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Interfaces with Other Disciplines

Meta-frontier and technology switchers: A nonparametric approach☆

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A B S T R A C T

The concept of meta-frontier has been proposed in order to deal with group heterogeneity among entities for nonparametric efficiency analysis. In brief, the meta-frontier is defined as the envelopment of the group-specific frontiers and naturally allows one to distinguish inefficiency from technology gap. While this concept has demonstrated its usefulness for empirical studies and been extended in several directions, two major shortcomings are the fixed number of groups and the static allocation of entities across groups. This is particularly problematic when dealing with panel data. In this paper, we extend the meta-frontier approach when technology switchers are considered, and quantify the impacts of the switchers on inefficient behavior and technology gap. We demonstrate the usefulness of our new methodology with the case of the technology clubs in the world economy.

1. Introduction

Nonparametric efficiency analysis (e.g. DEA after Charnes, Cooper, & Rhodes, 1978 FDH after Tulkens, 1993) is a technique used to evaluate an entity – such as a firm, a plant, a utility, a bank, or a country – by comparing its performance with other entities. This technique has demonstrated its usefulness in light of the significant number of applied works and extensions.[1] Remarkably, initiated as an operations research tool, this method has been set forth in a wide range of renowned journals and used to tackle various types of research questions.[2] Potential explanations for their success are their data-driven spirit – the technique is nonparametric in nature since no a-priori assumption is required about the entities' transformation process; instead, a production possibility set, capturing the entities' process, is reconstructed using data and imposing technology axioms – and its easy use – it suffices to solve linear programmings. In practice, (in)efficiency behavior is captured by the distance to the frontier of the reconstructed production possibility set.

Nevertheless, nonparametric efficiency analysis presents two important shortcomings; which likely account for its neglect beyond the operations research literature. First, its deterministic nature is often seen as restrictive. It implies, for instance, that there is no measurement errors and no outliers. Fortunately, well-established solutions have been proposed such as bias-corrected and robust nonparametric efficiency analysis methods (e.g. Daouia & Simar, 2007; Daraio & Simar, 2007; Simar & Vanhems, 2012). Second, nonparametric efficiency analysis usually assumes that entities use a similar (but unknown) transformation process. In other words, entities are homogeneous in terms of their process. For example, in a production context, it is assumed that firms use a similar (but unknown) production function. A well-established method to overcome this restriction while keeping the advantages of the initial nonparametric efficiency analysis models, is the concept of meta-technology (Hayami, 1969; Hayami & Ruttan, 1970) or meta-frontier (Battese & Rao, 2002; Battese, Rao, & O'Donnell, 2004; O'Donnell, Rao, & Battese, 2008).

Meta-frontier is a method tailored to deal with heterogeneity when entities are partitioned into different groups. Basically, a different production possibility set is reconstructed for each group, while an 'overall' set is defined as the envelopment of the group-specific counterparts. In practice, the meta-frontier approach requires to partition entities into several groups, each capturing a distinct technology. A common feature of all applied studies us-

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[1] According to Emrouznejad & Yang (2018), 10,300 DEA-related articles were published between 1978 and 2016, and up to 1000 journal articles were so annually in 2014, 2015 and 2016.

[2] Examples include macroeconomics and convergence (e.g. Färe, Grosskopf, Norris, & Zhang, 1994; Henderson & Russell, 2005; Kounetas, 2015), quality of life (e.g. Cherchye, Lovell, Moesen, & Puyenbroeck, 2007a; Cherchye, Moesen, Rogge, & Van Puyenbroeck, 2007b; Walheer, 2019), energy-environment-economics puzzle (e.g. Walheer, 2018b; Zhou, Ang, & Poh, 2008), public economics (e.g. Valdmanis, 1992), aquaculture (e.g. Sharma, Leung, Chen, & Peterson, 1999), tourism (e.g. Banker & Natarajan, 2011; Huang, Ho, & Chiu, 2014; Walheer & Zhang, 2018), health care (e.g. Biorn, Hagen, Iversen, & Magnussen, 2003), and management of organizations (e.g. Lewis & Sexton, 2004). These models, while deterministic, have also received attention from the statistics and econometrics literature (e.g. Sengupta, 1990; Banker & Natarajan, 2011; Simar, Vanhems, & Van Keilegom, 2016).

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0377-2217/

ing the concept of meta-frontier is the stability of their grouping procedure. That is, such research considers a fixed number of groups and allocates entities to each group once and for all. In other words, once the partitioning is made no modification is possible. While this setting may be useful in some contexts, it is generally restrictive or even unrealistic. For instance, new technologies can be discovered and others disappear. That is, the number of groups may not be constant over time. Also, the number of entities in each group may not be constant over time. That is, there may exist technology switchers, i.e. entities that adopt different technologies over time. These different features have been omitted from the meta-frontier technique. It is the purpose of this paper to allow for these options.

We apply our methodology to the case of the economic growth convergence amongst countries. This is probably the most famous empirical question involving technology switchers (here countries). In that case, a popular option is to partition countries into groups/clubs where technology is homogeneous inside but not between clubs (Azariadis & Drazen, 1990; Bernard & Jones, 1996; Durlauf & Johnson, 1995; Galor, 1996). Important efforts have been made to find coherent and consistent ways to define the clubs and the partitioning of countries amongst them (e.g. threshold method, PCA, variables and dimensions to consider). In fact, these two features are the main focus in the literature. In general, a stable number of groups is found while some countries move from one club to another over time, i.e. some countries are technology switchers. Different reasons can explain the willingness of a country to adopt another technology, but technology is recognized as a main source of economic development and a main factor of economic growth (Bernard & Jones, 1996; Gong & Keller, 2003; Hall & Jones, 1999; Islam, 1999; Prescott, 1998). Also, imitating or adopting new technologies is, generally, costly, and it is therefore important to be able to quantify the effects of the technology switch (Abramovitz, 1986). This is exactly the added value of our methodology in that empirical context: evaluate the impact of the technology switchers on the technology clubs and on the countries' (in)efficiency behavior.

The rest of the paper is structured as follows. In Section 2, we discuss the impact of the technoogy switchers on the meta-frontier. After, we set out defining some necessary concepts and present our notations in Section 3. Next, we motivate our new methodology by a simple illustration and define our objectives in Section 4. In Section 5, we define our concept of counterfactual technologies directly useful to define the switcher effects. In fact, the switcher effects are defined as ratios of well-known and well-established concepts in the efficiency literature and their counterfactual counterparts. In Section 6, we apply our technique with the case of the technology clubs and with two fictive scenarii. Finally, Section 7 concludes.

2. Meta-frontier and technology switchers

Meta-frontier is recognized as the main tool to deal with technology heterogeneity when conducting a nonparametric efficiency analysis. Indeed, this methodology has been applied to a large variety of topics revealing the attractiveness of this concept for empirical research. Examples of recent studies include Chen, Huang, & Yang (2009) for China; Kontolaimou & Tsekouras (2010) and Kontolaimou, Kounetas, Mourtos, & Tsekouras (2012) for European banks; Assaf, Barros, & Josiassen (2012) for hotels in Taiwan; Huang, Ting, Lin, & Lin (2013) for international tourist hotels; Lin & Du (2013) for Chinese regions; Beltran-Esteve, Gmez-Limn, Picazo-Tadeo, & Reig-Martnez (2014)) for Spanish olive producers; Jiang & Sharp (2015) for New Zealand dairy farms; Kounetas (2015) for European countries; Duygun, Sena, & Shaban (2016) for British commercial banks; Fu, Juo, Chiang, Yu, & Huang (2016) for Taiwanese and Chinese banks; Tsekouras, Chatzistamoulou, Kounetas, & Broadstock (2016) for the European transportation sectors; Azad, Munisamy, Masum, Saona, & Wanke (2017) for banks in Malaysia; Chang & Tovar (2017)) for the West Coast of South Pacific terminals; Li, Kopsakangas-Savolainen, Xiao, & Lau (2017) for the Japanese electricity distribution sector; Walheer (2018a) for European sectors.; Walheer (2019) for the Chinese electricity sector; Das & Drine (2020) for Africa; and He, Walheer, & (2020b) and Yang, Cheng, & Huang (2020) for the Chinese manufacturing sector.

