Meta-frontier: literature review and toolkit[*]

February 22, 2024

Abstract

Introduced in the 1970s and refined at the beginning of the 2000s, the concept of meta-frontier is now recognized as the most popular operations research technique to deal with technology heterogeneity when conducting an efficiency analysis. As proof, the number of publications has followed an exponential trend with almost 800 publications overall. In short, the concept is based on partitioning DMUs into groups where each group uses its technology. The meta-frontier is defined as the envelopment of the group-specific counterparts. Technology gap ratios are evaluated to distinguish inefficiency behaviours from technological differences. After 20 years of applications and extensions, it is now time to assess the impact of the meta-frontier in the efficiency analysis literature. In this paper, we present a systematic literature review of the concept of meta-frontier. We cover several important aspects such as its origins, developments, and applications, and discuss technical considerations. An important focus will be made on how the partitioning of the DMUs into groups is made in practice; a crucial aspect of the meta-frontier technique. Beyond a simple literature review, this paper represents a guideline and toolkit for practitioners.

Keywords: meta-frontier; data envelopment analysis; stochastic frontier analysis; technology gap; literature review.

[*]We wish to thank the Editor-In-Chief Nikolaos Fragkiskos Matsatsinis, the anonymous referees, and Thibault Piron for their comments that substantially improved the paper.

1 Introduction

Efficiency analysis is a technique used to evaluate the performances of Decision Making Units (DMUs; e.g. firms, farms, utilities, plants, hotels, countries, sectors, provinces, and regions) by comparing their inputs-outputs to those of other DMUs operating in a similar technological environment. The two more famous efficiency analysis methodologies are Data Envelopment Analysis (DEA after Charnes et al., 1978) and Stochastic Frontier Analysis (SFA after Aigner et al., 1977).[1] Initiated as an operations research tool, these methods have been set forth in a wide range of renowned journals and used for various types of applications.

In brief, DEA is a deterministic technique, nonparametric in nature, that uses the available data to estimate a production possibility set while imposing conditions (such as, for example, free disposability, convexity, returns-to-scale). Efficiency is measured as the distance to the frontier of the production possibility set. On the contrary, SFA is a stochastic technique, parametric in nature, that uses the available data to estimate an econometric model based on a production function. Efficiency is measured as the difference between the actual and estimated production function.

While both DEA and SFA have demonstrated their usefulness in light of the enormous number of applications, DEA is more popular. In their literature review, Lampe and Hilgers (2015) showed that over 4,785 publications about efficiency analysis between 1987 and 2011, 4021 used DEA and 761 SFA. Also, according to Emrouznejad and Yang (2018), 10,300 DEA-related articles were published between 1978 and 2016, and up to 1,000 journal articles were so annually in the period 2014–2016.

In many contexts, DMUs are naturally partitioned into several groups. For example, firms in different countries, provinces in different regions, sectors in different industries, hotels with different customer types, farms that use different systems, banks with different legal statutes, supermarkets with different ownerships, etc. In these cases, it is natural to question the relevance of assuming a common technological environment for all DMUs. While DEA or SFA can still be used to measure the efficiency performances in each group, i.e. intra-group efficiency analysis, they are not designed to analyze the performances between the groups, i.e. inter-group efficiency analysis. Relying on a common technological environment would, in fact, lead to an

[1] We highlight the existence of the Free Disposable Hull (FDH after Tulkens,1993) that, contrary to DEA, is not based on a convex technology. Nevertheless, the popularity of DEA is incomparable to the one of FDH.

unfair efficiency analysis.

This is where the concept of meta-production function (Hayami, 1969; Hayami and Ruttan, 1970) and meta-frontier (Battese and Rao; 2002, Battese et al., 2004; O'Donnell et al., 2008) can help. The basic idea is to recognize that each group uses its technology (called the group-specific technologies) while all DMUs have access to an overall technology (called the meta-technology). In practice, the meta-frontier, i.e. the boundary of the meta-technology, is defined as the envelopment of the group-specific frontiers. Several reasons may explain why the group-specific frontiers are different; for instance, the resource endowments, the government regulations, the adoption and diffusion of technology, the relative factor prices, the presence of asymmetry or uncertainty, and the economic and social environments.

