Aggregation of metafrontier technology gap ratios: the case of European sectors in 1995-2015*

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Abstract

Metafrontier-based methodologies have gained in popularity to assess the technology gaps of Decision Making Units (DMUs). One important indicator in this context is the technology gap ratio at the group level. Indeed, in metafrontier contexts, DMUs are partitioned into groups, capturing the heterogeneity present between DMUs. To date, no aggregation scheme has been suggested for this task. In practice, the arithmetic average is used. In this paper, we propose an alternative aggregation procedure, based on economic optimisation behaviour, given by the model, and easy to use and to interpret in practice. We apply our method to the case of 10 European sectors during the period 1995-2015. It represents a unique opportunity to apply the metafrontier methodology, and in particular, our aggregation scheme to sectors over a long period. Our findings reveal important patterns useful for policy-makers.

Keywords: data envelopment analysis; metafrontier; technology gap ratio; aggregation; sectors; Europe.

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1 Introduction

Efficiency analysis of production activities is a technique used to evaluate a Decision Making Unit (DMU; such as a firm, plant, utility, bank, country) by comparing its performance to that of other DMUs operating in a similar technological environment. Refer to Färe, Grosskopf and Lovell (1994), Cooper, Seiford and Zhu (2004), Coelli et al (2005), Cooper, Seiford and Tone (2007), Fried, Lovell and Schmidt (2008), and Cook and Seiford (2009) for reviews. While this type of analysis has demonstrated its usefulness in detecting the inefficiency behaviours of DMUs leading to potential cost reductions, or revenue or profit improvements; the "similar technological environment" assumption could be seen, in several contexts, as too restrictive. Indeed, DMUs could be partitioned into different categories or groups. For example, they can differ with respect to their ownership, geographical localisation, economic infrastructure, resource endowments, social environment, operational settings, and so on. These differences between DMUs imply the presence of heterogeneity in the efficiency analysis, making the "similar technological environment" assumption, at best, difficult to believe, and, at worst, completely wrong.

Building on this drawback in efficiency analysis, Battese and Rao (2002), Battese, Rao, and O'Donnell (2004), O'Donnell, Rao, and Battese (2008), and Amsler, O'Donnell, and Schmidt (2017) introduced, based on the notion of metaproduction function of Hayami and Ruttan (1970), the concept of metafrontier. Metaproduction function and metafrontier are tailored to deal with the heterogeneity present when DMUs are partitioned into different groups. Indeed, metafrontier-based analysis, contrary to more standard efficiency analysis techniques, allows for the possibility of technological differences in the efficiency evaluation. Basically, two frontiers are defined: one for each group, and one common and identical to all DMUs. The latter is obtained as a (convex or non-convex) envelopment of the group-specific frontiers.

In practice, for every DMU, technology gap ratios are computed to quantify the distance between the group-specific frontiers and the metafrontier. As such, this ratio provides a measure of the gap between the technology available to all DMUs and the technology available to a group of DMUs. Attractively, this ratio allows us to disentangle the actual inefficiency (i.e. the one with respect to the metafrontier) from the inefficiency with respect to the group. If no technology gap is detected, efficiency measurements obtained with the metafrontier approach will coincide with the ones obtained when comparing only with the group. In other words, it implies that the DMUs are homogeneous.

Metafrontier-based methodologies have been applied to a various range of topics revealing the attractiveness of this concept for empirical works. Recent applications in macroeconomic contexts include those of Chen, Huang and Yang (2009) on China; Lin, Chen, Chen

(2013) on more than 60 countries; Lin and Du (2013) on Chinese regions; Kounetas (2015) on European countries; Tsekouras et al (2016) on European transportation sectors; and Li et al (2017) for the Japanese electricity distribution sector. Recent applications in microeconomic contexts include those of Kontolaimou and Tsekouras (2010) and Kontolaimou et al (2012) on European banks; Assaf, Barros, and Josiassen (2012) on hotels in Taiwan; Huang et al (2013) for international tourist hotels; Beltran-Esteve et al (2014) on Spanish olive producers; Jiang and Sharp (2015) on New Zealand dairy farms; Duygun, Sena, and Shaban (2016) on British commercial banks; Fu et al (2016) on Taiwanese and Chinese banks; Hajihassaniasl and Kok (2016) on the Turkish manufacturing industry; Wanke and Barros (2016) on Brazilian insurance; Azad et al (2017) on banks in Malaysia; Barros and Wanke (2017) on African Insurance Companies; Chang and Tovar (2017) on the West Coast of South Pacific terminals; Chen, Lai, and Piboonrungroj (2017) on airports; and Molinos-Senante, Maziotis and Sala-Garrido (2017) on water companies in England and Wales.

For metafrontier-based empirical works, an important indicator is the technology gap ratio at the group level. Indeed, as DMUs are partitioned into groups, it is natural to provide an indicator of the technology gap at that level. Moreover, it also allows us to easily compare groups. To date, the arithmetic average has been used for this task. While this is probably the most natural aggregation scheme used in many settings, using the arithmetic average presents important drawbacks in metafrontier contexts. Firstly, this aggregation scheme is completely exogenous and thus lacks economic intuition. Indeed, it is not obtained by the model and is thus independent from the model specifications (for example, if convexity is allowed or not when defining the metafrontier). Also, it is not obtained by assuming any economic behaviours of the DMUs (for example, if they are cost minimisers, revenue or profit maximisers); while in practice, most of the time, DMUs have an economic optimisation behaviour. Next, using the arithmetic average implies that the same weights are assigned to all the DMUs in the group; implying for constant and similar compensatory (greater indicators will compensate for lower indicators at a constant and equal rate). On the contrary, we advocate for a compensatory that takes the relative importance of the DMUs in the group into account.[1]

In this paper, we take the lack of a consistent aggregation scheme in metafrontier contexts as a starting point to suggest a new way to obtain the group indicator for the technology gap ratio. That is, our aim is to find an aggregation scheme such that we keep a natural

[1]Compensatory is particularly important when constructing composite indexes. For these contexts, using an arithmetic average is, in general, not desirable as it implies a constant compensatory between indicators. In other words, compensatory is closely related with the concept of balance between the indicators. See, for example, Freudenberg (2003), Cherchye et al (2007), Mazziotta and Pareto (2016), and Walheer (2017b) for more discussion. For our metafrontier context, we may also see the weights of the aggregation procedure as a balance between the importance of the DMUs in the group.

way to interpret the group-level indicators (i.e. they fulfil desirable properties), that depend on the model specification (in particular, if convexity is allowed or not when defining the metafrontier) and on the economic optimisation behaviour of the DMUs, and that does not imply constant compensatory between DMUs (i.e. that takes the relative importance of the DMUs in the group into account). In fact, we will show that a linear weighting aggregation procedure meets all these requirements. This is particularly attractive since linear weightings are easy to use and to interpret in practice. Attractively, the suggested weights are coherent with several works on disaggregation (i.e., in our context, from group to DMUs) and aggregation (i.e., in our context, from DMUs to group) in the efficiency literature. Refer, for example, for disaggregation to Cherchye et al (2013), Cherchye, De Rock, and Walheer (2015, 2016) and Walheer (2017a, 2018a, b); and for aggregation to Färe and Zelenyuk (2003, 2007), Färe, Grosskopf, and Zelenyuk (2004), Zelenyuk (2006, 2016), and Färe and Karagiannis (2017).

We apply our technique to the case of 10 European sectors. Recently, increasing attention has been given to the study of sector performances. See, Cherchye et al (2014), Miao and Wang (2014), Zschille (2014), Iscan (2015), Zeira and Zoabi (2015), Walheer (2016a, b, 2018c), Magalhaes and Afonso (2017), and Stauvermann and Kumar (2017), to cite only a few. These works have studied the efficiency performances of one or several sectors empirically, but only very few have compared a large numbers of sectors, and investigated their technology gaps. See, for example, Tsekouras et al (2016) for the case of the technology gaps of the European transport sectors. Besides evaluating the technology gaps of the 10 sectors, we also investigate whether greater changes occur when technology gaps are smaller. If it is the case, it will indicate a convergence of the sectors in terms of technology. Next, we also investigate the relationships between technology gap and technical efficiency. Establishing a relationship may indicate the presence of path dependences (greater technology gap are associated with higher technical efficiency, and reciprocally), and the presence of spillovers (a sector can influence the metafrontier technology, and reciprocally). Clearly, it is important to use a consistent aggregation scheme to obtain the sector-level technology gap ratios. Otherwise, this could, at best, make the results suspicious, and at worst, bias the results. One other advantage of our aggregation scheme in this context is that it allows us to better understand the results for the sectors, and to identify the key countries in each sector. At this point, it is important to note that without a consistent aggregation scheme, investigating the contribution of each country in every sector is, by definition, impossible, as, in that case, they all contribute in the same proportion.

The rest of the paper is structured as follows. In Section 2, we present our aggregation scheme for the technology gap ratio. In Section 3, we demonstrate our application in the case of 10 European sectors for the period 1995-2015. In Section 4, we present our conclusions.

The meta-frontier approach is subject to the same limitations, as analysts must assign entities to groups based upon a priori knowledge. Separation approaches also reduce the discriminating power of the DEA models. Meanwhile, one stage models directly use the exogenous variable in the analysis.

2 Methodology

The distinguishing feature of the metafrontier approach is to consider that DMUs are split into groups, reflecting the presence of heterogeneity between DMUs. In particular, we assume that we have I groups where each group i contains K_i DMUs.[2] In each group i, every DMU k uses P inputs, captured by $\mathbf{x}_k^i$, to produce Q outputs, captured by $\mathbf{y}_k^i$, with their associated prices denoted by $\mathbf{p}^i$. Note that the prices are the same for all DMUs within a group. This assumption is needed to obtain our aggregation scheme. For many settings and applications, it is not a strong assumption; it is also a commonly agreed assumption when defining aggregation schemes.[3] Intuitively, to define an indicator at the group level, the members of the groups have to share certain properties; here captured by the output price. In practice, the common prices can be seen, in microeconomic contexts, as a benchmark or reference prices for the group (Kuosmanen, Cherchye and Sipilainen (2006)). In macroeconomic contexts, the common prices could represent the country, region, or sector prices (adjusted for purchasing-power parity or inflation). It is important to remark that any procedure can be used to obtain the group prices (see Section 2.3 for more detail). Finally, note that for one-output cases (as for our empirical application in Section 3), the aggregation procedure is price-independent (see Section 2.4 for discussion).

In this Section, we start by defining the group-specific and metafrontier technology and efficiency measurements. Without loss of generality, we consider the output side of the production process. That is, we investigate for revenue optimality and potential outputs. It is straightforward to extend the following to a cost minimisation (and input-oriented) or profit maximisation (and directional distance function) setting. Next, we introduce the concept of technology gap ratio, and explain how to aggregate this concept at the group level. Finally, we briefly explain how the aggregation works for settings with one output in the production process. In that case, the weights are price-independent. This last part also allows us to better contextualise our application (see Section 3). As a final remark, note that the different efficiency measurements can be computed by both Data Envelopment

[2] We do not impose that each group contains the same number of DMUs. Also, note that the total number of observed DMUs is given by: $K_1 + K_2 + \cdots + K_I = \sum_{i=1}^{I} K_i$.

[3] See, for example, Färe and Zelenyuk (2003, 2007), Färe, Grosskopf, and Zelenyuk (2004), Zelenyuk (2006, 2016), Cherchye, De Rock, and Walheer (2015, 2016), Walheer (2016a, b, 2017a, 2018a, b), and Färe and Karagiannis (2017).

Analysis (DEA) or stochastic models. See, for example, O'Donnell, Rao, and Battese (2008), Huang et al (2013), and Amsler, O'Donnell, and Schmidt (2017) for more detail about the computational aspects.

2.1 Technologies and efficiency measurements

As we are interested by the output side of the production process, we define the technology in terms of output requirement sets. In particular, for DMU k in group i, the output requirement set is defined as follows:

$$P^i(\mathbf{x}_k^i) = \{\mathbf{y} \mid \mathbf{x}_k^i \text{ can produce } \mathbf{y} \text{ in group } i\}. \tag{1}$$

The set $P^i(\mathbf{x}_k^i)$ contains all the combinations of the outputs that can be produced by the input quantities $\mathbf{x}_k^i$. We impose some regularity conditions on those sets, captured by three technology axioms. These three axioms form an empirically attractive minimal set of regularity conditions and are used in many models (see Färe and Primont (1995)).[4] The technology axioms are defined as follows:

Axiom T1 (nested output requirement set): $\mathbf{x}^i \leq \mathbf{x}^{i'} \implies P^i(\mathbf{x}^i) \subseteq P^i(\mathbf{x}^{i'})$.