The basic idea of the meta-frontier technique is to partition entities into groups such that each group uses a different technology. Common practice, common knowledge, or statistical methods could be used to form the groups and allocate entities across them. The partitioning has been made using several criteria in empirical studies such as ownership, geographical localization, economic infrastructure, resource endowments, social environment, operational settings, etc. The meta-frontier is then defined as an 'overall' frontier that envelops the group-specific technology frontier. Technology gap ratios are computed to quantify the distance between the group-specific frontiers and the meta-frontier. As such, this ratio provides a measure of the gap between the technology available to all entities and that available to a specific group of these. Attractively, this ratio enables us to disentangle actual inefficiency, i.e. with respect to the meta-frontier, from inefficiency with respect to the group.

A common feature of all papers cited above, and to the best of our knowledge, to the literature as a whole is the stability of their grouping procedure. They consider that entities are allocated to each group once for all, while the number of groups is fixed over time. The main reason for this procedure lies in the initial definition of the meta-frontier technique as given by Battese & Rao (2002) and their followers who considered this setting as their starting point. While useful in some cases, this setting is too restrictive, and, for some contexts, may lead to unrealistic results. For example, when dealing with panel data or large sample, several things may change over time requiring more flexibility for the grouping procedure.

The stability of the grouping procedure implies that some settings cannot be considered in the meta-frontier. First, it may be the case that a new technology is discovered (i.e. a new group is created) or that a technology disappears (i.e. an exiting group is deleted). Second, the number of entities in each group may not be constant over time. That is, some entities may change of group over time. Such entities are called technology switchers since they do not use the same technology over time. Putting this differently, an entity is a technology switcher in the meta-frontier context if it does not belong to the same group over time. One of the objectives of this paper is to allow for more flexibility in the meta-frontier by considering the possibility of group creation and disappearance, and by recognizing the existing of technology switchers.

Technology switchers have been found in several empirical works at microeconomic (e.g. Aravindakshan, Rossi, Amjath-Babu, Veettil, & Krupnik, 2018; Bos, Candelon, & Economidou, 2016; Bos, Economidou, Koetter, & Kolari, 2010b; He, Walheer, and, 2020b; Hynninen, Ojala, & Pehkonen, 2013) and macroeconomic levels (e.g. Amsler, O'Donnell, & Schmidt, 2017; Bos et al., 2010b; Castellacci, 2008; Castellacci, 2011; Castellacci & Archibugi, 2008; Castellacci & Natera, 2016; Owen, Videras, & Davis, 2009; Saba & David, 2020; Stollinger, 2013; Walheer, 2021). From an intuitive point of view, it is indeed difficult to believe that all entities keep the same technology over time. From a theoretical point of view, the existence of technology switchers requires new models with more flexibility (e.g. Acemoglu, Aghion, & Zilibotti, 2006; Green, 2005; Howitt, 2000; Howitt & Mayer-Foulkes, 2005; Orea & Kumbhakar, 2004; Tsionas & Kumbhakar, 2004). A feature that has been omitted so far is the impacts of the technology switchers on the (in)efficiency behavior and the technology gap. A second objective of this paper is to offer these options with the additional advantage of distinguishing the direct (on the switchers) and the indirect (on the non-switchers) effects.

All in all, the main novelty of this paper is to recognize the existing of technology switchers in the meta-frontier methodology. This implies, first, to allow for more flexibility in the meta-frontier by considering that the number of groups may not be fixed over time while some entities may change of groups. Once the existence of technology switchers is admitted, the next step is to quantify the impacts of such entities on the meta-frontier. This is the second contribution of this paper: provide an easy and intuitive way to quantify the impact of the technology switchers on the (in)efficiency behavior and the technology gap. In fact, we go a bit further by distinguishing the direct and indirect impact.

3. Preliminaries

The starting point of our approach is the observation of entities for several periods of time $\{1, \ldots, T\}$. The specificities of our setup is to consider technology heterogeneity among entities and the existence of technology switchers, i.e. entities that adopt another technology over time. We consider that there are I_t different technologies available at time t. That is, the number of technologies is not fixed over time: new technology may be developed and other be phased out over time.

We adopt a nonparametric approach when defining the technologies. In practice, the observed input-output data of the entities, defined by $\mathbf{x}$ and $\mathbf{y}$ respectively, are used to reconstruct the technologies by means of a production possibility sets. That is, it is known at time t which technology each entity has adopted at time t, and this for every $t \in \{1, \ldots, T\}$. Let us denote the group of firms adopting technology i at time t by S_t^i. We obtain the following production possibility set for a specific group i at time t:

$$T_t^i(S_t^i) = \{(\mathbf{x}, \mathbf{y}) \mid \mathbf{x} \text{ can produce } \mathbf{y} \text{ using the technology at time } t \text{ determined by } S_t^i\}. \tag{1}$$

$T_t^i(S_t^i)$ is the reconstruction of technology i at time t using the observed input-output data of entities that have adopted this technology. $T_t^i(S_t^i)$ contains all possible input-output combinations using technology i at time t. $T_t^i(S_t^i)$ therefore is an estimator of the unknown technology i at time t. These sets are directly useful to evaluate the (in)efficiency behavior of the entities that is captured by the distance to their frontier, i.e the boundary of the production possibility set. Without loss of generality, we consider an output-oriented technical efficiency measurement. That is, technical efficiency checks whether outputs could be increased given the inputs. In other words, we investigate for potential outputs. When selecting technology i at time t, the technical efficiency measurement of a particular entity operating at $(\mathbf{x}, \mathbf{y})$ is defined as follows:

$$TE_t^i(\mathbf{y}, \mathbf{x}) = \inf\left\{\theta \mid \left(\mathbf{x}, \frac{\mathbf{y}}{\theta}\right) \in T_t^i(S_t^i)\right\}. \tag{2}$$

$TE_t^i(\mathbf{y}, \mathbf{x})$ is smaller or equal to unity and a lower value indicates greater technical inefficiency. $TE_t^i(\mathbf{y}, \mathbf{x})$ represents how far away the actual outputs are from the potential outputs. When $TE_t^i(\mathbf{y}, \mathbf{x}) = 1$, it means that they coincide. When $TE_t^i(\mathbf{y}, \mathbf{x}) < 1$, it implies that the actual outputs represent $TE_t^i(\mathbf{y}, \mathbf{x}) \times 100\%$ of the potential output quantities. Graphically, the technical efficiency measurement is defined as the distance to the frontier of the reconstructed production possibility set. In practice, technical efficiency is computed by means of a linear programming which is given in Appendix A.

Table 1
Simulation - groups and switchers.