The distance between the meta-frontier and the group counterparts is therefore interpreted as a measure of technological gap. While informative, the technology gaps are also useful to distinguish (in)efficiency behaviour, with respect to the group frontier, from potential technological improvement, with respect to the meta-frontier. The resulting efficiency analysis is therefore fair as DMUs are benchmarked on a comparable basis. This feature is very important for practitioners of DEA and SFA.

After almost two decades of applied and theoretical works using the concept of meta-production function and meta-frontier, representing almost 800 publications, it is now time to present an overall literature review. As there is currently no such literature review available, we focus our attention on several aspects: the origin, technical background, development, applications, and technical extensions. Besides being the first to present a complete literature review, we also aim to provide a guideline and toolbox for practitioners with the ultimate objective that the concepts of meta-production function and meta-frontier will be better understood and used.

We start off with a brief technical background about the concept of meta-frontier in Section 2. Next, we present the origins and developments of the meta-frontier in Section 3. As it is by nature an applied concept, we discuss several important features of the applications in Section 4. In particular, we show how practitioners have defined the groups; a crucial aspect of the meta-frontier technique. In Section 5, we focus our attention on technical considerations, such as convexity and aggregation, and present the most important technical developments of the meta-frontier. All in all, our literature review represents a guideline and toolkit for practitioners. We end this paper by discussing some potential issues and possible extensions in Section 6.

2 Technical background

The starting point of the meta-frontier efficiency analysis is the observation of inputs $\mathbf{x}$ and outputs $\mathbf{y}$ for a set of DMUs where DMUs are naturally split into groups. Let us assume that there are I groups. It is not required that there be the same number of DMUs in each group. Nevertheless, a sufficient number is needed to be able to run an efficiency analysis as it is the case for DEA and SFA (Cooper et al., 2007).

A general way to define the technology in a multi-output multi-input setting is by means of a production set. When only one output is considered a production function can alternatively be defined (see Figure 1 for an illustration). Such a production set contains all possible input-output combinations that are technically feasible. In our group context, such a set is therefore defined for every group separately. For example, it is given for group i as follows:

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

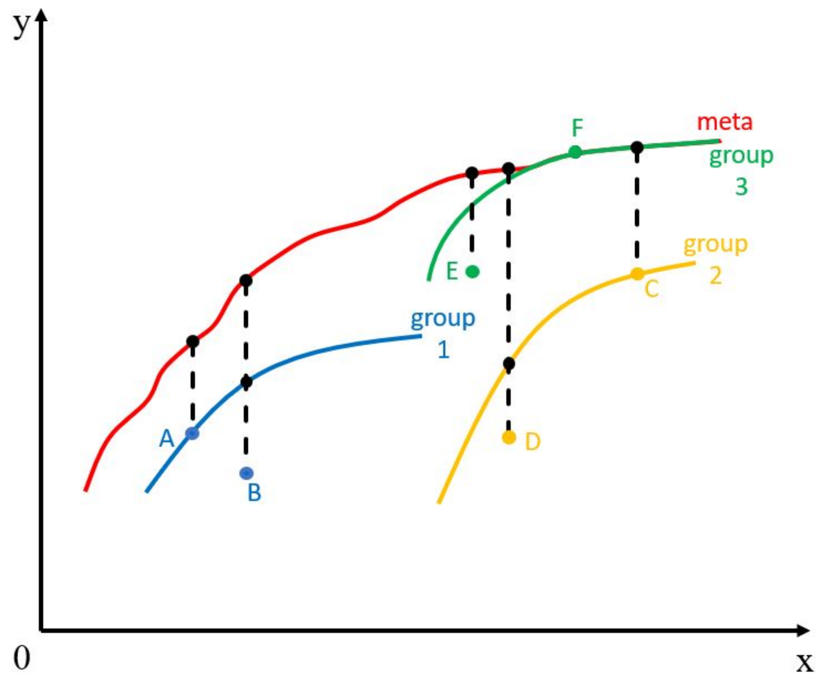
When a DMU lies on the boundary of its production set, i.e. the technical frontier, it is declared efficient. A DMU presents an inefficient behaviour when it is in the production set. In Figure 1, we consider a simple example where DMUs use one input x to generate one output y. There, we draw three group frontiers (they can also be seen as production functions) amongst the I groups and present six particular DMUs. Note that we assume here that the sets are observed (this is, in general, not the case, and then estimation matters, see Section 5).

