu^t_m \geq 0,\ \nu^t_n \geq 0,$$

where ν^{t*}_n and μ^{t*}_m denote the optimal input and output weights when evaluating the relative productivity with respect to all $j = 1, \ldots, J$ countries, including itself. Contrary to the equal weights formulations (2) and (3), program (5) identifies the most favorable inputs and outputs weights that result in the maximum feasible productivity level of (x^t_i, y^t_i) relative to that of the remaining innovation systems. Note that since the weights ν^t_n and μ^t_m constitute aggregator functions, both the objective function and set of $j = 1, \ldots, J$ restrictions represent proper definitions of productivity—a ratio of aggregate output to aggregate input, normalizing maximum productivity to 1. This normalization also allows to deem the solution to (5) as a relative (in)efficiency measure, justifying the efficiency innovation index notation: $\widehat{EII}^t_i$. When country i under evaluation maximizes relative productivity or efficiency, $\widehat{EII}^t_i = 1$. On the contrary, if $\widehat{EII}^t_i < 1$, the country does not maximize the relative productivity of its innovation system, and the lower the efficiency value, the worse the innovation performance, as in the previous indicators.

The productivity values calculated from (5) can be considered as estimates, since their values are subject to uncertainty due to sampling variation, measurement errors, etc. Simar and Wilson (1998) introduce bootstrap methods that, based on resampling, provide estimation bias, confidence intervals and allow hypotheses testing. We rely on the algorithms presented by these authors, following Daraio and Simar (2007) and Bogetoft and Otto (2011), to test the statistical significance of the attained results. The bootstrap algorithm can be summarized in the following steps:

1. Selection of B independent bootstrap samples—drawn from the original data set with replacements (i.e. 2000);

Table 1. The innovation output indicators of the Swedish national innovation system

Indicator	Score in 2014 [2015]	Ranking (out of 28) in 2014	Ranking (out of 28) in 2015	EU 28 average in 2014 [2015]	Leading countries (top 3) in 2014	Leading countries (top 3) in 2015
2.2.1 SMEs innovating in-house as % of SMEs	0.729 [0.779]	8	4	0.570 [0.513]	Germany (0.933) Cyprus (0.833) Denmark (0.813)	The Netherlands (0.797) Ireland (0.792) Germany (0.787)
2.3.3 Community trademarks per billion GDP (in PPP-€)	0.573 [0.661]	7	8	0.444 [0.580]	Luxembourg (1.0) Cyprus (1.0) Malta (1.0)	Cyprus (1.000) Luxembourg (1.000) Malta (1.000)
2.3.4 Community designs per billion GDP (in PPP-€)	0.574 [0.999]	8	3	0.566 [0.569]	Luxembourg (1.0) Austria (1.0) Denmark (0.971)	Denmark (1.000) Luxembourg (1.000) Sweden (0.999)
3.1.1 SMEs introducing product or process innovations as % of SMEs	0.781 [0.656]	4	6	0.577 [0.432]	Germany (1.0) Belgium (0.848) Luxembourg (0.792)	Luxembourg (0.732) Germany (0.717) Belgium (0.713)
3.1.2 SMEs introducing marketing or organizational innovations as % of SMEs	0.605 [0.540]	10	12	0.566 [0.495]	Germany (1.0) Luxembourg (0.960) Greece (0.801)	Luxembourg (0.851) Ireland (0.797) Germany (0.720)
3.2.2 Contribution of medium and high-tech product exports to trade balance	0.579 [0.648]	15	9	0.553 [0.658]	Germany (0.930) Slovenia (0.802) Hungary (0.756)	Hungary (0.899) Germany (0.892) Slovakia (0.850)
3.2.3 Knowledge-intensive services exports as % total service exports	0.510 [0.524]	10	11	0.606 [0.665]	Ireland (1.0) Luxembourg (1.0) Denmark (0.959)	Ireland (1.000) Luxembourg (1.000) Denmark (1.000)
3.2.4 Sales of new-to-market and new-to-firm innovations as % of turnover	0.248 [0.156]	21	24	0.664 [0.488]	Greece (1.0) Slovakia (1.0) Spain (0.982)	Denmark (1.000) Slovakia (0.869) Spain (0.590)
Average output result[12]	0.575 [0.620]	10	4	0.568 [0.550]	Germany (0.859) Luxembourg (0.754) Denmark (0.701)	Luxembourg (0.772) Denmark (0.728) Germany (0.723)

Source: Own elaboration based on European Union (2014, 2015).

2. Calculate an initial estimate for the productivity or efficiency score of each country $\widehat{EII}_i^t$ with respect to each bootstrapped sample and smooth their distribution by perturbating them with a random noise generated from a kernel density function with scale given with bandwith h;
3. Correct the original estimates for the mean and variance of the smoothed values;
4. Obtain a second set of bootstrapped samples generating inefficient countries inside the DEA attainable set and conditional on the original input—or output—mix;
5. Repeat the process and estimate the efficiency scores for each original country with respect to that second set, so as to obtain a set of B bootstrap estimates; and, finally,
6. Based on this distribution calculate the threshold values that truncate it according to the predetermined significance value α (i.e. 0.05), so as to determine the confidence intervals for the efficiency score of each country.

In addition, the bootstrapped scores can be used to obtain an estimate of the bias of the true efficiency value, and thereby a bias-corrected estimator, which we denote by $\widehat{bEII}_i^t$. In the empirical section the bias-corrected productivity values are presented along with their corresponding confidence intervals.

4. Empirical analysis

This section assesses the innovation performance of the Swedish national innovation system in relation to the rest of the EU28 Member States. However, what follows in this section is just an example of how our approach can be developed with regard to one country.

4.1 Output orientation

Table 1 summarizes the normalized scores for the eight output indicators considered, and the relative position that Sweden holds in relation to the EU28 countries for the latest year for which data are available. It also gives an average ranking and normalized score for Sweden for all output indicators.

According to the IUS 2014 and 2015, the SII for Denmark, Finland, Germany, and Sweden are well above those of the EU average. These countries are labeled the '*innovation leaders*', and Sweden is ranked number one. However, Table 1 gives a sharply different picture for Sweden. Taking into account the normalized values observed for the eight output indicators discussed above, and according to the IUS 2014 data, Sweden has an average normalized score of 0.575 for the innovation output indicators (0.620 for the IUS 2015), which is very close to the EU28 average of 0.568 (0.550 for the IUS 2015). Sweden thereby holds the 10th position among the EU28 (4th in the IUS 2015).