Entity	Group $t-1$	Group t	Switcher
A	2	2	no
B	1	2	yes
C	1	1	no
D	2	1	yes
E	2	2	no

Another focus of our investigation is the technology gap which measures whether entities have chosen the most productive technology available. It is defined as the distance between the group-level technology and an 'overall' or best practice technology for each period of time t. That is, the envelopment of the group-level technologies at that period of time:

$$T_t = \left\{T_t^1(S_t^1) \cup T_t^2(S_t^2) \cup \cdots \cup T_t^I(S_t^I)\right\}, \tag{3}$$

This is a standard way of defining the overall technology, which dates at least to Battese & Rao (2002). We notice that the envelop is non-convex in general (Jin, Kerstens, & Woestyne, 2020; Walheer, 2018a), while imposing convexity is possible if needed but represents an additional assumption about the production process. There is a tradition in the literature to define that 'overall' technology as the meta-technology (Hayami & Ruttan, 1970) and its frontier as the meta-frontier (Battese et al., 2004; O'Donnell et al., 2008).

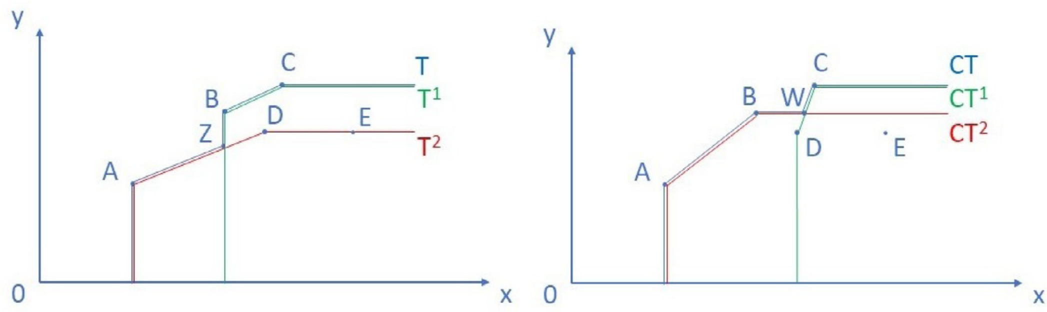
The technology gap is defined as the ratio of technical efficiency with respect to the meta- and group-specific frontiers. For a particular entity, operating at $(\mathbf{x}, \mathbf{y})$, and technology i we obtain the following:

$$TG_t^i(\mathbf{y}, \mathbf{x}) = \frac{TE_t(\mathbf{y}, \mathbf{x})}{TE_t^i(\mathbf{y}, \mathbf{x})}, \tag{4}$$

where $TE_t(\mathbf{y}, \mathbf{x}) = \inf\left\{\theta \mid \left(\mathbf{x}, \frac{\mathbf{y}}{\theta}\right) \in T_t\right\}$ is the technical efficiency measurement with respect to the meta-frontier at time t. This concept has to be interpreted as $TE_t^i(\mathbf{y}, \mathbf{x})$, but when the aggregated technology is selected. Also, by construction, we have that $TE_t(\mathbf{y}, \mathbf{x}) \leq TE_t^i(\mathbf{y}, \mathbf{x})$. This inequality is immediately verified when noticing that the group-specific technologies are included in the aggregated technology (it is defined as their envelopment in(3)). This also highlights the consequence of wrongly assuming technology homogeneity (technical efficiency would be overestimated). $TG_t^i(\mathbf{y}, \mathbf{x})$ is therefore smaller or equal to one by construction. If it is equal to unity, it means that there is no technology gap, i.e. the entity has chosen the best practice technology. Lower values indicate a larger technology gap, i.e. a better technology exists and technology improvement therefore is possible. $TG_t^i(\mathbf{y}, \mathbf{x})$ is computed a-posteriori after evaluating $TE_t^i(\mathbf{y}, \mathbf{x})$ and $TE_t(\mathbf{y}, \mathbf{x})$; see Appendix A for more detail.

4. Motivation and objectives

We provide a simple example to formulate our objectives. Assume we observe five entities labelled A, B, C, D, and E at two consecutive time periods $t-1$ and t. For simplicity, we assume that they produce one output using one input, and that the input-output levels are the same in both time periods. This allows us to only focus our discussion on the switcher effects. We also assume that two different technologies coexist and that entities are distributed as given in Table 1. Finally, we assume that entities B and D are switchers, i.e. they adopt another technology at time t. Practically, it means that they belong to a different group at time $t-1$ and t. On the contrary, entities A, C, and E are not technology switchers as they belong to the same group at time $t-1$ and t.



(a) Technologies (b) Counterfactual technologies

Fig. 1. Simulation - reconstructed technologies and counterfactual technologies at t.

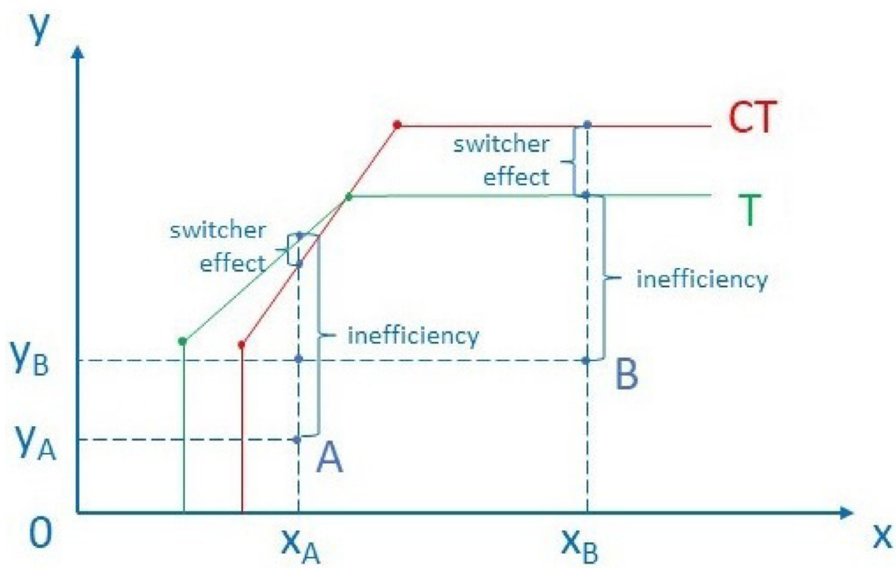


Fig. 2. Switcher effect – technical efficiency.

The reconstructed technologies at time t are given in Fig. 1(a). In particular, T^1 and T^2 are the group-specific production possibility sets at time t, while T is the meta-technology. To avoid trivial reconstructions and to match common practice, we assume that the group-specific production possibility sets satisfy some regularity conditions: they are monotone, convex, and satisfy variable returns-to-scale.[3]

The meta-frontier is defined by $AZBC$ at time t. Note that Z is a fictive entity and that the meta-frontier is non-convex, while the group-level frontiers are. All entities are efficient since they lie on their group-specific frontier. Also, entity D and E present a technology gap, i.e. they have not adopted the best practice technology since they are not on the meta-frontier.

Next, we construct counterfactual technologies at time t based on the groups as defined at $t-1$ in Fig. 1(b). That is, we reconstruct the technologies as if there were no switchers, i.e. all entities have the same technology at $t-1$ and t. This time, the meta-frontier is defined by $ABWC$; W is again a fictive entity. We immediately appreciate the significant effects of the switchers on the reconstructed technologies. First, the group-specific technologies are different, which directly impacts the (in)efficient behavior of the entities. For instance, entity E is no longer efficient. In other words, we may interpret the efficient behavior of entity E at time t as due to the switchers only. Second, the meta-technology is also different because of the switchers impacting the technology gaps of the entities. For example, entity D is closer to the frontier of the counterfactual meta-technology. We summarize our observations in Table 2.