We see that DMU A is declared efficiency as it lies on the frontier of the group 1 production set. On the contrary, DMU B is found to be inefficient as it is in the production set of group 1. A similar reasoning gives us that DMUs C and F are efficient while it is not the case for DMUs D and E. Such efficiency analysis is fair as the DMUs are compared to the peers that belong to their group technical frontier. It is an intra-group performance analysis.

Next, to obtain a fair comparison between groups, the concept of meta-frontier can be used. The meta-production set is defined as the envelopment of the group-level counterparts:

$$T^m = \left\{T^1 \cup T^2 \cup \cdots \cup T^I\right\}. \tag{2}$$

Figure 1: Group- and meta-frontiers



In words, T^m is defined as the union of the group production sets. Intuitively, T^m can therefore be seen as the 'overall' or best practice technology. At this point, we highlight that the union in (2) is by definition non-convex. It is, of course, possible to consider a convex union but this would lead to a larger meta-technology. More discussion about this feature is in Section 5.3. There are only two cases where the meta-production set coincides with a specific group production set. The first one is when there is one group. The second is when one group dominates the others in terms of technology. In all other cases, the meta-technology set is a different technology.

Of course, it would be unfair to run an efficiency analysis against the meta-frontier only. The role of the meta-frontier is different, it is used to provide a measure of technology gap across the groups. That is, the meta-frontier approach allows us to identify the best technologies and evaluate potential technological improvements. Putting this differently, it gives us the possibility to distinguish inefficient behaviour from the technological delay. It is an inter-group performance analysis.

In Figure 1, group 3 defines a part of the meta-frontier, the rest is defined by other groups that are not shown in the figure. We highlight once more that the meta-frontier is non-convex as it is defined as a non-convex union of the group-level frontiers. No technology gap is found for DMUs F but there is one for all the other

DMUs. We have to distinguish three cases. First, DMU E presents a technology gap (and an inefficient behaviour) whereas its group defines a part of the meta-frontier. This implies that technological improvement is still possible for DMUs in that group. Next, we have DMUs A and C that are fully efficient, with respect to their group technical frontier, but present a technology gap. These DMUs cannot be blamed as they present no inefficient behaviour but there is a technological delay at the group level. Second, DMUs B and D present both an inefficient behaviour and a technology gap. Improvements are possible for these DMUs.

With this simple example, we have shown that by using the concepts of meta- and group-frontiers, a fairer efficiency analysis can be conducted. In particular, DMUs are compared to reasonable peers as the group technical frontiers are used as the benchmarks. The resulting inefficiency behaviours obtained are therefore more useful as they represent a correct potential improvement. Next, the meta-frontier is used to highlight the technology gaps across groups. Better technologies are shown and technology delays are emphasized. All in all, the meta-frontier-based efficiency analysis allows us to conduct intra- and inter-efficiency analyses at the same time.