Axiom T2 (monotone output requirement set): $\mathbf{y}^i \in P^i(\mathbf{x}^i)$ and $\mathbf{y}^{i'} \leq \mathbf{y}^i \implies \mathbf{y}^{i'} \in P^i(\mathbf{x}^i)$.

Axiom T3 (convex output requirement set): $\mathbf{y}^i \in P^i(\mathbf{x}^i)$ and $\mathbf{y}^{i'} \in P^i(\mathbf{x}^i) \implies \forall \lambda \in [0,1]$: $\lambda \mathbf{y}^i + (1-\lambda)\mathbf{y}^{i'} \in P^i(\mathbf{x}^i)$.

The metafrontier technology is obtained as an envelopment of the group-specific technology sets. Usually, two ways are possible when taking an envelopment of sets: a convex or a non-convex envelopment. Initially, as given by O'Donnell, Rao, and Battese (2008), the metafrontier was defined as a non-convex envelopment of the group-specific technology sets.[5] Indeed, while the group-specific technologies are assumed to be convex (see axiom *T3*), nothing guarantees that this is the case for the metafrontier technology. The non-convex envelopment has been used in, for example, Tiedemann, Francksen and Latacz-Lohmann (2011), Huang et al (2013), Verschelde et al (2016), and Afsharian, Ahn and Harms (2017). Formally, we obtain:

$$P^{nc} = NonConvexHull\left\{P^1 \cup P^2 \cup \cdots \cup P^I\right\}. \tag{2}$$

[4] We point out that axioms *T2* and *T3* are imposed only for the technical efficiency measurement. In fact, imposing monotonicity and convexity do not alter the revenue evaluation (see, for example, Varian (1984) and Tulkens (1993) for discussion).

[5] At this point, we remark that while they do not impose convexity of the metafrontier technology, their DEA estimator is based on this assumption, which creates confusion for practitioners. We thank an anonymous referee for highlighting this important fact.

Note that, we clearly have the group output requirement sets included in the metafrontier technology, i.e. $P^i \subseteq P^{nc}$ for every group i.

Nevertheless, this is not the most used version of the metafrontier technology. Indeed, most of the practical works (see, for example, the references cited in the Introduction), make the additional assumption of convexity of the envelopment. Formally, we have:

$$P^c = ConvexHull\left\{P^1 \cup P^2 \cup \cdots \cup P^I\right\}. \tag{3}$$

It is clear that we also have the group output requirement sets included in the metafrontier technology for that case, i.e. $P^i \subseteq P^c$ for every group i. Also, as imposing convexity of the metafrontier technology implies more structures on this set, the convex hull is, by definition, larger than the non-convex one. We have: $P^{nc} \subseteq P^c$. Thus, imposing convexity has a direct impact on the estimators of technical efficiency and technology ratio gap (and on the weights in the aggregation scheme as shown below). Moreover, assuming a convex envelopment could imply some infeasible regions for the technology and therefore introduces a bias in estimating the metafrontier. All in all, the safest option is to assume a non-convex envelopment, as in the original definition of O'Donnell, Rao, and Battese (2008), while assuming a convex envelopment should be well-motivated. Statistical tests might help for that purpose, as those defined in Kneip, Simar and Wilson (2015). Finally, we remark that the debate about imposing convexity or not is not only specific to the metafrontier context, but also holds true for many concepts in the efficiency literature. See, for example, Deprins, Simar, and Tulkens (1984), Kerstens and Vanden Eeckaut (1999), Podinovski (2004a, b), and Leleu (2009) among others.

Therefore, for our aggregation procedures, we make an explicit difference between the convex and non-convex envelopment when defining the metafrontier technology. Given our previous discussion, we believe that this distinction is of interest from both theoretical and practical points of view. Also, as shown later, the weights are different for the two envelopments, revealing both the endogoneity of the weights, and the importance of justifying the choice of a convex envelopment. Finally, we point out that it is also possible to define the metafrontier when considering non-convex group output requirement sets (i.e. without axiom *T3*). We do not consider this case for the sake of compactness (see also Verschelde et al (2016) for an illustration of this case).

Based on the definitions of the group-specific and metafrontier technology sets, we can define our concepts of revenue and output-oriented efficiency measurements. The starting point of our concept of revenue efficiency is the maximal revenue. For every DMU k in group i, the maximal revenue is given by:

$$R^i(\mathbf{x}_k^i, \mathbf{p}^i) = \max_{\mathbf{y} \in P^i(\mathbf{x}_k^i)} \mathbf{p}^{i'} \mathbf{y}. \tag{4}$$

In words, $R^i(\mathbf{x}_k^i, \mathbf{p}^i)$ selects, given the output prices $\mathbf{p}^i$, the maximal output vector in the referent output requirement set. Intuitively, the maximal revenue can never be lower than the actual revenue, implying $R^i(\mathbf{x}_k^i, \mathbf{p}^i) \geq \mathbf{p}^{i'}\mathbf{y}_k^i$. $R^i(\mathbf{x}_k^i, \mathbf{p}^i) = \mathbf{p}^{i'}\mathbf{y}_k^i$ means that the maximal revenue is reached, while $R^i(\mathbf{x}_k^i, \mathbf{p}^i) > \mathbf{p}^{i'}\mathbf{y}_k^i$ reflects potential revenue improvement. Equivalently, we can define maximal revenues with respect to the (convex and non-convex) metafrontier technology as follows:

$$R^c(\mathbf{x}_k^i, \mathbf{p}^i) = \max_{\mathbf{y} \in P^c(\mathbf{x}_k^i)} \mathbf{p}^{i'} \mathbf{y}. \tag{5}$$

$$R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i) = \max_{\mathbf{y} \in P^{nc}(\mathbf{x}_k^i)} \mathbf{p}^{i'} \mathbf{y}. \tag{6}$$

The interpretation of these two maximal revenues are analogous to $R^i(\mathbf{x}_k^i, \mathbf{p}^i)$. The only difference is the output requirement set. Also, it is clear that $R^i(\mathbf{x}_k^i, \mathbf{p}^i) \leq R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i) \leq R^c(\mathbf{x}_k^i, \mathbf{p}^i)$. This directly follows from the relationship between the three output requirement sets discussed previously. In practice, it is more convenient to define a ratio to compare the maximal and actual revenues. In the tradition of Debreu (1951) and Farrell (1957), we define the group-level revenue efficiency measurement as:

$$RE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) = \frac{\mathbf{p}^{i'}\mathbf{y}_k^i}{R^i(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{7}$$

As discussed above, the actual revenue is the lower bound of the actual revenue (i.e. $R^i(\mathbf{x}_k^i, \mathbf{p}^i) \geq \mathbf{p}^{i'}\mathbf{y}_k^i$), making the revenue efficiency measurement smaller than one. When $R^i(\mathbf{x}_k^i, \mathbf{p}^i) = \mathbf{p}^{i'}\mathbf{y}_k^i$, $RE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}_k^i) = 1$ reflecting revenue efficient behaviour, and when $R^i(\mathbf{x}_k^i, \mathbf{p}^i) > \mathbf{p}^{i'}\mathbf{y}_k^i$, $RE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) < 1$, meaning that revenue could, in principle, be improved.[6] It is straightforward to extend the concept of revenue efficiency measurement to

[6]Note that, sometimes, revenue efficiency is defined as the maximal to the actual revenues. We adopt the actual to maximal revenue definition as it is the one used in metafrontier contexts. See Battese and Rao (2002), Battese, Rao, and O'Donnell (2004), O'Donnell, Rao, and Battese (2008), and Amsler, O'Donnell, and Schmidt (2017).

the (convex and non-convex) metafrontier technology as follows:

$$RE^c(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) = \frac{\mathbf{p}^{i'}\mathbf{y}_k^i}{R^c(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{8}$$

$$RE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) = \frac{\mathbf{p}^{i'}\mathbf{y}_k^i}{R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{9}$$

As a final remark, we established previously that $R^i(\mathbf{x}_k^i, \mathbf{p}^i) \leq R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i) \leq R^c(\mathbf{x}_k^i, \mathbf{p}^i)$, implying the following ranking between the revenue efficiency measurements: $RE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) \geq RE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) \geq RE^c(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)$. This reveals once more why it is important to justify the assumption of convexity for the metafrontier technology, as it can only decrease revenue efficiency.

Contrary to revenue efficiency, technical efficiency does not start from an economic optimisation behaviour. Instead, it compares the input-output performances of the DMUs. As such, it does not depend on the prices $\mathbf{p}^i$. In our context, technical efficiency checks if outputs could be increased given the inputs. In other words, technical efficiency investigates for potential outputs. For the group technology, it is defined as:

$$TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i) = \inf\left\{\theta \mid \frac{\mathbf{y}_k^i}{\theta} \in P^i(\mathbf{x}_k^i)\right\}. \tag{10}$$

Generally, $TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i)$ is smaller than 1, and a lower value indicates greater technical inefficiency. $TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i)$ represents how far away the actual outputs are from the potential outputs. When $TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i) = 1$, it means that they coincide. When $TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i) < 1$, it implies that the actual outputs represent $TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i) \times 100\%$ of the potential output quantities. As a final remark, note that $\frac{\mathbf{y}_k^i}{TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i)}$ defines the potential outputs.

Farrell (1957) noticed that there is no particular reason why revenue efficiency should coincide with technical efficiency, but he found a natural way to relate the two types of efficiency:

$$RE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) = TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i) \times AE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i). \tag{11}$$

$AE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)$, the output-oriented allocative efficiency measurement, is interpreted as inefficiency due to non-optimal allocation of outputs given the prices. As such, revenue and technical efficiency coincide when $AE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) = 1$; or in other words, when there is no inappropriate allocation of the outputs. Technical efficiency measurements based on the metafrontier technology are given as:

$$TE^{c}(\mathbf{y}_k^i, \mathbf{x}_k^i) = \inf\left\{\theta \mid \frac{\mathbf{y}_k^i}{\theta} \in P^{c}(\mathbf{x}_k^i)\right\}. \tag{12}$$

$$TE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i) = \inf\left\{\theta \mid \frac{\mathbf{y}_k^i}{\theta} \in P^{nc}(\mathbf{x}_k^i)\right\}. \tag{13}$$

Clearly, as for the revenue efficiency measurements, $TE^{i}(\mathbf{y}_k^i, \mathbf{x}_k^i) \geq TE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i) \geq TE^{c}(\mathbf{y}_k^i, \mathbf{x}_k^i)$ also holds true. Finally, we can also relate revenue and technical efficiency at the metafrontier level as follows:

$$RE^{c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) = TE^{c}(\mathbf{y}_k^i, \mathbf{x}_k^i) \times AE^{c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i). \tag{14}$$

$$RE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) = TE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i) \times AE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i). \tag{15}$$

$AE^{c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)$ and $AE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)$ are, respectively, allocative efficiency, with respect to the convex and non-convex metafrontier technology. They have to be interpreted in an analogous manner as $AE^{i}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)$.

2.2 Technology gap ratios

Technology gap ratio is defined, by Battese and Rao (2002), Battese, Rao, and O'Donnell (2004), and O'Donnell, Rao, and Battese (2008), as the ratio of efficiency with respect to the metafrontier technology and to the group-specific technology. For the revenue efficiency approach, they are defined for the convex and non-convex cases as follows:

$$RTG^{i,c}(\mathbf{x}_k^i, \mathbf{p}^i) = \frac{RE^{c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)}{RE^{i}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)} = \frac{R^{i}(\mathbf{x}_k^i, \mathbf{p}^i)}{R^{c}(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{16}$$

$$RTG^{i,nc}(\mathbf{x}_k^i, \mathbf{p}^i) = \frac{RE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)}{RE^{i}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)} = \frac{R^{i}(\mathbf{x}_k^i, \mathbf{p}^i)}{R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{17}$$

An initial observation is that the two ratios are smaller than unity. This follows directly from the relationship between the revenue efficiency measurements (i.e. $RE^{i}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) \geq RE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) \geq RE^{c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)$). Next, the ratios measure, for DMU k in group i, the gap between the group frontier and the (convex or non-convex) metafrontier. If they are equal to unity, it means that there is no gap, while lower values indicate a larger gap. Finally, these ratios do not depend on the actual output value, but only on the maximal revenue, as shown by the second equality.[7]

[7] The second equality is easily obtained by plugging-in (7) and (8) in (16); and (7) and (9) in (17).