Table 2
Simulation - impacts of the switchers at t.

Time	$t-1$		t	
Group Inefficient	1 /	2 E	1 /	2 /
Group frontier	D, C	A, B	B, C	A, D, E
Technology gap Meta-frontier	D, E ABWC		D, E AZBC	

It turns out that the switchers have a huge impact on their own behavior, but also on that of the other entities. All these impacts influence the reconstructed technologies. This fact has so far been completely ignored when dealing with the meta-frontier approach in both theoretical extensions and empirical works. In light of our

[3] Note that these regularity conditions are not essential for us; they are selected to make the graphical illustration as clear and simple as possible (and because they are popular to practitioners). The selecting reconstruction procedure is also known as Data envelopment analysis (DEA) after Charnes et al., 1978). It is fairly easy to make a similar example without assuming convex group technologies or using another returns-to-scale assumption. This will not change the positive impact of the switchers. The meta-technology is, as stated in(3), the envelopment of the group frontiers. There is no specific reason to obtain a convex set. In Fig. 1, it is indeed non-convex. Similar comments apply to Figs. 2 and 3.

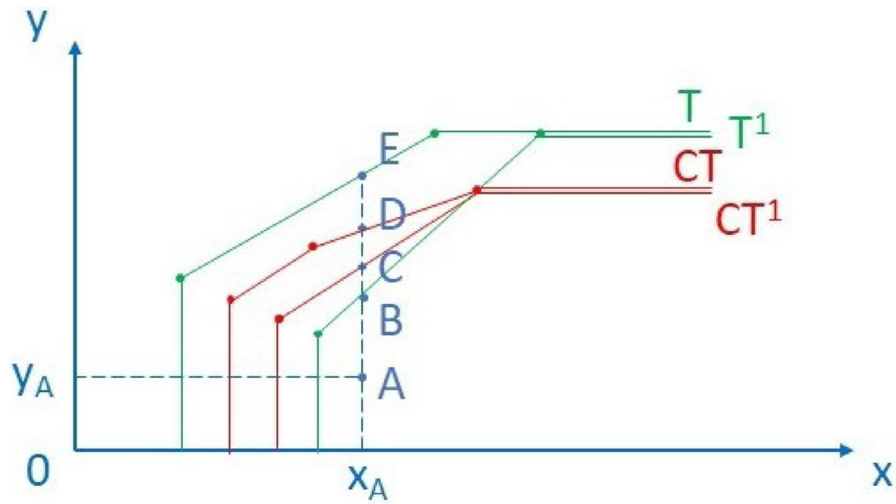


Fig. 3. Switcher effect – technology gap.

observations, we formulate our objectives as follows: (*i*) defining the impact of the switchers on the group-specific technologies [technical efficiency]; (*ii*) defining the impact of the switchers on the meta-technology [technology gap]; and (*iii*) be able to distinguish the effects on the switchers themselves from those on other entities [direct and indirect effects]. To do so, we build on the concept of counterfactual technologies formally defined in the next Section.

5. Counterfactual technologies and switcher effects

To quantify the impact of the switchers on the efficiency behavior and the technology gap, we make use of counterfactual technologies.[4] In particular, we define the notion of counterfactual production possibility set defined as the reconstruction of the hypothetical technology at time t using entities that have adopted this technology at the previous time period (i.e. at $t-1$). That is, it is as if no entity has left or joined the group between $t-1$ and t. It is given for group j as follows:

$$CT_t^j(S_{t-1}^j) = \{(\mathbf{x},\mathbf{y}) \mid \ \mathbf{x} \text{ can produce } \mathbf{y} \text{ using the technology at time } t \text{ determined by } S_{t-1}^j\}. \quad (5)$$

In words, this counterfactual set is defined at time t using input-output data at time t of entities belonging to group j at time $t-1$. We recall that S_{t-1}^j contains entities that have adopted technology j at time $t-1$.

The 'aggregated' counterfactual technology is defined as the envelop of the group-specific counterfactual technologies:

$$CT_t = \left\{CT_t^1(S_{t-1}^1) \cup CT_t^2(S_{t-1}^2) \cup \cdots \cup CT_t^l(S_{t-1}^l)\right\}, \quad (6)$$

CT_t is the envelopment of the counterfactual group-level sets. As the meta-technology T_t, given in (3), CT_t is defined using input-output data at time t, and is generally non-convex. We may thus label CT_t as the counterfactual meta-technology. The only difference between both sets is that CT_t is based on the group repartition of entities at time $t-1$ while it is the repartition at time t that is used for T_t. This twist, while simple, allows us to define switcher effects are explained after.

[4] The idea of using counterfactual technologies is, in fact, not new in the efficiency literature. For example, the Malmquist index, defined by Caves, Christensen, & Diewert (1982), is based on a similar concept. Counterfactual concepts are often present when time is involved in the efficiency analysis.

Our aim is to quantify the impact of switchers on the efficiency and technology gap of all entities. This concerns not only the switchers themselves but also the other entities. Using our counterfactual production possibility sets, we define the following technical efficiency measurement for a particular entity operating at $(\mathbf{x},\mathbf{y})$:

$$CTE_t^j(\mathbf{y},\mathbf{x}) = \inf\left\{\theta \mid \left(\mathbf{x},\frac{\mathbf{y}}{\theta}\right) \in CT_t^j(S_{t-1}^j)\right\}. \quad (7)$$

$CTE_t^j(\mathbf{y},\mathbf{x})$ is a counterfactual measurement since it is based on an hypothetical set. Nevertheless, it has to be interpreted as $TE_t^i(\mathbf{y},\mathbf{x})$, i.e. it is not greater than one while lower values indicate larger efficiency behaviour with respect to the counterfactual frontier. Using this new concept, we define the efficiency switcher effect of an entity operating at $(\mathbf{y},\mathbf{x})$ that has moved from technology j to technology i (denoted as $j\to i$) as follows:

$$ESE_t^{j\to i}(\mathbf{y},\mathbf{x}) = \frac{CTE_t^j(\mathbf{y},\mathbf{x})}{TE_t^i(\mathbf{y},\mathbf{x})}. \quad (8)$$

Clearly, when $ESE^{j\to i}(\mathbf{y},\mathbf{x}) = 1$, it means that the switchers have no impact on the efficiency behavior of the entity operating at $(\mathbf{y},\mathbf{x})$. This value therefore represents our benchmark scenario. When this is not the case, the impact is observed. We have to distinguish two cases: those when the efficiency switcher effect is larger or smaller than the unity. If $ESE^{j\to i}(\mathbf{y},\mathbf{x}) > 1$, it means that counterfactual technical efficiency, i.e. technical efficiency as if switchers have not joined or leaved the groups, is larger than actual technical efficiency, i.e. technical efficiency when switchers have joined or leaved the groups. Putting this differently, the entity operating at $(\mathbf{x},\mathbf{y})$ is away from the frontier because of switchers. That is, there are more potential output expansions thanks to the switchers. When $ESE^{j\to i}(\mathbf{y},\mathbf{x}) < 1$, it is the opposite: there is less potential output expansions due to the switchers.