3 Literature review

We start our investigation by conducting a systematic review from 1969 to 2021. Our first step was to take all papers from the Thomson Reuters Web of Science.[2] It covers most of the high-impact journals. To be sure to retrieve all relevant papers from this database, we selected four keywords: 'meta-frontier', 'meta-technology', 'meta-production function', and 'technology gap'. In the first stage, we select all papers containing these keywords in the title, abstract, or keywords. Next, after further examination, we keep only key articles about the meta-frontier. In particular, working papers, conference proceedings, book chapters, or other documents were not kept.

To be sure to miss no important articles, a similar procedure was made for Scopus, Google Scholar, Academic Search Premier, Business Source Premier, and EconLit. This procedure is done to avoid any potential bias that can occur when relying on

[2]We highlight that Web of Science is now owned by Clarivate. We have mainly used three sub-datasets since they are directly relevant to our research topic: Science Citation Index Expanded (SCIE), Social Sciences Citation Index, and Arts & Humanities Citation Index (A&HCI).

one database only (Birkle et al., 2020; Mongeon and Paul-Hus, 2016) and to permit repeatability (Liu, 2019). Note that in a similar context, Emrouznejad and Yang (2018) rely on Scopus only, and Lampe and Hilgers (2015) on the Web of Science only. Finally, we point out that while we have done our best to avoid potential limitations in our literature review, it may, however, be the case that we have forgotten some relevant contributions. For instance, we may have omitted some databases or sub-databases, forgotten to include relevant keywords, or misunderstood some abstracts or titles (Liu, 2023).

The literature consists of 796 publications between 1969 and 2021. We split this time period into two parts that we call the 'origins' (1969 to 2008) and the 'route so far' (2009 to 2021). The first part consists of 12 papers defining the basis of the meta-frontier technique. The second part is mainly composed of applied works while there are also some theoretical extensions and combinations with existing methods in the efficiency literature.

3.1 Origins

The first to mention the concept of meta-technology are Hayami (1969) and Hayami and Ruttan (1970). These authors were studying the agricultural productivity of countries and were not very comfortable with the assumption of a common-world technology. Instead, they considered group-specific production functions while defining the meta-production function as the envelopment of group production functions. From a practical point of view, they estimated an econometric model assuming a different Cobb-Douglas production function for each group of countries. The concept of meta-production function has then been used in several applied works with some soft extensions (e.g. assuming a translog production function, adding country fixed effects, adding or replacing some variables). All these contributions form the first stage of the development of the meta-frontier in Table 1: meta-production frontier using an econometric model.

Next, building on the stochastic frontier model of Aigner et al. (1977), Battese and Rao (2002) added an inefficiency term in the meta-production function. They also introduced the term meta-frontier as the frontier enveloping the group counterparts. However, the econometric technique developed by Battese and Rao (2002) does not guarantee that the estimated meta-frontier really envelops the group fron-

Table 1: Origins

Stage	Topics	Authors	Citations (Google Scholar May 2022)
1	meta-production function + econometric model	Hayami (1969)	435
		Hayami and Ruttan (1970)	904
		Yamada and Ruttan (1980)	87
		Mundlak and Hellingshausen (1982)	140
		Antle (1983)	482
		Kawagoe and Hayami (1985)	145
		Kawagoe et al. (1985)	277
		Lau and Yotopoulos (1989)	313
		Fulginiti and Perrin (1993)	288
2	meta-frontier + SFA	Battese and Rao (2002)	722
		Battese et al. (2004)	1311
3	meta-frontier + DEA	O'Donnell et al. (2008)	1333

tiers. Fortunately, Battese et al. (2004) came up with such an econometric technique. Their methodology enables us to compute technology gaps, defined as the distance between the meta-frontier and the group-frontier, and distinguish (in)efficiency between the group- and the meta-frontier. These two papers form the second stage in Table 1: combining SFA with meta-production function and introducing the concept of meta-frontier.