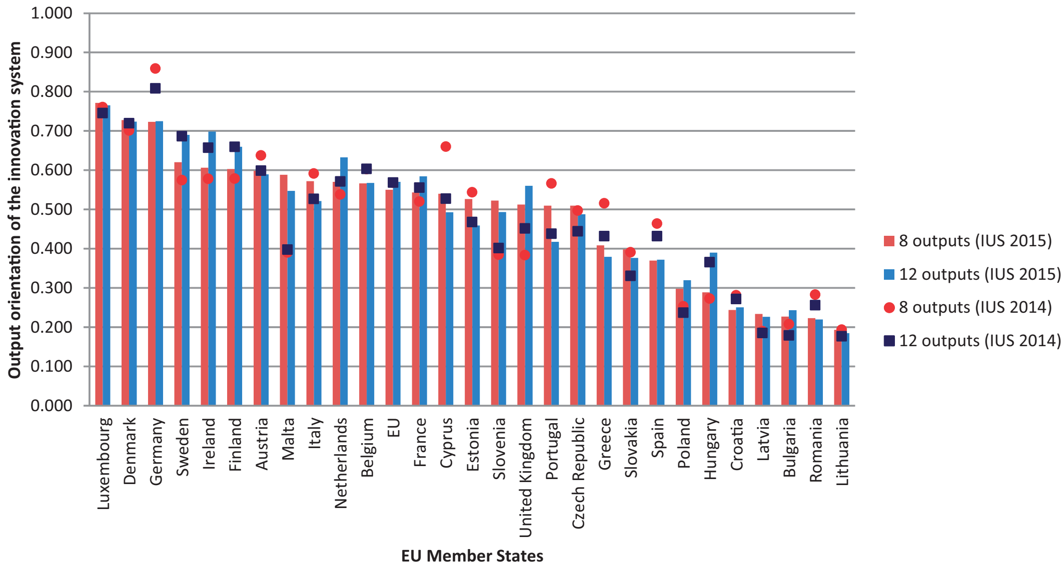

Figure 2. Output orientation of European innovation systems.

Our results mean that nearly a third of all EU countries have higher innovation outputs than Sweden based on the IUS 2014 data. The highest ranked countries, based on the IUS 2014 data, and with regard to innovation output, are Germany (0.859), Luxembourg (0.754), and Denmark (0.701). In turn, the highest ranked countries, based on the IUS 2015, are Luxembourg (0.772), Denmark (0.728), and Germany (0.723).

Figure 2 includes a sensitivity analysis of the results discussed above, showing the 2015 data with bars, and the 2014 data with markers. Countries have been sorted by the respective output scores for year 2015, according to the values achieved when 8 and 12 outputs are considered, respectively. Using this procedure with the IUS 2014 data, the ranking is led by Germany with a normalized score of 0.809, followed by Luxembourg (0.746) and Denmark (0.720). Sweden ranks 4th with a normalized value of 0.686. When comparing the average values with both approaches ($M = 8$ or $M = 12$) we get a correlation of $R^2 = 0.88$. This implies that the average output results and the subsequent rankings with 8 and 12 outputs show very similar values for the EU28 countries.[11]

4.2 Input orientation

The four IUS indicators which we consider as being important for the input side of innovation processes are listed in Table 2, where we also summarize Sweden's normalized scores and rankings for illustrative purposes.

According to our results, Sweden is at the very top with regard to its average input ranking (ranking number one in 2014 and second in 2015, with 0.698 and 0.715, respectively) among the other EU28 Member States. According to the IUS 2014 data, Finland has ranking number 2 (0.694) and Germany has ranking number 3 (0.631). Using the IUS 2015 data, Germany has ranking number 1 (0.718), and Estonia has ranking number 3 (0.688).

Here too we have conducted a sensitivity analysis to check to what extent the average input result for Sweden changes when additional input indicators are considered (N = 4 or N = 7). The results of this sensitivity analysis are plotted in Fig. 3. The ranking is still led by Sweden with a score of 0.771 in 2014 and 2015. When comparing the average values and rankings with both approaches (N= 4 inputs or N= 7), we get a correlation of $R^2 = 0.88$ in 2014 and $R^2 = 0.83$ in 2015.

4.3 Innovation performance

In this subsection we focus on the relation between the input and the output sides, i.e. on a measure of the innovation performance of national innovation systems (see Table 3). We define the innovation performance of a system as the ratio between innovation outputs and innovation inputs, using both the index number ($\widehat{PII}_i^t$) and the standard ($\widehat{EII}_i^t$) and bootstrapped ($\widehat{bEII}_i^t$) DEA approaches. Such ratios, show, in alternative ways to $\widehat{SII}_i^t$, how efficiently the countries or systems use their inputs, as $\widehat{SII}_i^t$ simply calculates the mean of all the 25 indicators, and does not relate them to each other in any other way.

Based on the data provided by the IUS 2014, Sweden is ranked extremely high with regard to the mean input indicator (0.698, 1st place in Table 2) and significantly lower with regard to output (0.575, 10th, Table 1). However, the IUS 2015 data show some improvement, particularly on the output side, as its rank improves to the 4th place-0.620. As shown in Table 3, this brings Sweden to the 1st place according to the overall SII ranking in both years. Indeed, Sweden presents the highest absolute and normalized values, e.g. in 2015, $SII_{SE}^{2015} = 0.750$ and $\widehat{SII}_{SE}^{2015} = 1.000$-as 0.750 is the maximum SII_j^{2015} score.

However, when assessing the performance of the Swedish innovation system with regard to its productivity, this leads to very low rankings regardless the definition employed, either the index number, the standard, or the robust DEA estimate. Considering the index number definition, the absolute value corresponding to the ratio of the aggregate output to the aggregate input is $PII_{SE}^{2015} = 0.824 = 0.575/0.698$. Once this value is normalized by the maximum productivity observed across all countries, corresponding to Cyprus: $\max_j(PII_j^{2015}) = 3.040$, Sweden ranks in the 22nd place with a normalized score of $\widehat{PII}_{SE}^{2015} = 0.327 = 0.824/3.040$. Its 2015 rank is two positions better than in 2014 (24th place), as a result of the improvements in the aggregate output, but nevertheless places

Table 2. The innovation input indicators of the Swedish national innovation system

Indicator	Score in 2014 [2015]	Ranking (out of 28) in 2014	Ranking (out of 28) in 2015	EU28 average in 2014 [2015]	Leading countries (top 3) in IUS 2014	Leading countries (top 3) in IUS 2015
1.3.1 Public R&D expenditures as % of GDP	0.979 [0.957]	2	3	0.639 [0.641]	Finland (0.990) Sweden (0.979) Denmark (0.918)	Denmark (0.989) Finland (0.957) Sweden (0.957)
1.3.2 Venture capital investments	0.503 [0.536]	8	7	0.478 [0.472]	Luxembourg (1.0) UK (0.762) Finland (0.544)	Luxembourg (0.858) UK (0.672) Denmark (0.604)
2.1.1 Business R&D expenditures as % of GDP	0.991 [0.956]	2	2	0.558 [0.559]	Finland (1.0) Sweden (0.991) Slovenia (0.926)	Finland (1.000) Sweden (0.956) Denmark (0.868)
2.1.2 Non-R&D innovation expenditures as % of turnover	0.319 [0.412]	10	10	0.275 [0.349]	Cyprus (0.936) Lithuania (0.701) Estonia (0.557)	Estonia (0.871) Latvia (0.764) Germany (0.746)
Mean aggregate input result[13]	0.698 [0.715]	1	2	0.488 [0.505]	Sweden (0.698) Finland (0.694) Germany (0.631)	Germany (0.718) Sweden (0.715) Estonia (0.688)

Source: Own elaboration based on European Union (2014, 2015).