At this point, we highlight that we have not specified whether the entity operating at $(\mathbf{y},\mathbf{x})$ is a switcher or not. Putting differently, $ESE^{j\to i}(\mathbf{y},\mathbf{x})$ can be evaluated for any input-output combinations, i.e. for any entities. When an entity is non-switcher, it implies that $i=j$, i.e. the entity keeps the same technology. It turns out that our definition of the efficiency switcher effect easily allows us to distinguish the switchers ($i\neq j$) from the other entities ($i=j$). Therefore, we are able to quantify the impacts of the switchers on their own efficiency behavior, i.e. a direct effect, and the impacts on the other entities, i.e. an indirect effect. See Section 6 for an empirical example.

We illustrate the efficiency switcher effect in Fig. 2. We there present the reconstructed production possibility set and the counterfactual counterpart for a fictive group.[5] We also consider two fictive entities belonging to that group: A and B. They are both inefficient since they do not lie on the frontier. Their inefficient behavior is evaluated as the distance to this set in the output direction. Next, the counterfactual production possibility set allows us to remove the switcher effect. It is shown that entity A is less inefficient due to the switchers. In other words, the switchers have deteriorated the efficiency behavior of entity A which therefore has more potential output expansions. It is the opposite situation for entity B: the switchers have improved its efficiency behavior so that this has less potential output expansion.

Our second focus is to quantify the impact of the switchers on the technology gap. The counterfactual technology gap ratio is defined for an entity operating at $(\mathbf{y}, \mathbf{x})$ as follow:

$$CTG_t^j(\mathbf{y}, \mathbf{x}) = \frac{CTE_t(\mathbf{y}, \mathbf{x})}{CTE_t^j(\mathbf{y}, \mathbf{x})}, \tag{9}$$

where $CTE_t(\mathbf{y}, \mathbf{x}) = \inf\left\{\theta \mid \left(\mathbf{x}, \frac{\mathbf{y}}{\theta}\right) \in CT_t\right\}$. Again, this counterfactual measurement has to be interpreted as the technology gap $CTG_t^j(\mathbf{y}, \mathbf{x})$ defined above with respect to the counterfactual frontiers.

We define the technology gap switcher effect for an entity operating at $(\mathbf{y}, \mathbf{x})$ that has moved from technology j to technology i as follows:

$$TGSE_t^{j\to i}(\mathbf{y}, \mathbf{x}) = \frac{CTG_t^j(\mathbf{y}, \mathbf{x})}{TG_t^i(\mathbf{y}, \mathbf{x})}. \tag{10}$$

As for the efficiency switcher effect, the benchmark value is unity. When $TGSE_t^{j\to i}(\mathbf{y}, \mathbf{x}) > 1$, it means that the technology gap is larger when switchers are taken into account. That is, the entity is further from the 'overall' or meta-frontier because of the switcher. In other words, the switchers have deteriorated the frontier of the technology adopted by the entity with respect the meta-frontier, meaning that there is more potential technology improvement. The opposite case is when $TGSE_t^{j\to i}(\mathbf{y}, \mathbf{x}) < 1$, the entity is closer to the overall frontier and less potential technology improvement is possible. Again we point out that our definition of the technology gap switcher effect is general enough to allow us to distinguish the effect on the switchers themselves or on the other entities. We provide an empirical example in Section 6.

Finally, we highlight that the efficiency and technology gap switcher effects can be related as follows:

$$ESE_t^{j\to i}(\mathbf{y}, \mathbf{x}) \times TGSE_t^{j\to i}(\mathbf{y}, \mathbf{x}) = \frac{CTE_t(\mathbf{y}, \mathbf{x})}{TE_t(\mathbf{y}, \mathbf{x})}. \tag{11}$$

We obtain this relationship by combining (8), (9), and (10). In words, this relationship could be understood as a decomposition of an 'overall' efficiency switcher effect (the right-hand side) into a group-specific efficiency switcher effect (ESE) and a technology gap switcher effect (TGSE). Putting this differently, the efficiency switcher effect could be seen as a residual part of the 'overall' efficiency switcher effect due to the group only once the technology gap switcher effect has been removed. As a final remark, we highlight that the decomposition is based on the well-established concepts in Section 3 and their counterfactual counterparts as defined in Section 5. The decomposition, therefore, is directly connected with the existing literature.

To illustrate the technology gap switcher effect and the above decomposition, we again use a simple example. Let us consider the case of entity A in Fig. 3. The meta-technology is T and entity A belongs to group 1 with associated technology T^1. Note that the technologies of the other groups are not represented for better readability, and that the meta-technology is obtained as an envelopment of the group frontiers. Entity A presents a technology gap that is captured by the ratio AB over AE. When using the counterfactual technologies, we obtain AC divided by AD for the technology gap. So, the switcher effect is AC/AD divided by AB/AE. Also, the switcher efficiency effect with respect to the group-specific technology is given by AB over AC. By multiplying the two switcher effects, we obtain the 'overall' efficiency switcher effect: AE/AD. This result highlights the above decomposition.

6. Empirical application

We apply our new concepts to the case of the technology clubs in the world economy. Several studies, initiated by Durlauf & Johnson (1995), Bernard & Jones (1996), Bernard & Durlauf (1996) and Galor (1996), have pointed out the existence of technology clubs among countries. This is probably the most famous empirical question involving technology switchers, i.e. countries that adopt another technology over time (e.g. Amsler et al., 2017; Bos, Economidou, & Koetter, 2010a; Castellacci, 2008; Castellacci, 2011; Castellacci & Archibugi, 2008; Castellacci & Natera, 2016; Owen et al., 2009; Saba & David, 2020; Stollinger, 2013; Walheer, 2021). Indeed, it is intuitively difficult to believe that all countries keep the same technology over time. In fact, technology change is recognized as a main source of economic development and a main factor of economic growth (Bernard & Jones, 1996; Gong & Keller, 2003; Hall & Jones, 1999; Islam, 1999; Prescott, 1998).

From a practical point of view, a popular option is to partition countries into groups/clubs where technology is homogeneous inside but not between clubs. While well-known statistical techniques have been used to compute the number of technology clubs and allocate countries into each club, two main problems remain. First, how to parametrically define the different club technologies ? Indeed, several production functions have to be specified, and even when strong arguments are found to choose specific functional forms, it could be computationally cumbersome given the limited number of countries in the world. The nonparametric approach can help here, and has gained attention in the empirical macroeconomic literature (Fiaschi & Lavezzi, 2007; Henderson & Russell, 2005; Kumar & Russell, 2002; Maasoumi, Racine, & Stengos, 2007; Walheer, 2016, 2021). Second, how to deal with switchers, i.e. countries that move across clubs ? The literature hardly evokes this second issue. This is where the suggested method can help.

Using our methodology, we are able to quantify the impact of the switchers on the meta-frontier and the group-specific frontiers, i.e. the impacts of the (in)efficiency behavior and the technology gaps. Attractively, our technique is flexible enough to allow us to distinguish the effects on the switchers themselves from those on the other entities; i.e. distinguishing the direct and indirect effects of the technology switchers. This gives us the opportunity to verify whether it was judicious to adopt a new technology and the nature of the impact on the entities left behind. Also, we are able to deal with the creation of new technology and the phasing out of a technology as highlighted with the two additional fictive scenarii considered. All in all, our new concepts allow us to provide new important information about how technology switchers impact technology clubs and countries' efficiency behavior. It therefore represents a complementary tool to existing ones.