Similarly, the technology gap ratios based on technical efficiency are defined as follows:

$$TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i) = \frac{TE^c(\mathbf{y}_k^i, \mathbf{x}_k^i)}{TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i)}. \tag{18}$$

$$TTG^{i,nc}(\mathbf{y}_k^i, \mathbf{x}_k^i) = \frac{TE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i)}{TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i)}. \tag{19}$$

As for the revenue-based technology gap ratios, these ratios are smaller than one. This can also be seen from the relationship between the technical efficiency measurements established before (i.e. $TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i) \geq TE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i) \geq TE^c(\mathbf{y}_k^i, \mathbf{x}_k^i)$). Unity means no technology gap, while a smaller value implies more gaps. Note that, as for the technical efficiency measurements (see (10), (12), and (13)), these ratios are price-independent. Also, in general, nothing guarantees that we have an equality between revenue- and technical-based technology gap ratios. Following the spirit of Farrell (1957), we can relate the two concepts by an allocative-based indicator (using (11), (14), and (15)):

$$\begin{aligned} RTG^{i,c}(\mathbf{x}_k^i, \mathbf{p}^i) &= \frac{TE^c(\mathbf{y}_k^i, \mathbf{x}_k^i) AE^c(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)}{TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i) AE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)}, \\ &= \frac{TE^c(\mathbf{y}_k^i, \mathbf{x}_k^i)}{TE^i(\mathbf{y}_k^i, \mathbf{x}_k^i)} \times \frac{AE^c(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)}{AE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)}, \\ &= TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i) \times ATG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i). \end{aligned} \tag{20}$$

$ATG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)$ represents the allocative technology gap ratio. It is defined as the ratio between allocative efficiency relative to the metafrontier technology to allocative efficiency relative to the group-specific technology. Note that there is no ranking between these two concepts, making $ATG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)$ unbounded. A similar decomposition can be done for the non-convex metafrontier technology gap ratio:

$$RTG^{i,nc}(\mathbf{x}_k^i, \mathbf{p}^i) = TTG^{i,nc}(\mathbf{y}_k^i, \mathbf{x}_k^i) \times ATG^{i,nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i), \tag{21}$$

where $ATG^{i,nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) = \frac{AE^{nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)}{AE^i(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i)}$.

2.3 Aggregation: group-level indicators

An important indicator for empirical work is the technology gap ratio at the group level. Indeed, as DMUs are partitioned into groups, it is natural to provide an indicator of the technology gap at that level. Also, group-level indicators give the option to easily compare groups. To date only the arithmetic average has been suggested to obtain the technology gap ratio for the group. We suggest an alternative way such that we keep a natural way to interpret the group-level indicators (i.e. they fulfil desirable properties), that depend on the model specification (in particular, if convexity is allowed or not when defining the metafrontier) and on the economic optimisation behaviour of the DMUs, and that does not imply constant compensatory between DMUs (i.e. that takes the relative importance of the DMUs into account).

To facilitate our notation, let $\mathbf{y}^i = (\mathbf{y}_1^i, \ldots, \mathbf{y}_{K_i}^i)$ and $\mathbf{x}^i = (\mathbf{x}_1^i, \ldots, \mathbf{x}_{K_i}^i)$ be the output and input (matrices) of the group. Note that no extra notation is needed to define the price vector of the group, it is given by $\mathbf{p}^i$. In practice, it could be the case that all DMUs in the group face the same prices, then it is easy to define $\mathbf{p}^i$. On the contrary, it could be the case that DMUs have different prices. In that case, any procedures can be used to define the group-level prices. For example, we may use a simple, weighted or uniform, average of the DMU-specific prices; or the least or most favourable prices. Nonlinear weighting procedures are also possible. The only requirement is to relate the group-specific prices to the DMU-specific prices. Different strategies have been discussed for aggregation contexts in, for example, Färe and Zelenyuk (2003, 2005), Färe, Grosskopf, and Zelenyuk (2004), Zelenyuk (2006, 2016), Cherchye, De Rock, and Walheer (2015, 2016), and Walheer (2016a, b, 2017a, 2018a, b); and also for non-aggregation contexts in, for example, Kuosmanen, Cherchye and Sipilainen (2006), Tohidi, Razavyan and Tohidnia (2012), Tohidi and Razavyan (2013), and Fang and Li (2015). Finally, note that when no prices are available for the DMUs, we can still use the aggregation procedure. In that case, we can rely on the shadow prices or use the input-output data to construct the group prices. See, for example, Cherchye, De Rock and Walheer (2016) and Walheer (2017b, 2018a) for more discussion about shadow prices, and Färe and Zelenyuk (2003) and Zelenyuk (2006) for using input-output data to reconstruct the group prices.[8]

As discussed in the Introductory, most of the previous aggregation techniques for efficiency and efficiency-related concepts are based on a weighted average. Therefore, in the tradition of these previous works, our aim is to find linear weights $\Big($with $\omega_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) \geq 0$,

[8]Note that it is also possible, in some particular cases, to use different prices in the aggregation procedure. One way we can highlight is to use the concept of Lindahl prices when some inputs are jointly used by the DMUs within a group. See, for example, Cherchye et al (2013), Cherchye, De Rock and Walheer (2016), and Walheer (2017a, 2018a, b) for discussion. It is straightforward to extend the following for this possibility. Note also that our framework can be used to define a model allowing for reallocation of inputs/outputs between DMUs within a group. Inspiration can be found, for example, in Nesterenko and Zelenyuk (2007) and Mayer and Zelenyuk (2014).

$\omega_k^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) \geq 0$, $\sum_{k=1}^{K_i} \omega_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = 1$, and $\sum_{k=1}^{K_i} \omega_k^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) = 1\Big)$ such that:

$$RTG^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = \sum_{k=1}^{K_i} \omega_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) \times RTG^{i,c}(\mathbf{x}_k^i, \mathbf{p}^i). \tag{22}$$

$$RTG^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) = \sum_{k=1}^{K_i} \omega_k^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) \times RTG^{i,nc}(\mathbf{x}_k^i, \mathbf{p}^i). \tag{23}$$

Note that, given our setting, the weights can only depend on the input quantities and the output prices. This is rather intuitive as all the concepts in equations (22) and (23) do not depend on the output quantities. An attractive feature of these weights is that they give the option of knowing the importance of each DMU in the group, i.e. the relative importance of each DMU in terms of technology gap.

As a first step, we can easily obtain a relationship between the group-level technology gap ratios and the minimal revenues as follows:

$$RTG^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = \frac{\sum_{k=1}^{K_i} R^i(\mathbf{x}_k^i, \mathbf{p}^i)}{\sum_{k=1}^{K_i} R^c(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{24}$$

$$RTG^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) = \frac{\sum_{k=1}^{K_i} R^i(\mathbf{x}_k^i, \mathbf{p}^i)}{\sum_{k=1}^{K_i} R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{25}$$

It is easy to verify that the group-level indicators share the same property as the DMU-level indicators. Indeed, before we established that $R^i(\mathbf{x}_k^i, \mathbf{p}^i) \leq R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i) \leq R^c(\mathbf{x}_k^i, \mathbf{p}^i)$. Summing over the K_i DMUs do not alter the inequality: $\sum_{k=1}^{K_i} R^i(\mathbf{x}_k^i, \mathbf{p}^i) \leq \sum_{k=1}^{K_i} R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i) \leq \sum_{k=1}^{K_i} R^c(\mathbf{x}_k^i, \mathbf{p}^i)$; implying that both $RTG^{i,c}(\mathbf{x}^i, \mathbf{p}^i)$ and $RTG^{i,nc}(\mathbf{x}^i, \mathbf{p}^i)$ are smaller than one. Also, if every DMU in the group has the same maximal revenues for the group-specific and metafrontier technologies ($\forall k$: $R^i(\mathbf{x}_k^i, \mathbf{p}^i) = R^c(\mathbf{x}_k^i, \mathbf{p}^i)$), the group-level indicator $RTG^{i,c}(\mathbf{x}^i, \mathbf{p}^i)$ equals one, reflecting no technology gap for the group. It suffices that for one DMU in the group, we have a difference (i.e. $R^i(\mathbf{x}_k^i, \mathbf{p}^i) < R^c(\mathbf{x}_k^i, \mathbf{p}^i)$ for at least one k) to make the group indicator smaller than one. Of course, in that case, it is important to be able to identify which DMU(s) are responsible, and how they contribute to the group. This once more demonstrates why the arithmetic average is probably not a good choice, and argues for the need of new weights. Similar reasoning applies for $RTG^{i,nc}(\mathbf{x}^i, \mathbf{p}^i)$. As a final remark, the relationships in (24) and (25) imply that the maximal revenues at the group level are immediately obtained as a simple sum of all member minimal revenues (see also Färe and Zelenyuk (2003) for related discussion).[9]

The relationships established in (24) and (25) are important since they show that the

[9] Equivalently, we can rewrite (24) and (25) in terms of group-specific revenue efficiency measurements

group indicators can be defined in terms of DMU-specific minimal revenues exclusively, but they do not match with the aggregation procedure defined in (22) and (23), i.e. weights that relate the group-specific technology gap ratio to the technology gap ratios of the members of the group. Nevertheless, the aggregation schemes can be obtained by multiplying and dividing (24) and (25) by $R^c(\mathbf{x}_k^i, \mathbf{p}^i)$ and $R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)$, respectively. Rearranging the terms gives:

$$RTG^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = \sum_{k=1}^{K_i} \frac{R^c(\mathbf{x}_k^i, \mathbf{p}^i)}{\sum_{k=1}^{K_i} R^c(\mathbf{x}_k^i, \mathbf{p}^i)} \times \frac{R^i(\mathbf{x}_k^i, \mathbf{p}^i)}{R^c(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{26}$$

$$RTG^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) = \sum_{k=1}^{K_i} \frac{R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)}{\sum_{k=1}^{n_i} R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)} \times \frac{R^i(\mathbf{x}_k^i, \mathbf{p}^i)}{R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{27}$$

We obtain the aggregation schemes by defining:

$$\omega_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = \frac{R^c(\mathbf{x}_k^i, \mathbf{p}^i)}{\sum_{k=1}^{K_i} R^c(\mathbf{x}_k^i, \mathbf{p}^i)} \text{ and } \omega_k^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) = \frac{R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)}{\sum_{k=1}^{K_i} R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)}. \tag{28}$$

Those weights fulfil our requirements. Firstly, it is easy to verify that they are non-negative and sum to unity. Next, they depend on the model specification. In particular, they are different subject to whether convexity is allowed or not when constructing the metafrontier. Afterwards, they take the economic optimisation behaviour of the DMUs (here a revenue maximisation condition) into account. Also, they represent the relative importance of the DMUs in the groups, and thus do not imply constant and equal compensatory between DMUs. Finally, we believe that it is more intuitive that they depend on the maximal revenue based on the metafrontier rather than on those defined with respect to the group-specific frontier; as in the latter case, it would mean that the weights do not take all the data into account, while the technology gap ratio does. All in all, we believe that using those weights is more reasonable than using an arithmetic average.