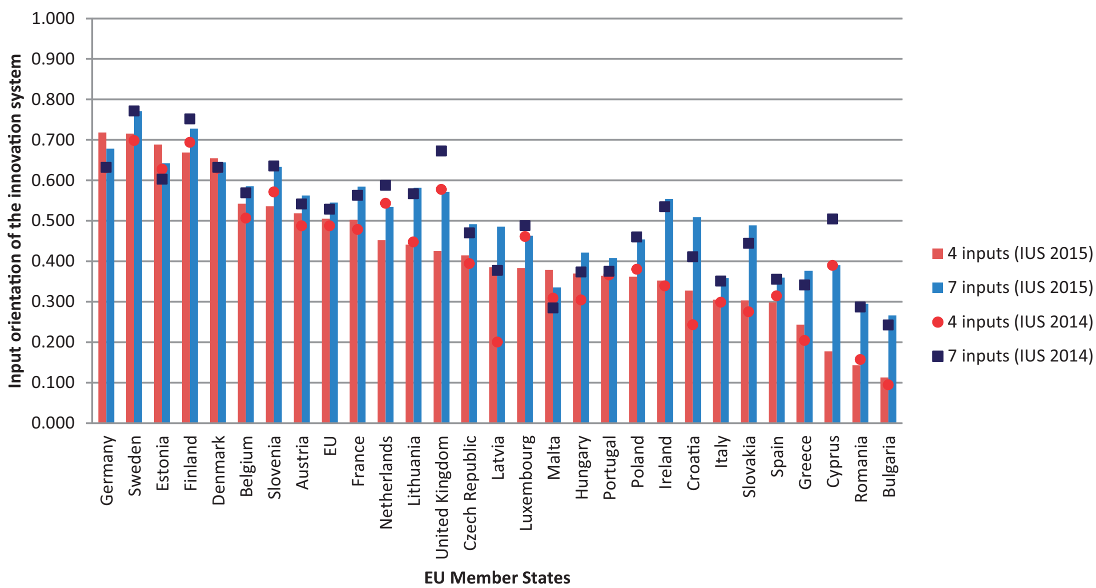

Figure 3. Input orientation of European innovation systems.

Sweden consistently at the lower tail of the productivity distribution. Obviously, the national innovation system in Sweden cannot be said to perform well at all from this efficiency point of view, and Sweden can certainly not be seen as an innovation leader in the EU, judging from the output and performance data.

This is further confirmed by the standard and bootstrapped DEA results. Even if DEA is benevolent when assessing the relative productivity by searching for the most advantageous input and output weights: ν_n^{t*} and μ_m^{t*}, it is to no avail. The standard and bootstrapped DEA scores: $\widehat{EII}_{SE}^{2014} = 0.604$ and $\widehat{bEII}_{SE}^{2014} = 0.562$ place Sweden in the second to last position in the rankings. This relative position marginally improves for 2015. It is worth highlighting that these results are statistically significant from the perspective of the bootstrapping methods, as all efficiency scores $\widehat{bEII}_i^t$ fall within the bootstrap confidence intervals—as presented in the last columns of the Appendix. We note in passing that the bootstrapped efficiency scores represent a valid solution to the low discriminatory power of standard DEA techniques. In both 2014 and 2015 a significant number of countries (16 and 15) are efficient with a unitary score (see Table 3). This precludes an individualized ranking, as these countries are tied in the first place. Therefore, bootstrapping techniques break the tie while informing about the statistical significance of their individual values, thereby providing comprehensive rankings.

Regarding our case study on Sweden, we conclude that whether one uses the fixed input and outputs weights $\bar{\nu}_n^t$ and $\bar{\mu}_m^t$, or the optimal—most favorable—weights ν_n^{t*} and μ_m^{t*}, the *innovation*

Table 3. The innovation performance of the Swedish national innovation system[14]

Performance index	Year	Scores	Ranking (out of 28)	Leading countries in IUS (top 3)
Summary innovation	2014	1.000 (=0.750/0.750)	1	Sweden (1.000), Denmark (0.971), Germany (0.945)
index (IUS) (2): $\widehat{SII}_i^t$	2015	1.000 (=0.740/0.740)	1	Sweden (1.000), Denmark (0.995), Finland (0.914)
Productivity Innovation	2014	0.327 = (0.824 = 0.575/0.698)/2.540	24	Greece (1.000), Bulgaria (0.869), Italy (0.786)
Index (4): $\widehat{PII}_i^t$	2015	0.285 = (0.870 = 0.620/0.715)/3.040	22	Cyprus (1.000), Luxembourg (0.662), Romania (0.650)
Efficiency Innovation	2014	0.604	27	17 countries are DEA efficient: $\widehat{EII}_i^t = 1.000$[a]
Index (5): $\widehat{EII}_i^t$	2015	0.706	23	15 countries are DEA efficient: $\widehat{EII}_i^t = 1.000$[b]
Bootstrapped Efficiency	2014	0.562*	27	Slovakia (0.917*), Croatia (0.913*), Portugal (0.904*)
Innovation Index, $\widehat{bEII}_i^t$	2015	0.647*	24	Slovenia (0.902*), Poland (0.897*), United Kingdom (0.881*)

[a]Austria, Bulgaria, Croatia, Cyprus, Czech Republic, France, Greece, Hungary, Ireland, Italy, Latvia, Luxembourg, Malta, Portugal, Romania, Slovakia, Spain.

[b]Austria, Bulgaria, Cyprus, Czech Republic, Denmark, Greece, Ireland, Italy, Luxembourg, Malta, Romania, The Netherlands, Slovakia, Spain, United Kingdom.

*denotes that the bootstrapped bias-corrected indices are statistically significant at the 5% significance level.

Source: Own elaboration based on data from the European Union (2014, 2015).

performance of Sweden can be consistently categorized as modest using the IUS denomination for countries below 50% of the EU average. Therefore, and quite unexpectedly, the fact that the DEA methods represent an optimistic approach that give observations the opportunity to perform the best possible way with respect to its peers does not result in significant improvements. This really tells us about how strongly dominated is Sweden by a large set of reference peers. On the contrary, compared to $\widehat{PII}_{SE}^t$ in 2014 and 2015, both the standard and booststrapped DEA results rank Sweden in lowest positions. For the same reason, as shown in Table 3 and the Appendix, unsuspected countries present innovation systems that, from a productivity perspective, perform fairly well, attaining high *relative* levels of outputs given the availability of innovation inputs. This is the case of Slovakia and Slovenia, leading the bootstrapped efficiency rankings in 2014 and 2015, respectively.