[5] The reconstructed sets are, in practice, obtained using observed input-output data while imposing some technology axioms. See our discussion of Fig. 1 and Appendix A.

Table 3
Technology switchers in 2000.

Club	Technology switchers	Splitting conditions
Advanced	-	literacy rate > 68% scientific articles > 334
Followers	Honk Kong, South Korea, Singapore, Austria, Belgium, France	literacy rate > 68%; scientific articles < 334
Marginalized	China, Indonesia, Vietnam, Iran, Oman, Albania, El Salvador, Honduras, Algeria, Botswana, Mauritius, Tunisia, Zimbabwe	literacy rate < 68% scientific articles < 334

6.1. Club definitions and technology switchers

While it is generally admitted that there is a club of rich countries, sub-groups are found amongst poor ones on the basis of additional variables, such as human capital (Castellacci, 2008; Durlauf & Johnson, 1995; Kalaitzidakis, Mamuneas, Savvides, & Stengos, 2001), institutional factors (Alfo, Trovato, & Waldmann, 2008), social conditions (Apergis, 2015), geographical characteristics (Bloom, Canning, & Sevilla, 2003), and ownership (He, Walheer, and, 2020a; Maasoumi et al., 2007). Recently, it has been argued that two main dimensions can capture countries' technology level: their innovative ability and their absorptive capacity (Castellacci, 2011; Castellacci & Archibugi, 2008; Howitt, 2000; Howitt & Mayer-Foulkes, 2005; Stokke, 2008; Castellacci & Natera, 2016).

Several options are available to define the groups/clubs such as common practice, common knowledge, or statistical methods. Note that any techniques can be used to define the groups and the technology switchers; this has not impact on the methodology exposed in this paper. In this application, we make used of a classification and regression tree analysis (CART) using the innovative ability and the absorptive capacity of a sample of 128 countries in 1990 and 2000. Innovative ability is measured by the number of patents and the number of scientific articles; absorptive capacity is measured by the level of human capital (literacy rate, total number of school years, secondary schooling, higher education) and technological infrastructures (fixed telephony, electricity, computers, Internet users). CART is a flexible non-parametric method of cluster analysis (Breiman, Friedman; Durlauf & Johnson, 1995). The general idea of CART is to construct a hierarchical classification where each step of the algorithm splits a group into two subgroups (nodes) based on one single predictor variable.

We obtain three technology clubs labelled 'Advanced', 'Followers', and 'Marginalized'. Advanced countries perform well in terms of both innovative ability and absorptive capacity; follower countries have low innovative ability but relatively high absorptive capacity; and marginalized economies are poor in both aspects. Countries are allocated in the clubs using slitting conditions provided by the CART. We find the presence of six switchers moving from the Followers to the Advanced club, and 13 from the Marginalized to the Follower club (see Table 3). Practically, a country is a technology switcher when it meets the slitting conditions of another club over time. We do not find evidence of technology regression. More detail on the countries is provided in Appendix B.

6.2. Efficiency and technology gap

As an initial step, we compute the average efficiency scores and the technology gaps for the three clubs in $t = 2000$.[6] They are given in Table 4. We point out that the averages are computed using specific weights. It has indeed been pointed out that relying on an arithmetic average is probably not a good solution for the efficiency measurement (Färe & Zelenyuk, 2003) and the technology gap ratio (Walheer, 2018a). Usually the weights depend on the output prices except when one output is present in the production process. In that case, the weights only depend on the actual and potential outputs, as it is the case here.

Table 4
Efficiency and technology gap in 2000.

Club	Efficiency TE_t^i	Technology gap TG_t^i
Advanced	0.79	0.99
Followers	0.55	0.92
Marginalized	0.51	0.81

The results in Table 4 confirm that the advanced club presents the best performances for both dimensions. The average technology gap is close to one indicating that this club defines the world technology. Next, we find the followers with good performance in technology gap, though they are, on average, further from their own frontier as indicated by the average efficiency scores. Finally, the marginalized countries have the worst performances in both dimensions. Overall, our results are coherent with the definition of the three clubs.

6.3. Switcher effects

Next, we compute the switcher effects for the efficiency measurement and for the technology gap. To do so, we rely on the concept of counterfactual technologies as explained in Section 5. The main idea is to reconstruct the technologies as if all countries use the same technology during the time span 1990–2000, i.e. there is no technology switchers. As an illustration, we provide the frontier (see (2)) and the counterfactual frontier (see (5)) for the Marginalized club for 2000 in Fig. 4. We immediately appreciate the important impacts of technology switchers on the technology frontier of that club. Such impacts will be computed using the efficiency switcher effect (see (8)) and the technology gap switcher effect (see (10)).

The averages of the switcher effects for all clubs are given in Table 5. As explained earlier, our methodology allows us to distinguish the effects on the switchers and on the other countries.[7] For example, we are able to verify how switchers in the Marginalized countries' group have impacted countries that have not leave the group ($ESE_t^{M\to M}(\mathbf{y},\mathbf{x})$), themselves ($ESE_t^{M\to F}(\mathbf{y},\mathbf{x})$), and the Followers' group ($ESE_t^{F\to F}(\mathbf{y},\mathbf{x})$).

Let us first introduce our discussion of this table with the effects of the switchers on the other entities. A first observation is that the switchers have no impact on the other entities in the advanced and follower clubs. This means that the switchers have not

[6] To avoid trivial reconstructions and to match common practice in empirical macroeconomics, we assume that the club-specific production possibility sets are monotone, convex, and satisfy constant returns-to-scale.

[7] Here, we rely on arithmetic averages since there is no theoretical framework for aggregating the switcher effects. See the Conclusion for more discussion.

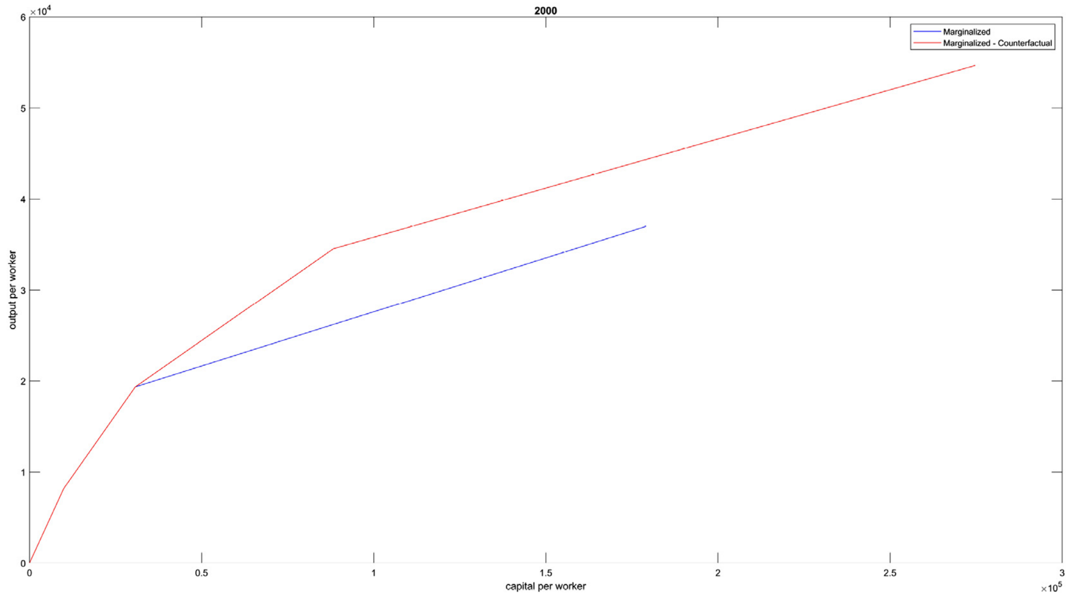


Fig. 4. Marginalized club frontiers in 2000.