For the technical-based technology gap ratio, the weights are easily obtained by combin-

(by multiplying and dividing by $\mathbf{p}^{i'} \sum_{k=1}^{K_i} \mathbf{y}_k^i$):

$$RTG^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = \frac{\frac{\mathbf{p}^{i'} \sum_{k=1}^{K_i} \mathbf{y}_k^i}{\sum_{k=1}^{K_i} R^c(\mathbf{x}_k^i, \mathbf{p}^i)}}{\frac{\mathbf{p}^{i'} \sum_{k=1}^{K_i} \mathbf{y}_k^i}{\sum_{k=1}^{K_i} R^i(\mathbf{x}_k^i, \mathbf{p}^i)}} = \frac{RE^c(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i)}{RE^i(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i)}.$$

$$RTG^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) = \frac{\frac{\mathbf{p}^{i'} \sum_{k=1}^{K_i} \mathbf{y}_k^i}{\sum_{k=1}^{K_i} R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)}}{\frac{\mathbf{p}^{i'} \sum_{k=1}^{K_i} \mathbf{y}_k^i}{\sum_{k=1}^{K_i} R^i(\mathbf{x}_k^i, \mathbf{p}^i)}} = \frac{RE^{nc}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i)}{RE^i(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i)}.$$

As such, the weights in Section 2.3 could equivalently be defined in terms of (outputs rescaled by) revenue efficiency, instead of maximal revenues.

ing our previous results with the decomposition of the revenue-based technology gap ratio into technical and allocative counterparts (see (20) and (21)); we obtain for the convex case:

$$RTG^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = \sum_{k=1}^{K_i} \omega_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) \times TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i) \times ATG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i). \tag{29}$$

As before, it suffices to multiply top and bottom by a certain factor to obtain the aggregation schemes. In that case, we make use of $\sum_{k=1}^{K_i} R^c(\mathbf{x}_k^i, \mathbf{p}^i)\, TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i)$ (the maximal revenue weighted by the technical technology gap ratio) as the factor; by rearranging the terms we obtain:

$$\begin{aligned} RTG^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = & \left(\sum_{k=1}^{K_i} \omega_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) \times TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i) \right) \\ & \times \left(\sum_{k=1}^{K_i} \widehat{\omega}_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) \times ATG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i) \right), \end{aligned} \tag{30}$$

where $\widehat{\omega}_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = \frac{R^c(\mathbf{x}_k^i, \mathbf{p}^i)\, TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i)}{\sum_{k=1}^{K_i} R^c(\mathbf{x}_k^i, \mathbf{p}^i)\, TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i)}$. Note that the weights for the technical technology gap ratio are the same as the weights of the revenue technology gap ratio. As a consequence, the weights depend on the output prices, which could be a bit surprising for a technical-based concept, but this reflects the economic optimisation behaviour required for our weights. That is, they are based on the revenue maximisation behaviour of the DMUs, and thus depend on the prices.[10] Note also that in one-output cases, the weights become price-independent (see Section 2.4). The weights for allocative efficiency are different: they correspond to the maximal revenue rescaled by the technical technology gap ratio. Let us define:

$$TTG^{i,c}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i) = \sum_{k=1}^{K_i} \omega_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) \times TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i). \tag{31}$$

$$ATG^{i,c}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i) = \sum_{k=1}^{K_i} \widehat{\omega}_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i) \times ATG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i). \tag{32}$$

By plugging-in the two above definitions in (30), we obtain:

$$RTG^{i,c}(\mathbf{x}^i, \mathbf{p}^i) = TTG^{i,c}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i) \times ATG^{i,c}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i). \tag{33}$$

This last equation implies that the decomposition of the revenue technology gap ratio into

[10] Similar price-dependent results are obtained, in different efficiency-related contexts, by for example, Färe and Zelenyuk (2003, 2007). Färe, Grosskopf, and Zelenyuk (2004), Zelenyuk (2006, 2016), and Färe and Karagiannis (2017).

technical and allocative counterparts holds also for the group level. Also, it is easy to verify that $TTG^{i,c}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i)$ and $ATG^{i,c}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i)$ share the same property as their DMU-level counterparts. In particular, we established above that $TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i) \leq 1$, with $TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i) = 1$ revealing no technology gap. Multiplying by the weight $\omega_k^{i,c}(\mathbf{x}^i, \mathbf{p}^i)$ (non-negative and summing to one by definition) and summing over all the members of the groups do not alter the inequality. We obtain $TTG^{i,c}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i) \leq 1$. $TTG^{i,c}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i)$ equals one only if $TTG^{i,c}(\mathbf{y}_k^i, \mathbf{x}_k^i) = 1, \forall k$. In words, the group technical technology gap ratio equals 1, only if every member in the group has a technology gap ratio equal to 1. A similar reasoning applies for the group-level allocative technology gap ratio. We obtain $ATG^{i,c}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i) = 1$, only when no allocative technology gap ratio is observed for every group member.

Clearly, the previous steps ((29) to (33)) can also be performed when non-convexity of the metafrontier technology is chosen. For the sake of compactness, we present below the mean results:

$$RTG^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) = TTG^{i,nc}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i) \times ATG^{i,nc}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i), \tag{34}$$

where

$$TTG^{i,nc}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i) = \sum_{k=1}^{K_i} \omega_k^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) \times TTG^{i,nc}(\mathbf{y}_k^i, \mathbf{x}_k^i). \tag{35}$$

$$ATG^{i,nc}(\mathbf{y}^i, \mathbf{x}^i, \mathbf{p}^i) = \sum_{k=1}^{K_i} \widehat{\omega}_k^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) \times ATG^{i,nc}(\mathbf{y}_k^i, \mathbf{x}_k^i, \mathbf{p}^i). \tag{36}$$

$$\widehat{\omega}_k^{i,nc}(\mathbf{x}^i, \mathbf{p}^i) = \frac{R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)\, TTG^{i,nc}(\mathbf{y}_k^i, \mathbf{x}_k^i)}{\sum_{k=1}^{n_i} R^{nc}(\mathbf{x}_k^i, \mathbf{p}^i)\, TTG^{i,nc}(\mathbf{y}_k^i, \mathbf{x}_k^i)}. \tag{37}$$

As such, we obtain similar results for the non-convex case. The only difference with the convex case is that the weighting procedure takes the non-convexity of the metafrontier into account (one of the features required for our aggregation scheme). Therefore, in general, the weights for the convex and non-convex cases are different.

2.4 One-output case

We briefly comment, in this last part, how the aggregation scheme works when the production process contains one output. This case is of particular interest since, as demonstrated below, the weights are price-independent. In that case, in each group i, every DMU k uses P inputs $\mathbf{x}_k^i$ to produce one output y_k^i at price p^i. An initial fact is that, by definition, no misallocation of the output is possible, making allocative efficiency equal unity. This holds true for the group-specific and metafrontier definitions: $AE^i(y_k^i, \mathbf{x}_k^i, p^i) = 1$, $AE^c(y_k^i, \mathbf{x}_k^i, p^i) = 1$, and $AE^{nc}(y_k^i, \mathbf{x}_k^i, p^i) = 1$. We obtain the following results (Proofs are given in Appendix B):

$$RTG^{i,c}(\mathbf{x}^i, p^i) = TTG^{i,c}(\mathbf{y}^i, \mathbf{x}^i). \tag{38}$$

$$RTG^{i,nc}(\mathbf{x}^i, p^i) = TTG^{i,nc}(\mathbf{y}^i, \mathbf{x}^i). \tag{39}$$

$$\omega_k^{i,c}(\mathbf{x}^i, p^i) = \frac{\frac{y_k^i}{TE^c(y_k^i, \mathbf{x}_k^i)}}{\sum_{k=1}^{K_i} \frac{y_k^i}{TE^c(y_k^i, \mathbf{x}_k^i)}}. \tag{40}$$

$$\omega_k^{i,nc}(\mathbf{x}^i, p^i) = \frac{\frac{y_k^i}{TE^{nc}(y_k^i, \mathbf{x}_k^i)}}{\sum_{k=1}^{K_i} \frac{y_k^i}{TE^{nc}(y_k^i, \mathbf{x}_k^i)}}. \tag{41}$$

In words, in a one-output case, allocative efficiency is irrelevant for technology gap ratios. Thus revenue and technical technology gap ratios are equivalent. Next, the weights are price-independent (they only depend on the input-output quantities). In fact, they correspond, for the revenue and technical technology gap ratios to the potential output shares with respect to the metafrontier (see our discussion of (10)). Refer also to our empirical study in Section 3 for more discussion of the weights in one-output cases.

3 Application

We apply our methodology to the case of 10 sectors in Europe (Agriculture, Mining, Manufacturing, Electricity, Gas and Water, Construction, Wholesale, Transport, Public Administration, Education, and Health), representing the groups. Each group/sector is composed of 19 countries (Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Slovakia, Slovenia, Spain, and Sweden). The time span is 1995-2015. The data are provided by a reliable institution: OECD. Indeed, sector-level data are, in general, more difficult to find and to rely on than country-level data. As such, this represents a unique opportunity to study sectors over a long period of time.

Using the metafrontier framework and, in particular, the new aggregation scheme allows us to answer several important policy-oriented questions. What are the key sectors and countries in terms of technology gaps in Europe? Are sectors performing better than others? How have the technology gap ratios changed over the period? Do greater changes occur more often in sectors/countries presenting smaller technology gap ratios? How are technology gap and technical efficiency related? Is there a path dependence for technology gap and technical efficiency? Are there spillovers between technology gap and technical efficiency? Clearly, to answer these questions, it is important to provide a consistent aggregation scheme to obtain sector technology gap ratios. Otherwise, this could, at best, make the results suspicious, and at worst, bias the results. Also, it is important to note that without a consistent aggregation scheme the ability to investigate the contribution of each country in every sector is, by definition, impossible, as, in that case, they would all contribute by the same proportion.

The data are taken from the OECD Detailed National Accounts database. This database proxies output by the Gross Added Value (in millions of the current national currency). We apply a double correction to this variable (inflation and purchasing power parity) to obtain comparable data. Also, data for two productions factors are provided by the OECD Detailed National Accounts database: labour (in thousands of people employed) and capital, proxied by the Gross Capital Formation (in millions of the current national currency). We also apply the double correction to capital. At this point, it is important to note that extra production factors (human capital, energy, etc.) are sometimes included when studying a specific sector. Given our multiple sector setting, we believe that it is more natural to consider only capital and labour as production factors. We see at least two theoretical reasons. On the one hand, including more production factors would imply that they are important for all the sectors. On the other hand, while there is consensus of including labour and capital as production factors, it is not the case for other production factors. For instance, energy is often modelled as an intermediate obtained via technological combinations of labour and capital; and human capital is, when included, modelled as an augmentation of labour, and not as a production factor. There is also a practical reason to not include more production factors; these data are not available at the sector level.

To obtain the technology gap ratios, we estimate the technical efficiency scores for the 19 countries in every sector for each year, with respect to the sector-level frontier and the (convex and non-convex) metafrontier. We make use of a DEA-based estimation method. Indeed, there are no theoretical guidelines to choose the production functions in multiple sector contexts; that could, in principle, be sector-specific. DEA-based estimation methods offer the advantages of not asking to specify the production functions. All the technical efficiency scores are computed by the means of linear programs. Those linear programs are analogous to the ones discussed in O'Donnell, Rao, and Battese (2008) for the convex case; and in Huang et al (2013) for the non-convex case. Given this similarity, we do not explicitly write the programs and refer to their paper for more details. As a final remark, we note that, as we are in a one-output case, technical- and revenue-based efficiency coincide, and the weights are price-independent and are interpreted as the relative potential output shares.

We present our main findings below. We start by contextualising our results by briefly presenting the relative importance of our 10 sectors in Europe for the period. Next, we present our results for the technology gap ratios and discuss the computed weights. Afterwards, we investigate the changes in technology gap ratios, and relate those numbers to the levels of technology gap ratios and to technical efficiency. Finally, we check whether spillovers and path dependences are present. All results are available in Appendix A.

Relative importance of the sectors in Europe. Before presenting the results, we give a rapid overview of the relative importance of our 10 sectors in Europe. This allows us to better contextualise the sector-level technology gap ratio results. Table 1 gives the (average over all years) relative shares during the period for the 10 European sectors. Overall, the two most important sectors are Manufacturing (largest shares of output, labour, and capital) and Wholesale. Note also the important shares of capital in the Transport and Public Administration sectors, and the important shares of labour in the Health, Public Administration, and Construction sectors. Finally, our 10 sectors represent around 75% of the output, 83% of labour, and 85% of capital for the period 1995-2015, giving credit to the results of this analysis.

Also, it is important to highlight differences between the sectors. A first distinction arises between sectors that are more production- or service-oriented. Agriculture, Mining, Manufacturing, Electricity, Gas and Water, and Construction are clearly more production-oriented, while Wholesale, Transport, Public Administration, Education, and Health are more service-oriented. Over recent decades, an important change in terms of contribution to economic growth of the sectors has been observed. Indeed, the share of Agriculture is relatively small in almost all European countries and the share of the industrial sectors has also fallen, while service-oriented sectors account for around 60% of the Gross Added Value in most European countries. Next, public firms are more present in some sectors, as, in the Transport, Public Administration, Education, and Health sectors. Of course, the proportion of public firms may vary importantly between European countries, but these sectors are often labour intensive. All in all, these differences between sectors are important as they might create technological constraints for the sectors, and thus be used to better understand the differences found for the technical efficiency and technological gap. Also, they have a direct impact on the architecture of the production process of the sectors in every country, and between countries (we may think to, for example, flexibility of the production process; variety of the products and services; cost constraint; job-shop, flow-shop, or group-shop; continuous or discrete flow; etc.).