We now proceed to compare the three alternative performance measures ($\widehat{PII}_i^t$,$\widehat{EII}_i^t$,$\widehat{bEII}_i^t$). Figure 4 shows the distribution of the scores obtained using $\widehat{SII}_i^t$, and our simplest productivity index number—$\widehat{PII}_i^t$—(using four input and eight output indicators) for both the IUS 2014 and 2015. If the two rankings coincided, one would expect the majority of countries to be distributed along a 45° line; i.e. laying on the southwest and northeast quadrants. However, this is certainly not the case. As can be observed, Sweden is not the only country where the two rankings are radically different, laying in the 'wrong quadrants'. In fact, this is the case for *most* countries, including innovation leaders, innovation followers, moderate innovators, and modest innovators.

As discussed by Zabala-Iturriagagoitia et al. (2007a), it is not evident that the innovation systems that invest larger amount of resources (i.e. inputs) are also the most efficient ones. This result is also confirmed by Chen and Guan (2012) and by Mahroum and Al-Saleh (2013) among others, pointing out that territories making modest investments in innovation still can enjoy significant innovation outputs, and therefore high performance in terms of efficiency.

Similarly, Fig. 5 provides a comparison of the $\widehat{EII}_i^t$ and the $\widehat{bEII}_i^t$ for years 2014 and 2015. Countries have been sorted according to the $\widehat{bEII}_i^t$, which is represented together with the upper and lower bounds of the confidence intervals. This figure complements the previous Fig. 4, offering a concise but complete visual overview of the results.

We also confirm the compatibility of the fixed weight $\widehat{PII}_i^t$ results with those obtained for its deterministic and bootstrapped DEA counterparts allowing for flexible weights. To explore the similarity between the productivity distributions, Table 4 shows the results of a series of tests checking alternative hypotheses. The null hypotheses of the Wilcoxon rank sum test and the two-sample *t*-test are that both samples come from distributions with equal medians and equal means, respectively, against the alternative that they are not. For both years the null hypothesis is rejected at the 99% confidence level, implying that the median and the mean between the two bilateral pairs of efficiency measures are different ($\widehat{PII}_i^t$ vs. $\widehat{EII}_i^t$, and $\widehat{PII}_i^t$ vs. $\widehat{bEII}_i^t$). However from the perspective of the rankings that these distributions yield, the Kendall and Spearman rank correlations show relatively high and significant values, particularly between the deterministic indices $\widehat{PII}_i^t$ and $\widehat{EII}_i^t$. Unsurprisingly, as reported in the last two columns, the bootstrapped results $\widehat{bEII}_i^t$ show that their 2014 and 2015 distributions are also different from their deterministic counterparts $\widehat{EII}_i^t$ in both years. Nevertheless, once again, the rankings correlate to a large extent.

5. Discussion, conclusions, and research agenda

According to the IUS, innovation performance implicitly means an average of 25 indicators measuring the determinants of innovations, inputs, innovations, as well as their consequences. In this article, we have discussed why innovation performance should be understood as the relationships between innovation inputs and outputs, as done in productivity and efficiency research.

The first purpose of this article was to assess whether the SII of the European Innovation Scoreboard (IUS) is a meaningful measure of innovation performance. Our conclusion is that it is not. The main reason is that it mixes input and output innovation indicators and calculates an average of them. In addition, it lacks an explicit definition of what is meant by innovation performance, beyond the indiscriminate arithmetic mean of all 25 IUS indicators.

The second purpose was to develop an alternative, productivity, or efficiency-based, measure of innovation system performance. By doing so, the article offers a critical review of the SII, and proposes to place more emphasis on the identification of and relation between

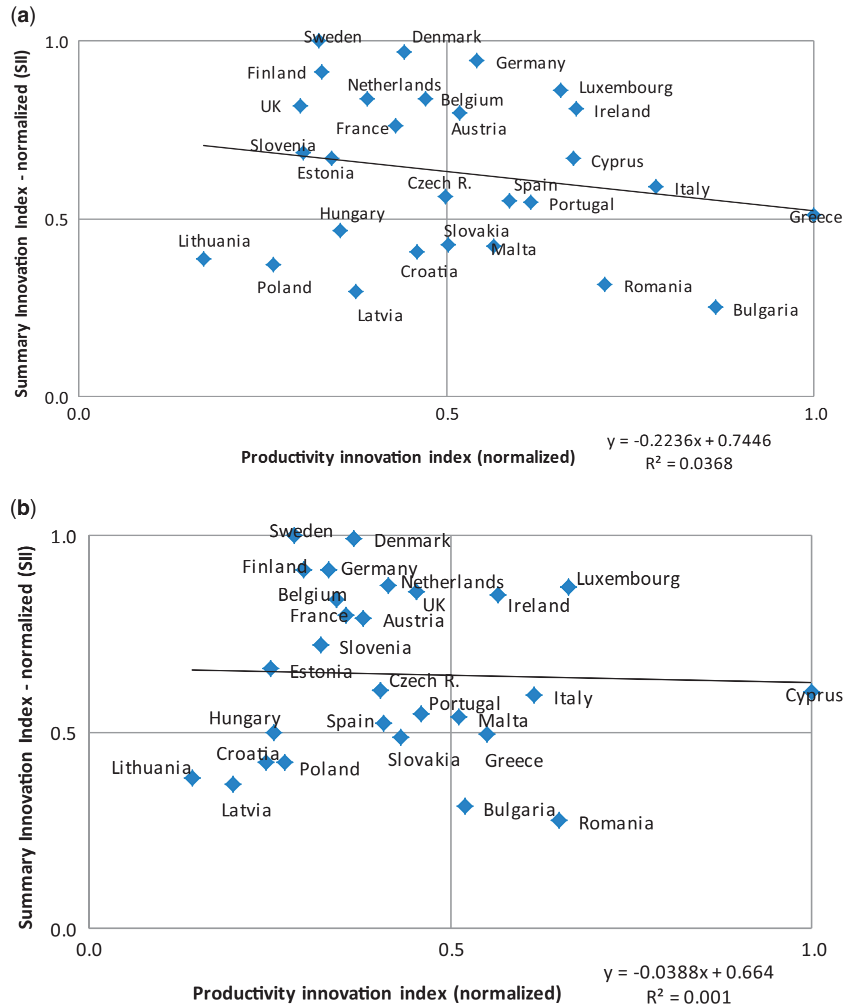

Figure 4. Comparison of the normalized IUS $\widehat{SII}_i^t$ and the normalized $\widehat{PII}_i^t$. (a) IUS 2014. (b) IUS 2015.

Source: Own elaboration.

input and output indicators. For this purpose we rely on the simplest productivity index number formulation, but we also supplement it with state-of-the-art productivity measurement methods in the form of robust (bootstrapped) DEA techniques that address the weaknesses of deterministic indices. Our article can be understood as a contribution to the need for a 'substantial research effort on conceptual foundations as well as empirics of innovation measurement' (Janger et al. 2017: 39). We use the existing data provided by the IUS but seen through a different (productivity) lens, with the purpose of increasing the breadth of sight of innovation policy makers and politicians.

By using both fixed and flexible weights we have assessed the performance of EU28 Member States by comparing alternative multi-input/multi-output relationships in a benchmark model, including four inputs and eight outputs. We justify this choice on theoretical grounds but encourage other researchers to improve on this 'standard model'. Our intention is to mimic the simplicity of the methods followed by the SII, though from a different (productivity) point of view.