Table 5
Switcher effects.

Club 1990	Club 2000	Efficiency switcher effect		Technology gap switcher effect	
Advanced	Advanced	$ESE_t^{A\to A}(\mathbf{y},\mathbf{x})$	1.00	$TGSE_t^{A\to A}(\mathbf{y},\mathbf{x})$	1.00
Followers	Advanced	$ESE_t^{F\to A}(\mathbf{y},\mathbf{x})$	1.07	$TGSE_t^{F\to A}(\mathbf{y},\mathbf{x})$	0.94
Followers	Followers	$ESE_t^{F\to F}(\mathbf{y},\mathbf{x})$	1.00	$TGSE_t^{F\to F}(\mathbf{y},\mathbf{x})$	1.00
Marginalized	Followers	$ESE_t^{M\to F}(\mathbf{y},\mathbf{x})$	1.27	$TGSE_t^{M\to F}(\mathbf{y},\mathbf{x})$	0.83
Marginalized	Marginalized	$ESE_t^{M\to M}(\mathbf{y},\mathbf{x})$	0.96	$TGSE_t^{M\to M}(\mathbf{y},\mathbf{x})$	1.05

modified the frontiers of these two clubs. This is not a fanciful result as we may expect that indeed switchers have joined these clubs to benefit from the knowledge or imitate the entities. Next, the marginalized club is directly impacted by the entities that have left the club. The efficiency switcher effect is below unity, meaning that less potential output expansion is possible, and the technology gap switcher effect is also smaller than one, meaning that less potential technology improvement is possible. This is rather bad news for this club.

Next, it is verified that the switchers have impacted their own efficiency behavior and technology gap by adopting another technology. The switchers that have joined the advanced club presents an average efficiency switcher effect larger than one, meaning that more potential output expansion is possible, while the average technology gap switcher effect is smaller than one, meaning that less potential technology improvement is possible. The latter could be understood as the direct effect of adopting a best practice technology. Similar findings are observed for entities that have switched from the marginalized club to the followers; the averages, though, are more extreme.

6.4. Fictive scenarii

To show how our methodology is used when the number of groups (and thus technologies) change over time we present two fictive scenarii for our empirical application. In the first scenario, we consider that some marginalized countries have developed a new technology instead of joining the followers.[8] In the second fictive scenario, we consider that all Advanced and Followers countries share the same technology in 2010. That is, one technology has been phased out over time. Table 6 summarizes our two additional scenarii. Note that these scenarii, while fictive, are directly inspired by findings in the literature. Indeed, while one club is found for the rich countries, two or three clubs are usually found amongst poor ones depending on the cluster technique and the variables used to define the clubs (e.g. Alfo et al., 2008; Bloom et al., 2003; Castellacci, 2008; Castellacci, 2011; Castellacci & Archibugi, 2008; Durlauf & Johnson, 1995; Kalaitzidakis et al., 2001; Maasoumi et al., 2007 Stokke, 2008; Apergis, 2015; He, Walheer, and, 2020a; Walheer, 2021).

As before, we start by presenting averages for the efficiency scores and the technology gaps for $t = 2000$ for our two fictive scenarii in Table 7. A first observation is that the results for the Advanced and Marginalized groups are similar for Scenario A than those found in Table 4. This means that the creation of a new technology by some Marginalized countries has not impacted these two group technologies. On the contrary, it has a clear impact on the results of the Followers that have now a lower average efficiency score and technology gap. We also note that the average technical efficiency score technology gap of the Emerging group lies between those of the Followers and Marginalized; this makes the Emerging countries the third best technology in the world. Under scenario B, we only have results for two groups in 2010 as the Followers' group has disappeared by that year. All these countries are now part of the Advanced group. We see a direct impact on the results for that group with respect to the benchmark case (see Table 4): greater average inefficiency and larger average technology gap.

Results for the average efficiency and technology gap switcher effects for the different groups and scenarii are given in Table 8. A first observation is that Advanced countries still represent the leading technology under the two fictive scenarii and are not impacted

[8] To do so we fix the number of groups to four in the CART.

Table 6
Scenario explanations.

Scenario	Explanation	Technologies	
		I_t	Label
Benchmark	Groups are those found using the CART approach.	3	Advanced, Followers, Marginalized.
A	Some marginalized countries define a new technology.	4	Advanced, Followers, Emerging, Marginalized.
B	Followers and Advanced countries share a common technology.	2	Advanced, Marginalized.

Table 7
Efficiency and technology gap in 2000 - Scenarii A and B.

Club	Scenario A		Scenario B	
	Efficiency TE_t^i	Technology gap TG_t^i	Efficiency TE_t^i	Technology gap TG_t^i
Advanced	0.71	0.98	0.59	0.91
Followers	0.59	0.97	/	/
Emerging	0.55	0.87	/	/
Marginalized	0.53	0.86	0.53	0.86

by the switchers (average efficiency and technology gap switcher effects are both equal to unity). A second observation is that the Marginalized technology is the still the worst one, and is negatively impacted by the switchers under both scenarii (average efficiency switcher effects less than one, and technology gap switcher effect larger than one). These two stylized facts, while interesting, have been found earlier before (see Table 5). What is interesting is to compare the effects of the switchers in the marginalized group for scenario A to the benchmark case, and to quantify the impact of the common technology of the Advanced and Followers in scenario B.

Under scenario A, we see greater potential output expansion for the switchers from the Marginalized group that have joined the Followers, but, at the same time, we see less technology improvement. This may be explained by the fact that switchers that have defined the Emerging group are those with the best technology. Note that there are no switcher effects for the Emerging group since that group does not exist at our starting year. We are able to evaluate the efficiency scores and the technology gaps of these countries (see Table 7), and the switcher effects could be computed for time periods after 2010. Next, we do not see any impacts on the Followers' group for scenario A.

Under scenario B, we see that the Followers have clearly benefited from joining the Advanced group: average efficiency switcher effect is smaller (with respect to the benchmark scenario in Table 5), i.e. more potential output expansion, and average technology gap switcher effect is smaller, i.e. more potential technology improvement. We may understand these results as a potential imitating effect. Similar observations are found for the switchers in the Marginalized group that have joined the Advanced technology club. Note that there are no switcher effects for the Followers group since that group no longer exists our ending year.

All in all, these two simple fictive scenarii show how our new technique can deal with the creation and the destruction of technologies over time. We are still able to compute and quantify the switcher effects in these cases.

7. Conclusion

Nonparametric efficiency analysis is a technique used to evaluate an entity by comparing its performance to that of other entities. While this technique has gained popularity in the operations research literature and beyond, it presents two important shortcomings. One of these is the assumption that entities use a similar (but unknown) transformation process. In other words, heterogeneity amongst entities is not considered. The concept of meta-technology and meta-frontier have been suggested to deal with group heterogeneity among entities for nonparametric efficiency analysis. In brief, the meta-frontier is defined as the envelopment of the group-specific frontiers, and naturally allows us to distinguish between inefficiency and technology gap.