Technology gap ratios under convexity and non-convexity. The (average over all the years) results for the technology gap ratios and the corresponding weights are shown in Table 2. An initial observation is that the technology gap ratios, under convexity and non-convexity, are rather close. To formally test this initial observation, we make use of the Spearman correlation coefficient. We choose this statistic rather than, for example, the Pearson correlation, as the correlation of Spearman is by nature nonparametric, and thus better fits in this context. The coefficient for the technology gap ratios between the convex and non-convex cases (when pooling all years, countries, and sectors together) is 0.9304 ($p-$value: 0). It implies that assuming convexity does not have a major impact and confirms our initial observation. As discussed in detail in Section 2.1, assuming convexity puts more structure on the metafrontier. Therefore, we decide to continue with the non-convex case. At the group level, Agriculture is clearly the sector presenting the smaller technology gap ratio (0.46). Next, the other sectors have scores close to each other (between 0.71 and 0.96). Note that the highest performances are for Manufacturing (0.96) and Wholesale (0.93); the two most important sectors in Europe (see Table 1). These results highlight the presence of important technological constraints for Agriculture, but do not suggest important differences between production- and service-oriented sectors. Also, sectors with more public firms have, on average, worse performances.

We can better understand the sector-level results by looking at the performances of the countries in each sector. For Agriculture, we can point out the poor performances of Estonia, Hungary, and Poland; and the better performances of France, Denmark, Spain, and Slovenia. For Mining, only Poland presents poor performances. For Manufacturing, all countries have a good performance except Poland, Luxembourg, Estonia, and Hungary. Next, for Electricity, Gas, and Water, note the poor scores of Luxembourg, Estonia, Hungary, and Ireland; and the good performances of Germany and Slovenia. In the Construction sector, only Belgium, Sweden, and Spain have lower performances. For Wholesale, Estonia, Hungary, Ireland, and Slovakia perform worse. For Transport, note the better scores of Italy, Spain, and France; and the poor scores of Estonia, Ireland, and Hungary. For Public Administration, we remark on the poor performances of all Eastern and Central European countries, and of Luxembourg. In the Education sector, note the good performance of Poland and Italy, and the poorer performances of Estonia. Finally, for Health, only Estonia and Hungary have a poor performance.

We complete our analysis by investigating how each country contributes to the sector-level technology gap ratios. Indeed, a country could have a good performance but a small contribution to the sector; while another country could have poor performance in a sector, but contribute a lot in that sector. This is the advantage of the aggregation scheme suggested, we can investigate how important countries are in each sector. We discuss this in the next part.

Relative importance of the countries for the technology gap ratios. Since assuming convexity of the metafrontier does not have a large impact on the technology gap ratio results, we can expect a similar conclusion for the weights. Again, we make use of the Spearman correlation coefficient. The value of the coefficient (when pooling all years, countries, and sectors together) is 0.9981 ($p-$value: 0), confirming our conclusion based on the technology gap ratios.

Clearly, the computed weights are not constant, arguing once more, that picking the arithmetic average for this task is probably not a good choice. As discussed in Section 2.4, they represent the relative potential value (with respect to the metafrontier) of each country in every sector. Overall, the most important countries are Germany, France, Italy, and Spain. This is not a surprise as those countries are the most important countries in Europe. Of course, the weights are different in each sector revealing the relative importance of each country in every sector. We can also point out some specific countries for some sectors. For example, Norway, the Netherlands, and Poland in the Mining sector; and Poland in the Agriculture sector.

Change in technology gap ratios. We continue our analysis by providing the average (absolute) changes per year for the technology gap ratios for every sector and every country in each sector. The results are given in Table 3 and have to be interpreted as follows: a positive value implies a greater technology gap ratio change (i.e. an improvement); a negative value implies the opposite. As most of the changes are small, we multiply the numbers by 100 for better readability of the Table. Most of the sectors present a negative small change, showing smaller technology gap ratio changes. Only positive changes occur for the Mining and Health sectors. Agriculture, the sector with the poorest performance, also presents a negative change. This goes in favour of the technological constraints found previously for this sector. Also, the stagnation (or small decrease) found for the majority of the sectors may be interpreted as a technological constraint. In other words, our results suggest that the sectors have reached a certain level of technology, and that they seem to stay at that level. Note that this holds true when considering production or service-oriented sectors, and when distinguishing between more private or public sectors.

These results are confirmed for almost all countries in every sector. We can point out the increase of the technology gap ratios of Hungary in Agriculture, Wholesale, and Public Administration; Slovakia in Agriculture and Manufacturing; Slovenia in Agriculture, Manufacturing, Electricity, Gas, and Water, Construction, Transport, and Public Administration; Denmark in Electricity, Gas, and Water; Spain in Construction, Public Administration, and Education; Italy in Construction, Wholesale, and Public Administration; Ireland in Construction; Finland in Construction and Wholesale; Estonia in Construction; Norway in

Wholesale; Luxembourg in Wholesale; Germany in Public Administration and Education; France in Education. For the Mining sector, only Poland presents a regress. For Health, Slovenia, Slovakia, the Netherlands, Italy, Hungary, France, Estonia, the Czech Republic, and Austria have negative changes.

An important question is how the changes and the levels of the technology gap ratios are related. In other words, we investigate whether higher positive changes occur when technology gap ratios are lower. We present the Spearman correlations in Table 4. Once more, we rely on the Spearman coefficient, rather than the Pearson or linear regressions, because of the presence of endogeneity between these two indicators. Almost all the coefficients are negative, showing that levels and changes go in opposite directions. As most of the changes are negative (see Table 3), it means that higher technology gap ratios are associated with higher negative changes. It advocates, once more, for a decrease in terms of technology gap ratio in the European sectors over the period (even if the decreases are rather small, as discussed for Table 3). Again, we might see this as a technological constraint for the European sectors. Note the high coefficients of Austria in Public Administration; Belgium in Construction; the Czech Republic in Manufacturing, Construction, and Health; Denmark in Manufacturing and Construction; Estonia in Agriculture, Manufacturing, Construction, and Health; Germany in Electricity, Gas, and Water and Wholesale; Hungary in Manufacturing and Public Administration; Luxembourg in Construction, Transport, and Public Administration; The Netherlands in Agriculture; Norway in Manufacturing; Poland in Education; Slovenia in Construction and Transport; and Spain in Wholesale.

Technology spillovers and path dependences. As a last step, we estimate the relationships between technology gap ratio and technical efficiency. Especially, we investigate whether technology gap ratio or technical efficiency in the past have an influence on current technology gap ratio and technical efficiency. If it is the case it would advocate for path dependences and spillovers. These types of relationship are important as they allow us to better understand the dynamic in terms of technology for sectors in a country, and between countries. That is, how sectors interact and what is the architecture of the production process for sectors. At this point, we want to emphasise that more advanced econometric techniques could be used (as, for example, GMM or nonparametric regressions). We prefer to stay with the Spearman correlation coefficients for the same reasons as those discussed before. We believe that it represents a good first approximation and compromise in this context. Before interpreting the results for the relationships, it is important to note that, overall, sectors and countries become more technically efficient over the period.[11] Indeed,

[11]The sector-level technical efficiency scores are also obtained by a specific aggregation scheme. See Färe and Zelenyuk (2003) for more general discussions on aggregation of technical efficiency, and Walheer (2016a, b) for a related discussion for sectors.

as shown in Table 5, except in Agriculture and Manufacturing, changes are positive overall. It also means that sectors are more efficient with their productive process.

The Spearman correlation coefficients between current technical efficiency and past technical efficiency, and past technology gap ratio are presented in Table 6. Clearly, there is a path dependence for technical efficiency (most of the coefficients are close to unity and significant), meaning that improvements in technical efficiency occur, more often, when technical efficiency is high. The two highest coefficients are in Manufacturing and Wholesale. This could be an explanation for the good performances observed for these sectors. The path dependence is not observed for all countries in every sector, but for the majority. Note that some coefficients are significantly negative. For example, Transport in France, and Electricity, Gas, and Water in Italy. The picture is less clear for the relationship between current technical efficiency and past technology gap ratio. This relationship captures the spillovers from the metafrontier to the group-specific frontiers. In other words, this relationship investigates whether sectors have benefitted from the metafrontier. Some coefficients are positive, meaning that larger past technology gap ratios are associated with higher current technical efficiency; but some are also negative implying the opposite. Also, overall, the coefficients are rather low. At the sector-level, we observe a positive coefficient for Agriculture, Manufacturing, Wholesale, Transport, Public Administration and Health. Once more, the highest are for Wholesale and Manufacturing. This pattern is not kept for all the countries. We point out the important negative coefficients of Austria and Finland in Agriculture; Finland in Health; Hungary, Poland, Spain and Italy in Construction; the Netherlands and Poland in Wholesale; Norway in Education and Transport; Poland in Manufacturing; Sweden in Transport and Education; and the important positive coefficients of Slovenia in Manufacturing. As a final remark, note that some coefficients are not calculated. This happens when a country in a sector has indicators always equal to unity. In this context, it means that the country is either technically efficient, or has a technology gap ratio of 1, or both.

The Spearman correlation coefficients between current technology gap ratio and past technical efficiency, and past technology gap ratio are presented in Table 7. The path dependence is observed for technology gap. Overall, all the coefficients are high and significant, but highest in Public Administration, Wholesale, Education and Manufacturing. The pattern is clearly confirmed at the country level. Next, we check for potential spillovers from the sector-specific frontiers to the metafrontier. At the sector-level, the coefficients are not all significant, but when they are, they are rather small and positive. In particular, the coefficients are highest in Manufacturing and Wholesale. Note the positive and small coefficients for Agriculture, Transport, Public Administration and Health; and the negative and small coefficients in Education. Finally, we highlight some important countries: negative coefficients in Agriculture for Austria and Finland; in Manufacturing, a negative coefficient in Poland and a positive coefficient in Slovenia; in Electricity, Gas, and Water, a positive coefficient for Finland and a negative coefficients for Hungary and Slovenia; in Construction, negative coefficients for Hungary and Poland; in Wholesale, negative coefficient for Poland; in Transport and Public Administration, negative coefficients for Poland; and in Education, negative coefficients for Norway and Sweden.

Summary and policy implications. We summarise our main findings in five main points:

- Manufacturing and Wholesale, the two most important sectors in Europe, have the highest technology gap ratios. Agriculture is the sector with the poorest performance.
- Eastern and Central European countries present, on average, poorer technology gap ratio performances, and in particular, Estonia and Hungary.
- There is a (small) decrease in the technology gap ratio for the period, but not in all sectors. Higher technology gap ratios are associated with higher negative (but small) changes. It goes in favour of technological constraints at the European level.
- Overall, the most important countries in terms of our aggregation scheme are: Germany, France, Italy, and Spain.
- There is a path dependence for both the technological gap ratio and technical efficiency in every sector and every country. These relationships allow us to better understand the architecture of the production process of the sectors. Spillovers are present but not for all sectors/countries, and overall, they are rather moderate. They are highest, in both directions, for Wholesale and Manufacturing.

All in all, the most important sectors present good results. Policy implementations should first target the Agriculture sector, and the Eastern and Central European countries. While the decrease of the technology gap ratio is rather low, policy implementations should be taken to avoid the decrease becoming important, and thus avoid a potential issue of technological constraint in Europe.

4 Conclusion

We suggest a new aggregation scheme to obtain the group-level technology gap ratio in metafrontier contexts. Our aggregation scheme presents several desirable properties. Firstly, our aggregation scheme takes the specification of the model into account (in particular, if convexity is allowed or not when defining the metafrontier), and the economic optimisation behaviour of the Decision Making Units (DMUs). Next, our aggregation scheme takes the relative importance of the DMUs in the group into account. Finally, our aggregation scheme provides a natural way to interpret the group-level indicator. Moreover, our aggregation scheme is consistent with several recent works on disaggregation and aggregation in the efficiency literature.