Finally, probably in light of the growing popularity of DEA models introduced by Charnes et al. (1978), O'Donnell et al. (2008) showed how DEA can be used to estimate a meta-frontier using group-specific production possibility sets. Note that SFA is also used in that paper, but there is no new theoretical contribution. They also explained how to decompose differences in performances into technical efficiency and technology gap effects. This paper represents the third and final stage of development of the concept of meta-frontier. This does not mean that there are no other theoretical extensions after 2008. We will discuss such extra extensions in Section 5 (see Table 12).

In terms of citations, the most three popular papers are those showing how DEA and SFA can be used to estimate a meta-frontier. We note that the SFA paper of Battese et al. (2004) and the DEA paper of O'Donnell et al. (2008) have almost the same number of citations.

3.2 The road so far

The literature consists of 796 publications between 1969 and 2021 in 287 different journals. As explained before, we distinguish two periods: 1969-2007 and 2008-2021. As we have discussed in detail the first period in Section 3.1, we focus our discussion on the second period in this part. We, first, present the number of publications per year, the cumulated frequencies, and the annual changes in Table 2.

Table 2: Number of publications over time

Time	#	Cum.	Change
1969-2008	15	15	
2009	6	21	
2010	8	29	
2011	16	45	
2012	17	62	
2013	32	94	
2014	39	133	21.88%
2015	50	183	28.21%
2016	58	241	16.00%
2017	76	317	31.03%
2018	82	399	7.89%
2019	102	501	24.39%
2020	123	624	20.59%
2021	172	796	39.84%

We see an exponential trend in the number of publications with the most important increases happening in 2021 and 2017. An interesting aspect is how important is the concept of meta-frontier with respect to all publications using DEA or SFA. Lampe and Hilgers (2015) found 4,785 publications about efficiency analysis between 1987 and 2011, while we only found 45, representing therefore only 1% of the total publications. A similar conclusion is found when compared with the literature review about DEA only by Emrouznejad and Yang (2018). There are 10,300 DEA-related articles published between 1978 and 2016, and up to 1,000 journal articles annually between 2014 and 2016. We have 241 publications for this period (DEA and SFA confounded), i.e. around 2%. All in all, the meta-frontier is rather a minor field in the efficiency analysis literature. Nevertheless, it is important to note that the publication number follows an exponential trend meaning that the relative importance of the concept of meta-frontier in the literature can only increase over time.

Next, we present in Tables 3 and 4 the most popular journals. We also give the field(s), and the first appearance in these tables.[3] Table 3 contains all journals with more than five publications on the period 1969-2021 while Table 4 the journals with four or three publications. This distinction is made only for the purpose of better readability.

Overall, the most popular journal categories are operations research, energy and environment, technology, and applied economics. The two most popular journals are the Journal of Cleaner Production with 6.78% of the total publications and Sustainability with 5.15%. Next, with 796 publications between 1969 and 2021 in 287 different journals, we obtain an average of 2.77 publications per journal. For the purpose of comparison, Emrouznejad and Yang (2018) obtained an average of 3.46 publications per journal for DEA in the period 1978-2016.

In terms of the first appearance, without big surprise, the first journals that have accepted papers about meta-frontier are those related to agriculture topics, applied economics, and operations research. Note that the two most popular journals (Journal of Cleaner Production and Sustainability) are not part of the first appearance group.

4 Applications

As highlighted before, the meta-frontier is an applied concept. Here, we review some important features of the applied works: the groups, the DMUs, and the data. Overall, this section represents a guideline and a toolkit for practitioners. A more critical discussion is provided in Section 6.