Meta-frontier-based methodologies have been applied to a various range of topics revealing the attractiveness of this concept for empirical research. In practice, the meta-frontier approach requires to partition entities into several groups, each capturing a distinct technology, and to allocate entities to each group. So far, this procedure has not provided enough flexibility since the number of groups is fixed, and once the entity partitioning is made, no modification is possible. This is rather restrictive or even unrealistic as when dealing with panel data where many things usually change over time. For instance, new technology can be discovered, while other may disappear; and entities can imitate an existing technology or adopt a new one. In this paper, we have extended the meta-frontier approach when technology switchers, i.e.

Table 8
Switcher effects - Scenarii A and B.

Club 1990	Club 2000	Efficiency switcher effect		Technology gap switcher effect	
Scenario A					
Advanced	Advanced	$ESE_t^{A\to A}(\mathbf{y},\mathbf{x})$	1.00	$TGSE_t^{A\to A}(\mathbf{y},\mathbf{x})$	1.00
Followers	Advanced	$ESE_t^{F\to A}(\mathbf{y},\mathbf{x})$	1.07	$TGSE_t^{F\to A}(\mathbf{y},\mathbf{x})$	0.94
Followers	Followers	$ESE_t^{F\to F}(\mathbf{y},\mathbf{x})$	1.00	$TGSE_t^{F\to F}(\mathbf{y},\mathbf{x})$	1.00
Marginalized	Followers	$ESE_t^{M\to F}(\mathbf{y},\mathbf{x})$	1.35	$TGSE_t^{M\to F}(\mathbf{y},\mathbf{x})$	0.91
Marginalized	Emerging	$ESE_t^{M\to E}(\mathbf{y},\mathbf{x})$	/	$TGSE_t^{M\to E}(\mathbf{y},\mathbf{x})$	/
Marginalized	Marginalized	$ESE_t^{M\to M}(\mathbf{y},\mathbf{x})$	0.96	$TGSE_t^{M\to M}(\mathbf{y},\mathbf{x})$	1.05
Scenario B					
Advanced	Advanced	$ESE_t^{A\to A}(\mathbf{y},\mathbf{x})$	1.00	$TGSE_t^{A\to A}(\mathbf{y},\mathbf{x})$	1.00
Followers	Advanced	$ESE_t^{F\to A}(\mathbf{y},\mathbf{x})$	1.15	$TGSE_t^{F\to A}(\mathbf{y},\mathbf{x})$	0.90
Marginalized	Advanced	$ESE_t^{M\to A}(\mathbf{y},\mathbf{x})$	1.46	$TGSE_t^{M\to A}(\mathbf{y},\mathbf{x})$	0.71
Marginalized	Marginalized	$ESE_t^{M\to M}(\mathbf{y},\mathbf{x})$	0.96	$TGSE_t^{M\to M}(\mathbf{y},\mathbf{x})$	1.05

entities that adopt another technology over time, are considered, and quantified the impacts of the switchers on the inefficiency behavior and the technology gap. In particular, we have defined the concept of efficiency switcher effect and technology gap switcher effect.

We applied our methodology to probably the most famous empirical question involving technology switchers: the economic growth convergence amongst countries. A popular option is to partition countries into groups/clubs where technology is homogeneous inside but not between clubs. While important efforts have been made to find coherent and consistent ways to define the clubs and the partitioning of countries amongst them, the literature rarely evokes the impacts of the technology switchers. This is exactly the added value of our methodology to the economic growth convergence: provide a simple nonparametric method to evaluate the impact of the technology switchers on the technology clubs and on the countries' (in)efficiency behavior.

Our concept of efficiency switcher effect and technology gap switcher effect can be extended in several directions. A first obvious extension is to define the dynamic version of the concepts. To do so, an index can be defined (see e.g. the Malmquist index introduced by Caves et al., 1982). An important point would be whether the resulting index is circular or not. Most of the well-established concepts in the efficiency literature are not circular. This is simply explained by the observation that imposing circularity requires extra assumption about the production process. This is not easy to defend in a nonparametric approach. Next, a second extension is to generalize the efficiency switcher effect and technology gap switcher effect considering other orientations (e.g. output or directional distance function). Also, providing a theoretical framework about how to aggregate the efficiency switcher effect and technology gap switcher effect to obtain group averages is an important extension. Inspirations can be found in Färe & Zelenyuk (2003) and Walheer (2018a) that have provided aggregation schemes for the efficiency measurement and technology gap, respectively. A last idea for further research is to think about how using the switcher effects to conduct second stage analysis.

Appendix A. linear programmings

The technical efficiency score of a particular entity operating at $(\mathbf{x},\mathbf{y})$ with respect to the technology defined by S_t^i is computed using the following linear programming: **(LP-G)**:

$$TE_t^i(\mathbf{y},\mathbf{x}) = \min \theta$$
$$\frac{\mathbf{y}}{\theta} \leq \sum_{s\in S_t^i} \lambda_{st}^i \mathbf{y}_{st}^i$$
$$\mathbf{x} \geq \sum_{s\in S_t^i} \lambda_{st}^i \mathbf{x}_{st}^i$$
$$\sum_{s\in S_t^i} \lambda_{st}^i = 1$$
$$\lambda_{st}^i \geq 0$$
$$\theta \geq 0.$$

The 'overall' technical efficiency score of a particular entity operating at $(\mathbf{x},\mathbf{y})$ is computed as follows:

$$TE_t(\mathbf{y},\mathbf{x}) = \max_{i=1,\dots,I_t} \left\{ TE_t^i(\mathbf{y},\mathbf{x}) \right\}$$

The procedure is an enumeration algorithm as to obtain the 'overall' technical efficiency score, it is required to first use **(LP-G)** I_t times, once with respect to each group. Note that the 'overall' technical efficiency score can be obtained in one step following the procedure described in Afsharian (2018).

Appendix B. Clubs in 1990

An arrow (↑) indicates a country shifting towards the club above between 1990 and 2000.

Club 1 (Advanced): Japan, US, Germany, Netherlands, Switzerland, UK, Denmark, Finland, Iceland, Norway, Sweden, Australia, Canada, New Zealand, Israel.

Club 2 (Followers): Honk Kong (↑), South Korea (↑), Singapore (↑), Malaysia, Philippines, Thailand, Fiji, Austria (↑), Belgium (↑), France (↑), Luxembourg, Cyprus, Greece, Ireland, Italy, Malta, Portugal, Spain, Turkey, Bahrain, Jordan, Kuwait, Lebanon, Saudi Arabia, Syria, United Arab Emirates, Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Jamaica, Mexico, Panama, Paraguay, Peru, Uruguay, Venezuela, South Africa, Trinidad and Tobago, Armenia, Azerbaijan, Belarus, Bulgaria, Croatia, Czech Republic, Georgia, Estonia, Hungary, Kazakhstan, Kyrgyz Republic, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russian Federation, Slovak Republic, Slovenia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan.

Club 3 (Marginalized): China (↑), Indonesia (↑), Vietnam (↑), Bangladesh, India, Mongolia, Nepal, Pakistan, Sri Lanka, Iran (↑), Oman (↑), Yemen, Albania (↑), El Salvador (↑), Honduras (↑), Guatemala, Haiti, Nicaragua, Algeria (↑), Botswana (↑), Mauritius (↑), Tunisia (↑), Zimbabwe (↑), Benin, Cameroon, Central African Republic, Congo Rep., Cote dIvoire, Egypt, Gabon, Ghana, Kenya, Lesotho, Madagascar, Malawi, Morocco, Mozambique, Namibia, Nigeria, Senegal, Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia.

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