We apply our method to the case of 10 European sectors, during the period 1995-2015, using the OECD Detailed National Accounts database. It represents a unique opportunity to apply the metafrontier methodology, and in particular, our aggregation scheme to sectors over a long period. We also investigate whether higher changes occur when technology gap ratios are smaller, the relationships between technology gap ratio and technical efficiency, and for the presence of spillovers and path dependences. Our aggregation scheme allows us to better understand the results for each sector, and to identify the key countries for every sector. Our findings reveal important patterns useful for policy-makers.

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Appendix A[12]

Table 1: Relative shares per sector

Group	Output	Labour	Capital
A	2.80	5.38	4.85
Mi	1.35	0.37	1.99
Ma	19.69	19.58	24.56
EG	2.26	0.83	5.25
C	6.49	8.23	4.91
W	13.27	16.25	9.51
T	6.69	6.21	11.67
PA	8.26	8.95	12.55
E	5.80	7.25	4.64
H	8.98	10.26	6.03
Total	75.58	83.32	85.95

[12] We make use of the following abbreviations in the Appendix: Agriculture (A), Mining (Mi), Manufacturing (Ma), Electricity, Gas and Water (EG), Construction (C), Wholesale (W), Transport (T), Public Administration (PA), Education (E), and Health (H); in 19 European countries: Austria (A), Belgium (B), Czech Republic (CZ), Denmark (DK), Estonia (EE), Finland (FIN), France (F), Germany (D), Hungary (H), Ireland (IRL), Italy (I), Luxembourg (L), Netherlands (NL), Norway (N), Poland (PL), Slovakia (SK), Slovenia (SI), Spain (E), and Sweden (S). (G) correspond to group.

Table 2: Technology gap ratios and weights under non-convexity (top) and convexity (bottom)

	G	**A**	**B**	**CZ**	**DK**	**EE**	**FIN**	**F**	**D**	**H**	**IRL**	**I**	**L**	**NL**	**N**	**PL**	**SK**	**SI**	**E**	**S**
A	0.46	0.43	0.49	0.44	0.41	0.35	0.42	0.53	0.54	0.28	0.45	0.49	0.52	0.40	0.45	0.31	0.45	0.66	0.57	0.44
		0.05	0.01	0.03	0.02	0.00	0.03	0.14	0.12	0.04	0.02	0.15	0.00	0.06	0.01	0.15	0.01	0.01	0.10	0.02
Mi	0.90	1.00	1.00	0.89	1.00	1.00	1.00	0.99	0.85	0.95	1.00	0.99	1.00	1.00	1.00	0.54	0.98	0.82	0.97	1.00
		0.01	0.00	0.05	0.04	0.00	0.01	0.04	0.09	0.00	0.02	0.09	0.00	0.11	0.30	0.14	0.01	0.00	0.05	0.03
Ma	0.96	1.00	0.98	0.94	1.00	0.79	0.99	1.00	1.00	0.74	1.00	1.00	0.67	1.00	1.00	0.68	0.98	0.95	0.98	0.98
		0.03	0.03	0.04	0.02	0.00	0.02	0.12	0.27	0.03	0.02	0.16	0.00	0.04	0.01	0.08	0.02	0.00	0.08	0.03
EG	0.74	0.68	0.69	0.79	0.58	0.43	0.63	0.82	0.99	0.55	0.51	0.75	0.35	0.61	0.66	0.69	0.70	0.91	0.75	0.56
		0.04	0.04	0.05	0.02	0.01	0.02	0.12	0.17	0.02	0.03	0.12	0.00	0.05	0.02	0.09	0.03	0.01	0.11	0.05
C	0.92	0.87	0.67	0.99	0.98	0.97	0.95	1.00	1.00	0.86	0.97	0.99	0.99	0.98	0.82	0.97	0.92	0.99	0.82	0.76
		0.03	0.04	0.04	0.01	0.00	0.01	0.15	0.18	0.02	0.01	0.15	0.00	0.04	0.02	0.08	0.01	0.01	0.18	0.03
W	0.93	0.91	0.80	0.90	0.87	0.62	0.84	1.00	1.00	0.64	0.68	1.00	0.95	0.92	0.82	0.89	0.71	0.85	0.98	0.83
		0.03	0.04	0.03	0.02	0.00	0.01	0.14	0.20	0.02	0.02	0.15	0.00	0.06	0.02	0.09	0.01	0.01	0.12	0.03
T	0.76	0.67	0.70	0.68	0.67	0.50	0.68	0.90	0.81	0.50	0.36	0.93	0.52	0.77	0.68	0.58	0.60	0.59	0.92	0.65
		0.04	0.04	0.04	0.03	0.00	0.02	0.13	0.19	0.03	0.03	0.13	0.01	0.05	0.03	0.07	0.02	0.01	0.10	0.04
PA	0.71	0.55	0.67	0.56	0.62	0.27	0.60	0.75	0.80	0.49	0.66	0.81	0.29	0.69	0.54	0.59	0.58	0.46	0.77	0.56
		0.03	0.04	0.03	0.02	0.00	0.02	0.19	0.20	0.02	0.01	0.12	0.01	0.06	0.02	0.06	0.01	0.01	0.12	0.03
E	0.84	0.68	0.83	0.88	0.70	0.36	0.62	0.89	0.87	0.74	0.86	1.00	0.75	0.69	0.61	1.00	0.65	0.63	0.77	0.91
		0.04	0.04	0.03	0.03	0.00	0.03	0.18	0.21	0.02	0.01	0.11	0.00	0.06	0.03	0.07	0.01	0.00	0.09	0.04
H	0.84	0.73	0.78	0.80	0.80	0.52	0.79	0.96	0.82	0.52	0.83	0.87	0.89	0.85	0.84	0.72	0.74	0.71	0.78	0.84
		0.03	0.04	0.02	0.03	0.00	0.02	0.18	0.25	0.01	0.01	0.11	0.00	0.08	0.03	0.05	0.01	0.00	0.07	0.04
A	0.40	0.38	0.36	0.39	0.39	0.25	0.35	0.49	0.47	0.26	0.39	0.46	0.57	0.35	0.37	0.29	0.36	0.83	0.50	0.34
		0.05	0.02	0.03	0.02	0.01	0.03	0.14	0.12	0.03	0.02	0.15	0.00	0.06	0.02	0.15	0.01	0.00	0.11	0.03
Mi	0.82	0.89	0.85	0.67	0.98	0.53	0.85	0.84	0.76	0.50	0.93	0.87	0.57	1.00	1.00	0.48	0.62	0.89	0.74	0.90
		0.01	0.00	0.06	0.03	0.00	0.01	0.04	0.09	0.01	0.02	0.09	0.00	0.10	0.28	0.14	0.01	0.00	0.06	0.03
Ma	0.90	0.90	0.83	0.80	0.91	0.65	0.87	0.95	1.00	0.66	1.00	0.96	0.49	0.94	0.93	0.64	0.82	0.91	0.86	0.81
		0.03	0.03	0.05	0.02	0.00	0.02	0.12	0.25	0.03	0.01	0.15	0.00	0.04	0.01	0.08	0.02	0.00	0.08	0.04
EG	0.66	0.61	0.64	0.65	0.54	0.39	0.57	0.71	0.93	0.41	0.49	0.68	0.34	0.55	0.60	0.55	0.59	0.89	0.67	0.52
		0.04	0.04	0.05	0.02	0.01	0.02	0.13	0.16	0.03	0.02	0.12	0.00	0.05	0.02	0.10	0.03	0.00	0.11	0.05
C	0.85	0.79	0.59	0.90	0.83	0.50	0.85	0.99	1.00	0.77	0.92	0.91	0.77	0.86	0.73	0.89	0.80	0.79	0.73	0.68
		0.03	0.04	0.04	0.02	0.00	0.02	0.14	0.16	0.02	0.01	0.15	0.00	0.05	0.02	0.08	0.01	0.01	0.18	0.03
W	0.88	0.75	0.72	0.79	0.74	0.49	0.74	1.00	1.00	0.59	0.60	0.95	0.71	0.86	0.74	0.83	0.62	0.66	0.92	0.71
		0.03	0.04	0.04	0.02	0.00	0.02	0.13	0.18	0.02	0.02	0.14	0.00	0.06	0.02	0.09	0.01	0.01	0.12	0.03
T	0.67	0.53	0.56	0.60	0.49	0.34	0.59	0.83	0.75	0.45	0.30	0.85	0.43	0.66	0.54	0.50	0.50	0.43	0.80	0.53
		0.04	0.04	0.04	0.03	0.01	0.02	0.13	0.18	0.02	0.03	0.12	0.01	0.05	0.03	0.07	0.02	0.01	0.10	0.05
PA	0.63	0.53	0.59	0.51	0.50	0.18	0.46	0.71	0.75	0.45	0.51	0.72	0.26	0.53	0.42	0.52	0.49	0.34	0.68	0.49
		0.03	0.04	0.03	0.02	0.00	0.02	0.18	0.19	0.02	0.01	0.12	0.01	0.06	0.03	0.06	0.01	0.01	0.12	0.03
E	0.76	0.63	0.76	0.80	0.64	0.25	0.53	0.83	0.76	0.66	0.72	1.00	0.53	0.61	0.52	0.95	0.52	0.50	0.65	0.82
		0.03	0.04	0.03	0.03	0.00	0.03	0.17	0.21	0.02	0.01	0.10	0.00	0.06	0.03	0.07	0.01	0.01	0.10	0.04
H	0.76	0.63	0.64	0.72	0.76	0.21	0.74	0.90	0.71	0.46	0.74	0.83	0.61	0.80	0.76	0.68	0.63	0.55	0.71	0.80
		0.03	0.04	0.02	0.03	0.00	0.02	0.18	0.26	0.01	0.01	0.11	0.00	0.08	0.03	0.04	0.01	0.00	0.07	0.04

Table 3: Average changes in the technology gap ratio per year

	A	**Mi**	**Ma**	**EG**	**C**	**W**	**T**	**PA**	**E**	**H**
G	-0.56	0.27	-0.02	-0.98	-0.16	-0.11	-1.05	-0.05	-0.40	0.30
A	-1.44	0.00	0.00	-0.71	0.00	-0.38	-1.90	-0.54	-1.94	-0.67
B	-1.26	0.00	0.00	-0.15	-1.94	-0.29	-2.17	-0.47	-1.18	0.47
CZ	-1.03	0.91	-0.29	-1.52	0.00	-0.74	-1.11	-0.72	-0.70	-0.35
DK	-0.66	0.00	0.00	0.42	-0.11	-0.43	-1.95	-2.07	-2.73	1.08
EE	-0.24	0.00	-0.64	-0.16	0.72	-3.23	-0.24	-2.04	-4.20	-1.00
FIN	-1.82	0.00	0.00	-0.61	0.02	0.46	-1.00	-1.16	-2.63	1.44
F	-0.95	0.00	0.00	-1.43	0.00	0.00	-1.39	-0.11	0.40	-0.02
D	-0.87	1.41	0.00	0.00	0.00	0.00	-0.32	0.90	0.64	0.80
H	0.14	2.73	-0.19	-0.88	-0.96	0.46	-0.28	0.04	-1.80	-1.80
IRL	-1.49	0.00	0.00	-0.48	0.69	-1.63	-1.40	-2.57	-1.11	0.62
I	-0.18	0.00	0.00	-1.27	0.18	-0.02	-1.31	0.18	0.00	-0.57
L	-1.35	0.00	0.39	-0.91	0.00	0.23	-0.57	-0.21	-1.50	1.27
NL	-0.85	0.00	0.00	-2.42	0.00	-0.63	-1.60	-0.13	-0.55	-0.41
N	-1.35	0.00	0.00	-0.84	-1.64	0.83	-1.48	-0.36	-2.70	0.51
PL	-0.25	-1.28	-0.51	-1.64	-0.45	-0.62	-0.16	-0.04	0.00	0.12
SK	1.33	0.00	0.78	-0.01	-1.17	-0.38	-0.26	-1.97	-2.86	-2.52
SI	2.27	0.00	1.35	2.47	0.35	-2.59	0.78	0.45	-2.95	-1.32
E	-0.03	0.00	0.00	-1.76	0.57	0.80	-1.43	0.12	1.22	1.31
S	-2.15	0.00	0.00	-0.85	-1.29	-0.45	-1.45	-0.45	-0.57	0.84

Table 4: Spearman correlation coefficients between levels and changes for the technology gap ratio