The simple productivity index and its sophisticated DEA counterparts result in very similar rankings. The more sophisticated method is actually not needed to reach the basic result. If one is interested in this result, rather than in specific and individual numerical values (because distributions have been shown to be different), the simplest productivity definition performs well. However, the relevance of statistically robust methods such as bootstrapped DEA is clear, as they allow addressing some of the weaknesses of the deterministic approached; most particularity, the presence of innovation performance outliers emerging from the (IUS) data.

As can be observed in the Appendix, the top 10 EU national innovations systems ranked in terms of the bootstrapped efficiency score for 2015 are Slovenia, Poland, the UK, Malta, Austria, France, Denmark, Italy, Portugal, and Spain. Sweden is ranked number 23. No matter how unbelievable it may appear, this efficiency ranking is appropriate to the extent that the IUS data are correct and our approach to dealing with them is sensible and robust. The ranking goes against stylized facts and seems counterintuitive, since many of the top-ranked countries are less developed economies with less comprehensive innovation systems. In turn, the countries that traditionally lead innovation rankings (such as the SII) get lower standings with regard to innovation performance. To fully explain the reasons for these results in a detailed manner, we would need sophisticated methods

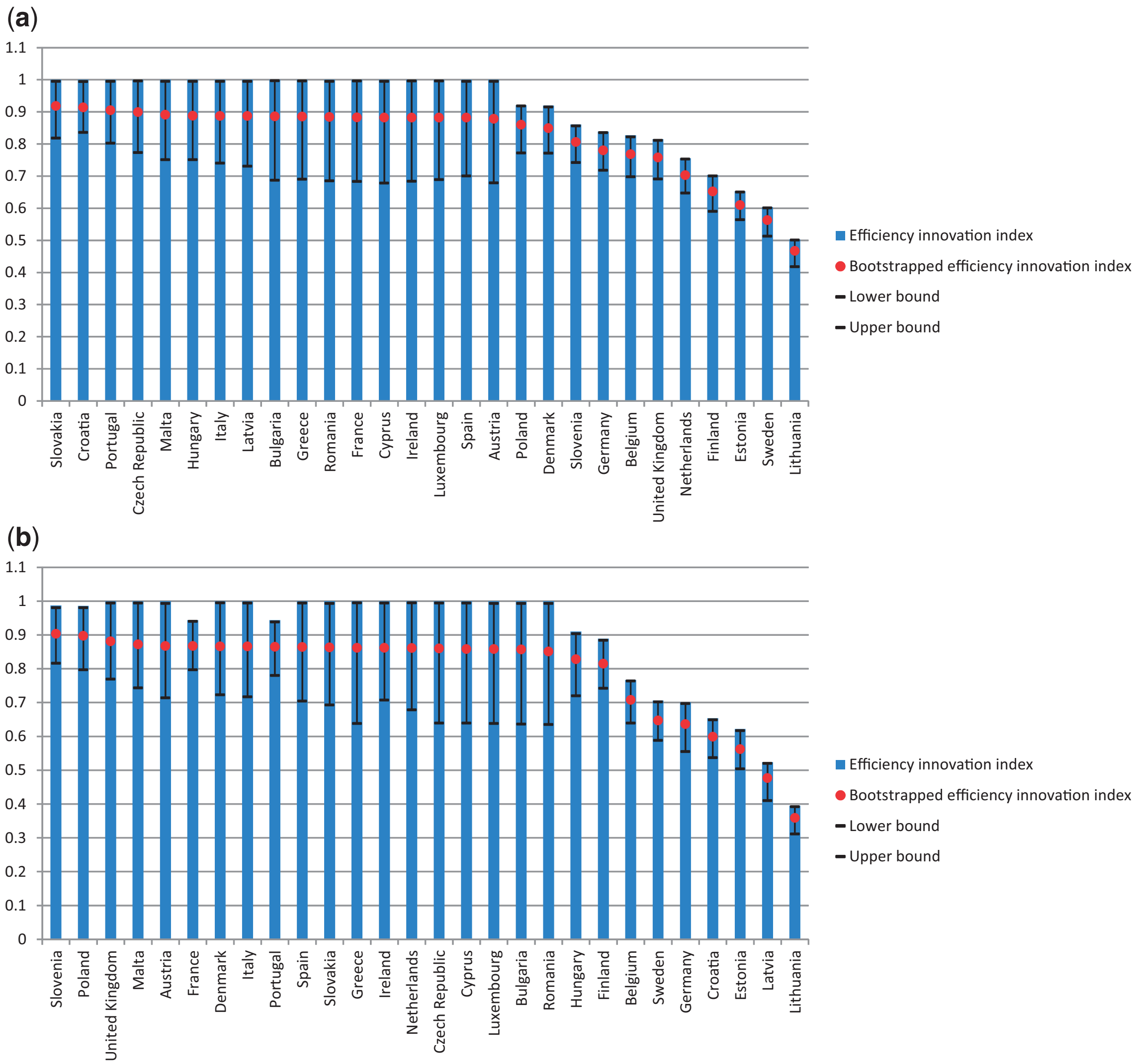

Figure 5. Comparison of the $\widehat{EII}_i^t$ and the bootstrapped efficiency innovation index ($\widehat{bEII}_i^t$). (a) IUS 2014. (b)- IUS 2015.

Table 4. Tests of hypotheses between alternative productivity measures

Test	$\widehat{PII}_i^t$ vs. $\widehat{EII}_i^t$		$\widehat{PII}_i^t$ vs. $\widehat{bEII}_i^t$		$\widehat{EII}_i^t$ vs. $\widehat{bEII}_i^t$	
	2014	2015	2014	2015	2014	2015
Wilcoxon rank sum test[a]	−5.649	−5.803	−5.170	−5.416	2.504	2.474
P-value	0.000	0.000	0.000	0.000	0.015	0.017
Two-sample *t*-test[b]	−8.855	−10.214	−7.361	−8.685	0.992	0.990
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Kendall's τ rank correlation[c]	0.549	0.694	0.365	0.265	0.800	0.520
P-value	0.000	0.000	0.006	0.050	0.000	0.000
Spearman's ρ correlation[c]	0.706	0.843	0.531	0.402	0.881	0.630
P-value	0.000	0.000	0.004	0.035	0.000	0.000

[a] H_0 is that both distributions are the same.
[b] H_0 is the equality of means.
[c] H_0 is that both variables are independent.

that allow controlling for key aspects such as sectoral structure, diversification, degree of internationalization, firm size, and institutional conditions, which remains for further research.

One partial explanation to these seemingly contradictory results is that many of these small EU countries devote very limited resources to inputs. According to the approach followed here, the lower the inputs, the higher the efficiency. Besides, they manage to obtain reasonable outputs in relation to the invested inputs. For example, Sweden invested 7.35 times more than Bulgaria in innovation inputs, according to IUS 2014 (see Appendix). At the same time Sweden achieved an output figure that is only 2.77 times higher than Bulgaria's. The figures are similar for the other EU countries that rank high on traditional innovation performance calculations (such as the SII).