	G	**A**	**B**	**CZ**	**DK**	**EE**	**FIN**	**F**	**D**	**H**	**IRL**	**I**	**L**	**NL**	**N**	**PL**	**SK**	**SI**	**E**	**S**
A	-0.31	-0.23	-0.36	-0.29	-0.36	-0.76	-0.48	-0.24	-0.25	-0.38	-0.35	-0.26	-0.36	-0.65	-0.34	-0.39	-0.46	-0.44	-0.34	-0.55
	0.20	0.34	0.13	0.23	0.13	0.00	0.04	0.32	0.30	0.11	0.15	0.28	0.13	0.00	0.16	0.10	0.05	0.06	0.15	0.02
Mi	-0.30	-	-	-0.36	-	-	-	-0.51	-0.22	-0.75	-0.73	-0.75	-	-	-	-0.52	-0.77	-0.60	-0.89	-0.73
	0.21	-	-	0.13	-	-	-	0.03	0.36	0.00	0.00	0.00	-	-	-	0.02	0.00	0.01	0.00	0.00
Ma	-0.48	-	-0.39	-0.63	-0.73	-0.55	-0.37	-	-	-0.65	-	-	-0.35	-	-0.84	-0.25	-0.33	-0.54	-0.08	-0.41
	0.04	-	0.10	0.00	0.00	0.02	0.12	-	-	0.00	-	-	0.15	-	0.00	0.31	0.16	0.02	0.76	0.08
EG	-0.41	-0.29	-0.49	-0.49	-0.53	-0.51	-0.38	-0.37	-0.75	-0.43	-0.49	-0.29	-0.47	-0.27	-0.35	-0.40	-0.36	-0.33	-0.40	-0.29
	0.08	0.23	0.03	0.03	0.02	0.02	0.11	0.12	0.00	0.07	0.03	0.22	0.04	0.26	0.14	0.09	0.13	0.16	0.09	0.22
C	-0.20	-0.39	-0.47	-0.46	-0.78	-0.60	-0.50	-	-	-0.35	-0.15	-0.42	-0.73	-0.41	-0.38	-0.28	-0.28	-0.93	-0.15	-0.51
	0.40	0.10	0.04	0.05	0.00	0.01	0.03	-	-	0.14	0.55	0.07	0.00	0.08	0.11	0.24	0.24	0.00	0.53	0.03
W	-0.38	-0.37	-0.54	-0.21	-0.50	-0.65	-0.60	-	-0.73	-0.68	-0.56	-	-0.27	-0.14	-0.56	0.16	-0.56	-0.53	-0.97	-0.52
	0.11	0.12	0.02	0.40	0.03	0.00	0.01	-	0.00	0.00	0.01	-	0.27	0.56	0.01	0.51	0.01	0.02	0.00	0.02
T	-0.14	-0.39	-0.45	-0.34	-0.35	-0.75	-0.57	-0.19	-0.38	-0.56	-0.36	-0.13	-0.64	-0.52	-0.25	-0.28	-0.54	-0.60	-0.22	-0.40
	0.57	0.10	0.05	0.15	0.14	0.00	0.01	0.45	0.11	0.01	0.13	0.58	0.00	0.02	0.29	0.24	0.02	0.01	0.37	0.09
PA	-0.54	-0.78	-0.51	-0.28	-0.31	-0.62	-0.39	-0.39	-0.29	-0.71	-0.37	-0.24	-0.81	-0.40	-0.35	-0.19	-0.35	-0.53	-0.15	-0.51
	0.02	0.00	0.03	0.25	0.20	0.01	0.10	0.10	0.22	0.00	0.12	0.32	0.00	0.09	0.15	0.43	0.14	0.02	0.53	0.03
E	-0.31	-0.32	-0.34	-0.50	-0.12	-0.75	-0.39	-0.29	-0.44	-0.36	-0.47	-	-0.57	-0.19	-0.41	-0.84	-0.26	-0.62	-0.02	-0.38
	0.19	0.18	0.15	0.03	0.61	0.00	0.10	0.23	0.06	0.13	0.04	-	0.01	0.43	0.08	0.00	0.29	0.00	0.92	0.11
H	-0.18	-0.51	-0.53	-0.60	-0.27	-0.75	-0.37	-0.53	-0.39	-0.35	-0.54	-0.50	-0.29	-0.45	-0.43	-0.36	-0.32	-0.43	0.10	-0.33
	0.47	0.03	0.02	0.01	0.27	0.00	0.12	0.02	0.10	0.14	0.02	0.03	0.22	0.05	0.07	0.13	0.18	0.07	0.68	0.16

Table 5: Technical efficiency scores: levels (top) and changes (bottom)

	G	**A**	**B**	**CZ**	**DK**	**EE**	**FIN**	**F**	**D**	**H**	**IRL**	**I**	**L**	**NL**	**N**	**PL**	**SK**	**SI**	**E**	**S**
A	0.62	0.45	0.92	0.64	0.72	0.62	0.77	1.00	0.72	0.70	0.54	0.89	1.00	0.93	0.50	0.55	0.88	0.23	1.00	0.98
Mi	0.54	0.68	0.87	0.42	0.87	0.50	0.33	0.59	0.77	0.51	0.19	0.59	1.00	1.00	1.00	0.81	0.59	0.92	0.55	0.34
Ma	0.63	0.83	0.91	0.49	0.58	0.36	0.76	0.94	1.00	0.39	1.00	0.85	1.00	0.88	0.61	0.53	0.35	0.89	0.95	0.88
EG	0.63	0.73	0.87	0.51	0.83	0.60	0.69	0.89	1.00	0.64	0.45	1.00	1.00	0.86	0.99	0.57	0.40	0.26	0.89	0.88
C	0.68	1.00	0.95	0.39	0.81	0.74	0.94	1.00	1.00	0.38	0.86	0.82	1.00	0.90	0.88	0.44	0.71	0.53	0.88	0.88
W	0.67	0.94	1.00	0.44	0.79	0.65	0.90	1.00	1.00	0.45	0.72	0.93	1.00	0.87	0.94	0.59	0.62	0.54	0.68	0.93
T	0.69	0.83	0.95	0.53	0.78	0.78	0.98	1.00	1.00	0.50	0.71	1.00	1.00	0.93	0.88	0.62	0.57	0.60	0.76	0.89
PA	0.73	1.00	1.00	0.56	0.97	0.96	0.75	0.99	1.00	0.59	0.99	1.00	1.00	1.00	0.79	0.57	0.55	0.60	0.85	0.84
E	0.68	0.95	1.00	0.44	0.73	0.89	0.78	1.00	1.00	0.47	0.80	1.00	1.00	0.90	0.76	0.34	0.65	0.83	0.86	0.73
H	0.70	0.78	0.86	0.43	0.85	0.96	0.89	1.00	1.00	0.64	0.98	1.00	1.00	0.73	0.74	0.45	0.52	0.80	0.96	0.99
A	-0.28	0.20	-0.34	0.44	-0.54	1.29	1.28	0.00	-0.29	-1.72	-1.54	0.16	0.00	0.00	-1.28	-2.03	1.08	-1.98	0.00	-0.12
Mi	0.16	2.21	0.05	-0.75	3.54	0.68	-1.54	-0.62	0.00	-0.91	-1.79	0.36	0.00	0.00	0.00	0.00	3.82	0.00	-0.98	-1.12
Ma	-0.02	-0.47	-0.86	0.82	-0.29	0.70	-0.92	-0.42	0.00	-0.91	0.00	-0.92	0.00	-0.16	-0.76	0.59	-0.70	2.16	1.01	0.72
EG	0.16	-0.92	-0.50	0.70	1.29	0.09	-0.46	0.00	0.00	2.79	0.86	0.00	0.00	0.93	0.00	1.88	-0.61	-1.64	-1.17	-0.27
C	0.42	-0.08	0.14	0.23	0.19	3.23	0.20	0.00	0.00	0.02	-0.51	-0.67	0.00	-0.11	-0.24	0.92	3.59	0.30	0.12	0.71
W	0.46	-0.07	0.14	0.42	0.53	3.81	-0.50	0.00	0.00	-1.21	0.10	-0.15	0.00	1.18	0.00	0.11	1.16	2.43	-0.30	1.09
T	0.38	0.90	0.35	-1.13	1.42	3.53	0.61	-0.06	0.00	-0.72	1.31	0.00	0.00	0.82	1.03	-0.30	-1.26	0.00	-0.28	0.96
PA	0.05	0.00	0.00	0.26	-0.32	4.06	-0.43	-0.12	0.00	-3.60	0.00	0.03	0.00	0.00	0.84	-2.38	0.53	0.33	0.76	1.01
E	0.79	-0.33	0.00	0.21	0.42	4.22	0.59	0.00	0.00	0.67	1.08	0.00	0.00	0.14	1.26	1.01	2.38	1.40	0.26	1.75
H	0.48	-0.07	-0.42	1.04	-0.49	4.24	-1.08	0.00	0.00	1.00	0.00	-0.04	0.00	0.14	0.90	1.92	-0.29	1.14	0.00	1.03

Table 6: Spearman correlation coefficients between current technical efficiency and past technical efficiency (top) and past technology gap ratio (bottom)