The above figures imply that some less developed countries manage to use their (more limited) resources in a more productive/efficient way. It also indicates that there might be Decreasing Returns to Scale (DRS) obtained by investments in innovation input activities, so countries investing a large amount of innovations resources cannot achieve large returns. The DEA methodology provides ancillary results that shed light on the role that returns to scale (i.e. input size) play for inefficient performance. The last column in the Appendix shows whether IRS, CRS, or DRS prevail locally for each country—see the footnote to program (5) on how to determine the nature of returns to scale. The suspected widespread presence of DRS is confirmed, with as many as 10 countries exhibiting a suboptimal scale size as a result of an excessive relative usage of inputs. Among this, we find several SII leading countries, including Sweden, Germany, Finland, etc. On the contrary, incurring in innovation inefficiency due to IRS (i.e. relatively low use of inputs) does not seem to be an issue, as only three countries, Croatia, Latvia, and Lithuania, exhibit this type of returns.

As Zabala-Iturriagagoitia et al. discuss (2007a: 667), another partial explanation may be that countries with comprehensive innovation systems are usually, oriented toward radical innovation and the development of new industries, often in knowledge-intensive sectors and high-tech industries. Such innovation efforts are characterized by uncertainty, high-risk, failures, and large time lags. In contrast, countries with smaller innovation input resources tend to absorb and adopt embodied knowledge and innovations from other countries. Such absorption involves lower innovation input costs, but may, at the same time, be more efficient, as they may avoid the inherent risk involved in the development of these innovations, so that the 'new' knowledge is more rapidly and cheaply adapted and adopted than in the country where it was developed.

According to Freeman and Soete (1988), the efficient diffusion of innovations is often much more important for development and growth than being the lead innovator. Countries regarded as innovation leaders by the IUS may thus be more prone to the creation of new-to-the-world innovations, while follower countries are more prone to the absorption and later diffusion of these innovations, as long as the required levels of absorptive capacity and learning are in place. This is highly relevant from an innovation policy point of view, a partial objective of which may be to catch up with the leading countries by absorbing innovations from abroad.

We want to stress the irrelevance of the notion of optimality in an innovation context, given the impossibility to specify an ideal or optimal innovation system. The only way to identify problems that should be subject to innovation policy is therefore to compare existing innovation systems with each other. Unfortunately, the ranking of the efficiency of the EU28 innovation systems in the Appendix provides limited guidelines from the point of view of innovation policy development. There are no reasons whatsoever to benchmark Sweden's national innovation system with those of Slovenia, Poland, Greece, Cyprus, etc., in attempting to develop an analysis to form a basis for innovation policy changes. Such comparisons should, instead, be made between innovation systems that are more similar in a structural sense and at a similar level of development, that have the same size, that score similarly on innovation output or innovation input, etc. A restricted DEA analysis for countries with similar characteristics could be helpful here.

One implication of this analysis is that considerable efforts should be made to identify the sources of the inefficiencies and problems in the national systems of innovation. Existing innovation intensities are influenced by a number of forces that affect innovation processes, forces which we call determinants of innovations. Many of these determinants can be influenced by the state. When the state (through its public agencies) influences these determinants to increase innovation intensities of certain kinds or change the direction of innovation processes, it is actually pursuing innovation policy. Public bodies should be able to know and monitor the evolution of these determinants and their impact on innovation.

The SII does however not help to do so. Since it includes inputs, determinants, innovations, and consequences, this synthetic indicator is not useful from the point of view of innovation policy design. The SII score will increase if a country puts more (input) resources into its innovation system, regardless of how the resources are used or what the (innovation) output might be. A worrisome property of the SII index is that its value increases even if the innovation output resulting from more inputs is 0 (i.e. the marginal productivity of inputs is 0). These results should call for a serious reconsideration of who the real European 'innovation leaders' may be, and in what sense they are leaders. These findings also call into question the way that the European Commission analyzes the innovation data presented in the IUS.

The IUS is intended to have a real impact on the design of innovation policies of the EU Member States. According to our results, the SII is flawed with regard to measuring innovation performance and may therefore mislead researchers, policy makers, politicians, as well as the general public. Policy makers in the field of innovation should be able to identify the policy problems in their innovation systems and relate them to their causes to be able to select policy instruments to mitigate the problems. Our approach can be useful for the design of policy. For example, if we know that Sweden is much weaker on the output side than on the input side, our approach can tell policy makers and politicians to concentrate more on making a more efficient use of existing inputs than on increasing the volume of the inputs, for example through the articulation of an instrument-mix that considers demand-side innovation policy instruments. To further develop such a kind of disaggregated analysis to identify policy problems is much more useful as a basis for innovation policy design, than to aggregate data into single ranking numbers of countries. In this way, the individual indicators that constitute composite indicators should be analyzed in much more depth, and this should be done in a comparative manner.

We believe that the simplicity of our definition of productivity as a ratio of (aggregate) outputs to (aggregate) inputs, along with the proved confirmation by using DEA methods, reinforces the credibility of our results. Although the analyses can be further refined, we do claim that this trajectory is also a fruitful one for future research as remarked in the different extensions that we propose: use of bootstrapped Malmquist productivity indices where the relative sources of productivity change, such as technological progress vs. catching-up processes, could be measured, restricted frontiers by country categories, etc.

It can be argued that the rationale used in this article follows a linear logic, as opposed to a systemic and holistic one (e.g. Edquist 2014a, 2014b, 2014c, 2018). As mentioned at the end of Section 3.1, an ideal basis for the design of innovation policy should aim to include a fully articulated holistic innovation systems approach. Such an approach would include knowledge about all determinants of the development and diffusion of innovations—knowledge which we do not possess. This would mean overcoming the linear model of innovation that still dominates innovation policy in all countries, despite the fact that it has been completely rejected in innovation research (Edquist 2014a, 2018). Developing such a holistic view would make it possible to account for all determinants of innovations as inputs when measuring innovation performance and efficiency of innovation systems. This would mean that the linear approach (a focus on input–output relationships) used out of necessity in this article, could be overcome and transcended. The linear and holistic approaches would become compatible and reconciled. However, we are not yet there.

Notes

1. For illustrative purposes, we use Sweden as an example when we discuss the data, methodology, and results. However, in the Appendix, we present the data for all 28 EU Member States. This means that the reader can substitute Sweden by any other of the 27 EU countries.
2. These steps include development of a theoretical framework, data selection, development of an exploratory multivariate analysis, imputation of missing data, normalization, weighting and aggregation, and robustness and sensibility checks among others (see Nardo et al. 2005).
3. The IUS performs a max–min normalization by subtracting the minimum value and diving by the observed range: $\hat{\imath}^t_{li} = (\imath^t_{li} - \min(\imath^t_{lj}))/(\max(\imath^t_{lj}) - \min(\imath^t_{lj}))$, $j = 1,\ldots, 34$ countries. Therefore, 'The maximum re-scaled score is thus equal to 1 and the minimum re-scaled score is equal to 0' (European Union 2015: 79).
4. For the detailed interpretation of each of the output and input indicators considered, please see European Union (2014: 86–90). All 25 indicators are also listed in Fig. 1.
5. Following Hagedoorn and Cloodt (2003: 1367), for whom the concept of innovation performance excludes 'the possible economic success of innovations as such', we do neither consider the consequences (i.e. outcomes or impacts) of innovations, such as economic growth or employment, to be innovation output indicators.
6. The exclusion of indicator 2.3.1 (Patent Cooperation Treaty (PCT) patent applications) is made for a different reason. As long as a product or a process has not been commercialized and connected to the market, it cannot be considered to be an innovation. An *application* for a patent is far from being a product introduced to the market. Not even granted patents are product innovations, although they may be a basis for future innovations. Patents are rather an indicator of research results or inventions, as they reflect that something is technologically new. This implies that patents are a throughput, rather than an output of innovation (see also Lee 2015; Janger et al. 2017).
7. The additional indicators considered were PCT patent applications (2.3.1), Employment in fast-growing enterprises in innovative sectors (3.1.3), Employment in knowledge-intensive activities (3.2.1), and License and patent revenues from abroad (3.2.5).
8. Of these two indicators, R&D expenditures in the business sector are certainly to a very large extent directly undertaken to enhance innovation (see Lee 2015). R&D expenditures in the public sector are to a lesser extent undertaken directly for this purpose, since a substantial proportion is pursued to develop new scientific knowledge, part of which may result (or not) in innovations. In spite of this, we include both of these indicators in the category of input indicators, although a part of the public sector R&D expenditures may result in innovations only after a substantial time lag, or not at all for some kinds of public R&D financing.
9. The additional indicators considered were New doctorate graduates (1.1.1), Percentage of population aged 30–34 years having completed tertiary education (1.1.2), and Percentage youth aged 20–24 years having attained at least upper secondary education (1.1.3).
10. Program (5) corresponds to a fractional (ratio form) formulation, which after some transformations can be expressed as a linear program, and whose resulting objective function is linearly homogeneous of degree one, thereby defining a productivity frontier characterized by constant returns to scale (CRS), Cooper, Seiford, and Tone (2007: chapter 2). Its dual−primal−formulation corresponds to the input-oriented envelopment form:

$$E\hat{I}I^t_i = \min_{\theta,\lambda} \left\{ \theta : \sum_{j=1}^{J} \lambda^t_j \hat{x}^t_{jn} \le \theta \hat{x}^t_n,\ n = 1,\ldots,N;\ \sum_{j=1}^{J} \lambda^t_j \hat{y}^t_{jm} \ge \hat{y}^t_m, \right.$$
$$\left. m = 1,\ldots,M;\ \sum_{j=1}^{J} \lambda^t_j = 1,\ \lambda_j \ge 0,\ j = 1,\ldots,J \right\},$$

where λ_j are intensity variable identifying the benchmark countries conforming the reference facet. Resorting to the envelopment form, it is possible to determine the nature of returns to scale at this benchmark frontier: increasing, constant, and decreasing, by examining the value of the sum of the optimal lambdas—Cooper, Seiford, and Tone (2007: chapter 5):

   i. Decreasing Returns to Scale (DRS) prevails for $(x^t_i, y^t_i) \iff \sum_j \lambda^*_j > 1$ for all optimal solutions.
   ii. Increasing Returns to Scale (IRS) prevails for $(x^t_i, y^t_i) \iff \sum_j \lambda^*_j < 1$ for all optimal solutions.
   iii. CRS prevails for $(x^t_i, y^t_i) \iff \sum_j \lambda^*_j = 1$ for some optimal solutions.

Therefore, by solving the dual to program (5) we can determine what type of returns to scale locally predominate for (x^t_i, y^t_i)—which, in turn, implies that a suboptimal scale is at play if the innovation system turns out to be inefficient. In the discussion section we recall this result to substantiate one of the possible reasons why innovation performance is deficient depending on the innovation size of the countries.

11. When using the IUS 2015 data, the ranking is led by Luxembourg (0.765), followed by Germany (0.725) and Denmark (0.724). Sweden ranks 5th with a normalized value of 0.690. When comparing the average values with both approaches ($M = 8$ or $M = 12$) a correlation of $R^2 = 0.93$ in 2015 is obtained.

12. Calculation is based on the arithmetic mean of the normalized scores of each output indicator.
13. Calculation is based on the arithmetic mean of the normalized scores for each input indicator.
14. The data and rankings for all EU28 Member Countries are presented in the Appendix.

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Appendix

The Efficiency of the EU28 Innovation Systems

Table A1. Year 2014

Country	Output (M = 8)	Input (N = 4)	Summary Innovation Index SII_i^t	Normalized Summary Innovation Index $\widehat{SII}_i^t$	Ranking $\widehat{SII}_i^t$	Productivity Innovation Index PII_i^t	Normalized Productivity Innovation Index $\widehat{PII}_i^t$	Ranking $\widehat{PII}_i^t$	Efficiency Innovation Index $\widehat{EII}_i^t$	Ranking $\widehat{EII}_i^t$	Bootstrapped Efficiency Innovation Index $\widehat{bEII}_i^t$	Ranking $\widehat{bEII}_i^t$	Lower bound	Upper bound	Returns to scale (IRS, CRS, DRS)
Austria	0.637	0.488	0.599	0.799	10	1.305	0.519	12	1.000	1	0.878	17	0.679	0.995	CRS
Belgium	0.603	0.507	0.627	0.836	7	1.189	0.473	15	0.827	22	0.768	22	0.698	0.822	DRS
Bulgaria	0.207	0.095	0.188	0.251	28	2.179	0.866	2	1.000	1	0.886	9	0.687	0.997	CRS
Croatia	0.281	0.243	0.306	0.408	23	1.156	0.459	16	1.000	1	0.914	2	0.836	0.994	CRS
Cyprus	0.66	0.39	0.501	0.668	14	1.692	0.672	6	1.000	1	0.882	15	0.678	0.995	CRS
Czech Rep.	0.497	0.395	0.422	0.563	16	1.258	0.500	14	1.000	1	0.899	4	0.773	0.996	CRS
Denmark	0.701	0.63	0.728	0.971	2	1.113	0.442	17	0.920	19	0.849	19	0.771	0.915	DRS
Estonia	0.544	0.628	0.502	0.669	13	0.866	0.344	22	0.653	26	0.610	26	0.564	0.650	DRS
Finland	0.579	0.694	0.684	0.912	4	0.834	0.331	23	0.704	25	0.652	25	0.590	0.700	DRS
France	0.52	0.479	0.571	0.761	11	1.086	0.431	18	1.000	1	0.883	12	0.683	0.996	CRS
Germany	0.859	0.631	0.709	0.945	3	1.361	0.541	11	0.839	21	0.780	21	0.718	0.835	DRS
Greece	0.516	0.205	0.384	0.512	19	2.517	1.000	1	1.000	1	0.885	10	0.690	0.996	CRS
Hungary	0.273	0.304	0.351	0.468	20	0.898	0.357	21	1.000	1	0.888	6	0.751	0.995	CRS
Ireland	0.578	0.339	0.606	0.808	9	1.705	0.677	5	1.000	1	0.882	16	0.684	0.996	CRS
Italy	0.591	0.299	0.443	0.591	15	1.977	0.785	3	1.000	1	0.887	8	0.740	0.995	CRS
Latvia	0.19	0.2	0.221	0.295	27	0.950	0.377	20	1.000	1	0.887	7	0.731	0.995	CRS
Lithuania	0.193	0.447	0.289	0.385	24	0.432	0.172	28	0.503	28	0.467	28	0.418	0.501	IRS
Luxembourg	0.761	0.461	0.646	0.861	5	1.651	0.656	7	1.000	1	0.882	14	0.689	0.996	CRS
Malta	0.391	0.309	0.319	0.425	21	1.265	0.503	13	1.000	1	0.891	5	0.751	0.995	CRS
Netherlands	0.538	0.543	0.629	0.839	6	0.991	0.394	19	0.756	24	0.703	24	0.647	0.753	DRS
Poland	0.253	0.38	0.279	0.372	25	0.666	0.265	27	0.921	18	0.860	18	0.772	0.918	DRS
Portugal	0.566	0.366	0.41	0.547	18	1.546	0.614	8	1.000	1	0.905	3	0.802	0.995	CRS
Romania	0.283	0.157	0.237	0.316	26	1.803	0.716	4	1.000	1	0.884	11	0.685	0.995	CRS
Slovakia	0.391	0.275	0.318	0.424	22	1.422	0.565	10	1.000	1	0.918	1	0.818	0.995	CRS
Slovenia	0.44	0.571	0.513	0.684	12	0.771	0.306	25	0.861	20	0.806	20	0.742	0.856	DRS
Spain	0.464	0.315	0.414	0.552	17	1.473	0.585	9	1.000	1	0.882	13	0.700	0.995	CRS
Sweden	0.575	0.698	0.75	1.000	1	0.824	0.327	24	0.604	27	0.563	27	0.513	0.601	DRS
UK	0.439	0.577	0.613	0.817	8	0.761	0.302	26	0.815	23	0.758	23	0.691	0.811	DRS