	G	**A**	**B**	**CZ**	**DK**	**EE**	**FIN**	**F**	**D**	**H**	**IRL**	**I**	**L**	**NL**	**N**	**PL**	**SK**	**SI**	**E**	**S**
A	0.87	0.80	0.33	0.13	0.73	0.34	0.88	-0.06	-0.08	0.45	0.70	0.64	-	0.63	0.78	0.76	-0.02	0.70	-	0.28
	0.00	0.00	0.17	0.60	0.00	0.15	0.00	0.82	0.73	0.05	0.00	0.00	-	0.00	0.00	0.00	0.92	0.00	-	0.25
Mi	0.81	0.54	0.48	0.51	0.53	0.52	0.67	0.54	0.58	0.05	0.63	0.69	-	-	-	0.58	-0.31	0.60	0.64	0.37
	0.00	0.02	0.04	0.03	0.02	0.02	0.00	0.02	0.01	0.83	0.00	0.00	-	-	-	0.01	0.20	0.01	0.00	0.12
Ma	0.97	0.65	0.83	0.76	0.71	0.50	0.77	0.69	-	0.60	-	0.89	-	0.48	0.61	0.84	0.44	0.79	0.80	0.76
	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	-	0.01	-	0.00	-	0.04	0.01	0.00	0.06	0.00	0.00	0.00
EG	0.89	0.41	0.80	0.71	0.58	0.54	-0.10	0.80	-	0.75	0.64	-0.42	-	0.73	-0.02	0.86	0.56	0.76	0.85	0.61
	0.00	0.08	0.00	0.00	0.01	0.02	0.68	0.00	-	0.00	0.00	0.07	-	0.00	0.93	0.00	0.01	0.00	0.00	0.01
C	0.86	0.73	0.47	0.14	0.37	0.43	-0.11	-	-	0.79	0.76	0.90	-	0.49	0.52	0.85	0.36	0.78	0.91	0.54
	0.00	0.00	0.04	0.56	0.12	0.07	0.65	-	-	0.00	0.00	0.00	-	0.03	0.02	0.00	0.13	0.00	0.00	0.02
W	0.92	0.53	0.73	0.59	0.60	0.36	0.48	-	-0.06	0.22	0.66	0.90	-	0.85	0.86	0.90	0.64	0.84	0.41	0.91
	0.00	0.02	0.00	0.01	0.01	0.13	0.04	-	0.82	0.35	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.09	0.00
T	0.88	0.73	0.78	0.23	0.28	0.45	0.89	-0.73	-	0.53	0.81	-0.06	-	0.76	0.80	0.83	0.20	0.70	0.58	0.79
	0.00	0.00	0.00	0.34	0.25	0.05	0.00	0.00	-	0.02	0.00	0.82	-	0.00	0.00	0.00	0.40	0.00	0.01	0.00
PA	0.88	0.33	0.00	0.48	0.51	0.00	0.66	0.63	-0.06	0.63	0.51	-	-	-0.06	0.76	0.80	0.27	0.58	0.74	0.78
	0.00	0.17	1.00	0.04	0.03	1.00	0.00	0.00	0.82	0.00	0.02	-	-	0.82	0.00	0.00	0.26	0.01	0.00	0.00
E	0.86	0.67	-	0.49	0.59	0.56	0.91	-0.06	-	0.50	0.91	-	-	0.34	0.90	0.71	0.36	0.22	0.47	0.94
	0.00	0.00	-	0.03	0.01	0.01	0.00	0.82	-	0.03	0.00	-	-	0.15	0.00	0.00	0.13	0.36	0.04	0.00
H	0.86	0.54	0.66	0.51	0.74	0.00	0.85	-	-	0.43	0.41	0.83	-	0.68	0.92	0.74	0.23	0.07	0.71	0.73
	0.00	0.02	0.00	0.03	0.00	1.00	0.00	-	-	0.07	0.08	0.00	-	0.00	0.00	0.00	0.35	0.79	0.00	0.00
A	0.12	-0.90	0.40	-0.26	0.35	-0.46	-0.89	0.26	-0.01	-0.44	0.49	-0.12	-	-0.35	0.60	-0.12	0.28	-0.68	-	-0.04
	0.02	0.00	0.09	0.29	0.15	0.05	0.00	0.29	0.96	0.06	0.03	0.63	-	0.15	0.01	0.62	0.25	0.00	-	0.88
Mi	-0.06	-	-	-0.46	-	-	-	-0.37	0.38	0.21	0.17	-0.12	-	-	-	0.22	0.06	-0.30	-0.63	-0.17
	0.23	-	-	0.04	-	-	-	0.12	0.11	0.39	0.48	0.64	-	-	-	0.36	0.81	0.21	0.00	0.48
Ma	0.29	-	0.00	-0.33	-0.13	-0.35	-0.37	-	-	-0.30	-	-	-	-	0.17	-0.79	-0.47	0.89	-0.42	-0.11
	0.00	-	0.99	0.17	0.60	0.14	0.12	-	-	0.21	-	-	-	-	0.49	0.00	0.04	0.00	0.08	0.67
EG	-0.06	0.54	0.56	-0.43	-0.39	-0.58	0.12	0.58	-	-0.69	-0.18	0.07	-	-0.17	0.15	-0.21	-0.28	-0.64	0.41	-0.18
	0.28	0.02	0.01	0.06	0.10	0.01	0.62	0.01	-	0.00	0.47	0.76	-	0.49	0.53	0.39	0.25	0.00	0.08	0.45
C	-0.05	-0.22	-0.48	0.22	0.29	0.24	0.47	-	-	-0.82	0.04	-0.78	-	-0.17	-0.28	-0.77	-0.42	-0.24	-0.80	-0.30
	0.39	0.37	0.04	0.36	0.22	0.32	0.04	-	-	0.00	0.86	0.00	-	0.49	0.24	0.00	0.07	0.32	0.00	0.21
W	0.27	-0.37	-0.39	-0.64	0.24	0.01	0.04	-	0.06	0.03	0.58	-	-	-0.72	0.05	-0.91	-0.25	-0.15	-0.61	-0.17
	0.00	0.12	0.10	0.00	0.32	0.97	0.86	-	0.82	0.90	0.01	-	-	0.00	0.83	0.00	0.30	0.54	0.01	0.49
T	0.13	-0.38	-0.58	0.27	-0.58	-0.44	-0.24	0.03	-	-0.10	-0.34	0.16	-	-0.36	-0.72	-0.67	-0.28	-0.52	0.17	-0.72
	0.01	0.11	0.01	0.26	0.01	0.06	0.32	0.90	-	0.68	0.15	0.52	-	0.13	0.00	0.00	0.25	0.02	0.49	0.00
PA	0.21	-0.07	-0.03	0.23	0.53	-0.30	0.09	0.10	0.17	-0.15	0.11	-	-	0.26	-0.31	-0.67	-0.31	-0.40	0.52	-0.28
	0.00	0.78	0.90	0.33	0.02	0.21	0.72	0.68	0.48	0.54	0.65	-	-	0.29	0.19	0.00	0.20	0.09	0.02	0.25
E	-0.14	-0.18	-	-0.15	-0.61	-0.21	-0.55	-0.13	-	-0.68	-0.11	-	-	0.07	-0.92	0.19	-0.47	0.20	0.06	-0.72
	0.01	0.46	-	0.55	0.01	0.38	0.02	0.60	-	0.00	0.66	-	-	0.79	0.00	0.43	0.04	0.40	0.80	0.00
H	0.19	-0.28	-0.65	0.33	-0.64	-0.22	-0.77	-	-	-0.65	0.55	0.49	-	-0.06	0.50	-0.18	-0.29	-0.26	0.24	0.22
	0.00	0.24	0.00	0.17	0.00	0.38	0.00	-	-	0.00	0.01	0.03	-	0.79	0.03	0.46	0.23	0.29	0.33	0.38

Table 7: Spearman correlation coefficients between current technology gap ratio and past technology gap ratio (top) and past technical efficiency (bottom)

	G	A	B	CZ	DK	EE	FIN	F	D	H	IRL	I	L	NL	N	PL	SK	SI	E	S
A	0.81	0.90	0.79	0.78	0.39	0.43	0.83	0.83	0.78	0.59	0.49	0.75	0.40	0.86	0.49	0.77	0.48	0.90	0.79	0.81
	0.00	0.00	0.00	0.00	0.10	0.07	0.00	0.00	0.00	0.01	0.04	0.00	0.09	0.00	0.03	0.00	0.04	0.00	0.00	0.00
Mi	0.70	0.89	0.63	0.55	0.30	0.56	0.70	0.88	0.86	0.66	0.42	0.45	0.15	-	-	0.35	0.18	0.83	0.50	0.74
	0.00	0.00	0.00	0.02	0.21	0.01	0.00	0.00	0.00	0.00	0.08	0.06	0.53	-	-	0.14	0.46	0.00	0.03	0.00
Ma	0.84	0.70	0.67	0.13	0.45	0.42	0.80	0.86	-	0.13	-0.06	0.81	0.65	0.67	0.48	0.77	0.36	0.92	0.78	0.83
	0.00	0.00	0.00	0.61	0.06	0.08	0.00	0.00	-	0.60	0.82	0.00	0.00	0.00	0.04	0.00	0.13	0.00	0.00	0.00
EG	0.76	0.74	0.52	0.46	0.49	0.47	0.63	0.45	0.31	0.72	0.40	0.71	0.35	0.79	0.73	0.68	0.46	0.85	0.64	0.75
	0.00	0.00	0.02	0.05	0.04	0.04	0.00	0.06	0.20	0.00	0.09	0.00	0.14	0.00	0.00	0.00	0.05	0.00	0.00	0.00
C	0.79	0.74	0.62	0.57	0.54	0.28	0.56	0.67	-	0.75	0.76	0.83	0.29	0.34	0.62	0.74	0.02	0.39	0.62	0.39
	0.00	0.00	0.01	0.01	0.02	0.25	0.01	0.00	-	0.00	0.00	0.00	0.23	0.15	0.01	0.00	0.92	0.10	0.01	0.10
W	0.86	0.55	0.59	-0.02	0.58	0.08	0.10	-0.06	-0.06	0.03	0.66	0.50	0.45	0.62	0.63	0.82	-0.11	-0.12	0.86	0.62
	0.00	0.02	0.01	0.92	0.01	0.74	0.68	0.82	0.82	0.92	0.00	0.03	0.05	0.01	0.00	0.00	0.65	0.64	0.00	0.01
T	0.80	0.83	0.80	0.75	0.76	0.29	0.42	0.80	0.83	0.20	0.75	0.87	0.52	0.72	0.70	0.75	0.42	0.54	0.84	0.89
	0.00	0.00	0.00	0.00	0.00	0.22	0.08	0.00	0.00	0.40	0.00	0.00	0.02	0.00	0.00	0.00	0.07	0.02	0.00	0.00
PA	0.87	0.59	0.56	0.63	0.86	0.15	0.47	0.50	0.52	0.18	0.73	0.42	0.17	0.69	0.78	0.65	0.74	0.59	0.56	0.69
	0.00	0.01	0.01	0.00	0.00	0.55	0.04	0.03	0.02	0.45	0.00	0.08	0.48	0.00	0.00	0.00	0.00	0.01	0.01	0.00
E	0.85	0.78	0.89	0.82	0.93	0.03	0.86	0.58	0.64	0.72	0.74	-	0.54	0.70	0.90	0.43	0.69	0.41	0.86	0.45
	0.00	0.00	0.00	0.00	0.00	0.92	0.00	0.01	0.00	0.00	0.00	-	0.02	0.00	0.00	0.07	0.00	0.08	0.00	0.05
H	0.82	0.65	0.39	0.66	0.66	0.52	0.78	0.65	0.70	0.68	0.80	0.69	0.73	0.61	0.76	0.49	0.58	0.32	0.70	0.74
	0.00	0.00	0.10	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.04	0.01	0.18	0.00	0.00
A	0.15	-0.72	0.47	-0.18	0.54	0.00	-0.82	0.13	-0.11	-0.33	0.62	0.29	-	-0.01	0.34	0.13	0.17	-0.68	-	-0.02
	0.01	0.00	0.04	0.47	0.02	0.99	0.00	0.60	0.66	0.17	0.01	0.23	-	0.98	0.16	0.60	0.49	0.00	-	0.92
Mi	-0.07	-	-	-0.31	-	-	-	-0.19	0.09	0.14	-0.13	-0.28	-	-	-	-0.07	-0.13	-0.03	-0.24	0.34
	0.19	-	-	0.19	-	-	-	0.43	0.73	0.55	0.60	0.25	-	-	-	0.78	0.58	0.90	0.33	0.15
Ma	0.30	-	-0.27	-0.41	0.09	-0.28	-0.54	-	-	-0.50	-	-	-	-	-0.37	-0.75	-0.53	0.78	-0.30	0.02
	0.00	-	0.27	0.08	0.73	0.25	0.02	-	-	0.03	-	-	-	-	0.12	0.00	0.02	0.00	0.20	0.92
EG	-0.08	0.27	0.59	-0.51	-0.25	-0.48	-0.16	0.70	-	-0.72	-0.11	0.01	-	-0.39	-0.28	-0.50	-0.51	-0.71	0.25	-0.36
	0.15	0.26	0.01	0.03	0.31	0.04	0.52	0.00	-	0.00	0.64	0.96	-	0.10	0.24	0.03	0.03	0.00	0.30	0.13
C	-0.04	-0.25	-0.39	-0.18	-0.10	0.07	0.45	-	-	-0.81	0.16	-0.59	-	-0.02	-0.30	-0.77	-0.29	-0.39	-0.45	-0.54
	0.48	0.31	0.10	0.46	0.67	0.77	0.06	-	-	0.00	0.52	0.01	-	0.92	0.21	0.00	0.22	0.10	0.06	0.02
W	0.30	-0.54	-0.21	-0.68	0.14	0.00	-0.11	-	0.06	0.06	0.69	0.00	-	-0.68	-0.17	-0.85	-0.06	-0.37	-0.50	-0.06
	0.00	0.02	0.39	0.00	0.58	0.99	0.64	-	0.82	0.82	0.00	1.00	-	0.00	0.49	0.00	0.81	0.12	0.03	0.80
T	0.18	-0.41	-0.61	0.55	-0.56	0.03	-0.16	-0.26	-	0.04	-0.43	0.17	-	-0.44	-0.60	-0.78	-0.02	-0.55	0.50	-0.69
	0.00	0.08	0.01	0.02	0.01	0.90	0.52	0.28	-	0.86	0.07	0.48	-	0.06	0.01	0.00	0.92	0.02	0.03	0.00
PA	0.17	-0.16	0.09	-0.42	0.13	0.06	0.37	-0.09	0.26	-0.21	0.05	0.09	-	0.04	-0.34	-0.88	-0.55	-0.11	0.18	0.02
	0.00	0.51	0.72	0.08	0.59	0.81	0.12	0.70	0.29	0.39	0.84	0.73	-	0.86	0.16	0.00	0.01	0.64	0.46	0.95
E	-0.08	0.10	-	-0.13	-0.65	-0.19	-0.58	0.04	-	-0.51	0.01	-	-	-0.11	-0.89	0.26	-0.01	-0.12	-0.17	-0.78
	0.00	0.68	-	0.59	0.00	0.44	0.01	0.86	-	0.02	0.97	-	-	0.65	0.00	0.28	0.95	0.61	0.49	0.00
H	0.25	0.24	-0.24	0.50	-0.66	0.50	-0.66	-	-	-0.39	0.20	0.21	-	0.08	0.52	0.06	-0.54	-0.27	0.40	0.53
	0.00	0.33	0.32	0.03	0.00	0.03	0.00	-	-	0.10	0.41	0.38	-	0.76	0.02	0.81	0.02	0.26	0.09	0.02