Source: Own elaboration from European Union (2014).

Table A2. Year 2015

Country	Output (M = 8)	Input (N = 4)	Summary Innovation Index SII_i^t	Normalized Summary Innovation Index $\widehat{SII}_i^t$	Ranking $\widehat{SII}_i^t$	Productivity Innovation Index PII_i^t	Normalized Productivity Innovation Index $\widehat{PII}_i^t$	Ranking $\widehat{PII}_i^t$	Efficiency Innovation Index $\widehat{EII}_i^t$	Ranking $\widehat{EII}_i^t$	Bootstrapped Efficiency Innovation Index $\widehat{bEII}_i^t$	Ranking $\widehat{bEII}_i^t$	Lower bound	Upper bound	Returns to scale (IRS, CRS, DRS)
Austria	0.599	0.519	0.585	0.791	11	1.154	0.380	15	1.000	1	0.867	5	0.714	0.993	CRS
Belgium	0.566	0.543	0.619	0.836	9	1.044	0.343	18	0.767	22	0.708	22	0.639	0.764	DRS
Bulgaria	0.227	0.144	0.229	0.309	27	1.582	0.520	7	1.000	1	0.857	18	0.636	0.993	CRS
Croatia	0.244	0.328	0.313	0.423	23	0.744	0.245	26	0.654	25	0.599	25	0.537	0.649	IRS
Cyprus	0.540	0.178	0.445	0.601	15	3.040	1.000	1	1.000	1	0.858	16	0.639	0.994	CRS
Czech Republic	0.510	0.415	0.447	0.604	14	1.228	0.404	14	1.000	1	0.860	15	0.639	0.994	CRS
Denmark	0.728	0.655	0.736	0.995	2	1.112	0.366	16	1.000	1	0.866	7	0.723	0.995	CRS
Estonia	0.526	0.688	0.489	0.661	13	0.765	0.252	25	0.622	26	0.562	26	0.504	0.617	DRS
Finland	0.603	0.669	0.676	0.914	3	0.902	0.297	21	0.889	21	0.815	21	0.742	0.884	DRS
France	0.544	0.502	0.591	0.799	10	1.082	0.356	17	0.944	19	0.867	6	0.797	0.940	DRS
Germany	0.723	0.718	0.676	0.914	4	1.007	0.331	19	0.701	24	0.636	24	0.555	0.697	DRS
Greece	0.408	0.244	0.365	0.493	21	1.677	0.552	6	1.000	1	0.862	13	0.638	0.995	CRS
Hungary	0.289	0.370	0.369	0.499	20	0.782	0.257	24	0.910	20	0.828	20	0.720	0.903	DRS
Ireland	0.606	0.352	0.628	0.849	8	1.721	0.566	5	1.000	1	0.862	12	0.707	0.994	CRS
Italy	0.572	0.305	0.439	0.593	16	1.873	0.616	4	1.000	1	0.866	8	0.717	0.994	CRS
Latvia	0.234	0.385	0.272	0.368	26	0.607	0.200	27	0.524	27	0.477	27	0.410	0.520	IRS
Lithuania	0.194	0.441	0.283	0.382	25	0.438	0.144	28	0.395	28	0.359	28	0.311	0.392	IRS
Luxembourg	0.772	0.383	0.642	0.868	6	2.014	0.662	2	1.000	1	0.858	17	0.638	0.993	CRS
Malta	0.589	0.379	0.397	0.536	18	1.554	0.511	8	1.000	1	0.872	4	0.743	0.994	CRS
The Netherlands	0.570	0.452	0.647	0.874	5	1.261	0.415	12	1.000	1	0.861	14	0.678	0.995	CRS
Poland	0.298	0.362	0.313	0.423	24	0.823	0.271	23	0.986	17	0.897	2	0.797	0.980	DRS
Portugal	0.510	0.365	0.403	0.545	17	1.399	0.460	9	0.944	18	0.865	9	0.780	0.938	DRS
Romania	0.223	0.113	0.204	0.276	28	1.976	0.650	3	1.000	1	0.851	19	0.635	0.993	CRS
Slovakia	0.398	0.304	0.360	0.486	22	1.311	0.431	11	1.000	1	0.863	11	0.693	0.993	CRS
Slovenia	0.523	0.536	0.534	0.722	12	0.974	0.320	20	0.987	16	0.903	1	0.816	0.980	DRS
Spain	0.370	0.299	0.385	0.520	19	1.239	0.408	13	1.000	1	0.864	10	0.704	0.994	CRS
Sweden	0.620	0.715	0.740	1.000	1	0.867	0.285	22	0.706	23	0.647	23	0.588	0.702	DRS
United Kingdom	0.586	0.426	0.636	0.859	7	1.376	0.453	10	1.000	1	0.881	3	0.769	0.994	CRS

Source: Own elaboration from European Union (2015).