4.1 Groups

Defining the groups represents the core of the meta-frontier technique. Indeed, the groups define the group-specific frontiers that define the meta-frontier. Wrong group partitioning thus implies a wrong meta-frontier estimation. We have to distinguish the grouping procedures from the groups. It is indeed possible to define sub-groups

[3]Fields are those given by Scimago. For better readability, we adopt the following categories: A: Business, Management and Accounting; B: Energy; C: Engineering; D: Environmental Science; E: Computer Science; F: Social Sciences; G: Economics, Econometrics and Finance; H: Decision Sciences; I: Mathematics; J: Medicine; K: Agricultural and Biological Sciences; L: Psychology; M: Multidisciplinary; N: Health Professions; O: Nursing; P: Biochemistry, Genetics and Molecular Biology; Q: Earth and Planetary Sciences; R: Arts and Humanities; S: Psychology

Table 3: Most popular journals − more than five publications

Journal	Field	#	First appearance
Journal of Cleaner Production	ABCD	54	2015
Sustainability	BDEF	41	2014
Energy Economics	BG	22	2010
Journal of Productivity Analysis	AFG	19	2004
Energy Policy	BD	16	2013
European Journal of Operational Research	ECHI	15	2009
Economic Modelling	G	14	2009
Environmental Science and Pollution Research	DJ	14	2018
Ecological Indicators	DHK	13	2015
Socio-Economic Planning Sciences	AHFG	13	2015
Energy	BCDI	12	2013
International Journal of Environmental Research and Public Health	DJ	10	2017
Journal of Environmental Management	DJ	10	2015
Technological Forecasting & Social Change	AL	10	2016
Annals of Operations Research	H	9	2015
Applied Energy	BCD	9	2014
Journal of the Operational Research Society	AHI	9	2011
Renewable and Sustainable Energy Reviews	B	9	2017
Applied Economics	G	8	2016
Energies	BCI	8	2017
Science of the Total Environment	D	7	2020
PLOS ONE	M	6	2018
Journal of Air Transport Management	ADF	5	2009
Journal of Banking & Finance	G	5	2007
Land Use Policy	DFK	5	2014
Maritime Policy & Management	CDF	5	2016
Telematics and Informatics	CEF	5	2017

Table 4: Most popular journals − four or three publications

Journal	**Field**	#	**First appearance**
Agricultural Economics	GK	4	2008
China Economic Review	G	4	2008
Emerging Markets Finance and Trade	G	4	2014
Empirical Economics	FGI	4	2008
Expert Systems with Applications	CE	4	2011
Industrial Management & Data Systems	ACE	4	2020
Managerial and Decision Economics	AH	4	2020
Omega	AH	4	2016
Polish Journal of Environmental Studies	D	4	2014
Resources Policy	DFG	4	2018
Resources, Conservation & Recycling	DG	4	2019
Review of Agricultural and Applied Economics	–	4	2014
Utilities Policy	ADFG	4	2017
African Journal of Agricultural and Resource Economics	GK	3	2016
Agrekon	AFG	3	2015
Agricultural Economics – Czech	GK	3	2015
Aquaculture Economics & Management	DFK	3	2000
Asian Journal of Technology Innovation	AG	3	2017
Carbon Management	D	3	2018
Energy Efficiency	B	3	2019
Eurasian Business Review	AG	3	2016
Global Finance Journal	G	3	2018
Healthcare	JNO	3	2019
ICAE	–	3	2015
Journal of Agricultural Science	KP	3	2014
Natural Hazards	DQ	3	2017
North American Journal of Economics and Finance	G	3	2015
SAGE Open	FR	3	2020
Scientometrics	EF	3	2021
Social Indicators Research	FRS	3	2017
Sustainable Production and Consumption	BCD	3	2021
Telecommunications Policy	ACDEFG	3	2012
Tourism Economics	AF	3	2012
World Development	GF	3	2020

for each group and even sub-sub-groups for each sub-groups. Figure 2 provides the number of grouping procedures and groups for all papers. We find that there are, on average, 1.10 grouping procedures (the median is 1) indicating that practitioners do not often use hierarchical grouping procedures, but rather prefer to stay with one grouping procedure. Note that the maximal number of grouping procedures is four. Next, the average number of groups of 3.92 (the median is 3), the minimal is 2 and the maximal is 164. The median number of DMUs and observations per group are 15 and 130, respectively.[4]

Table 5: Groups − criteria

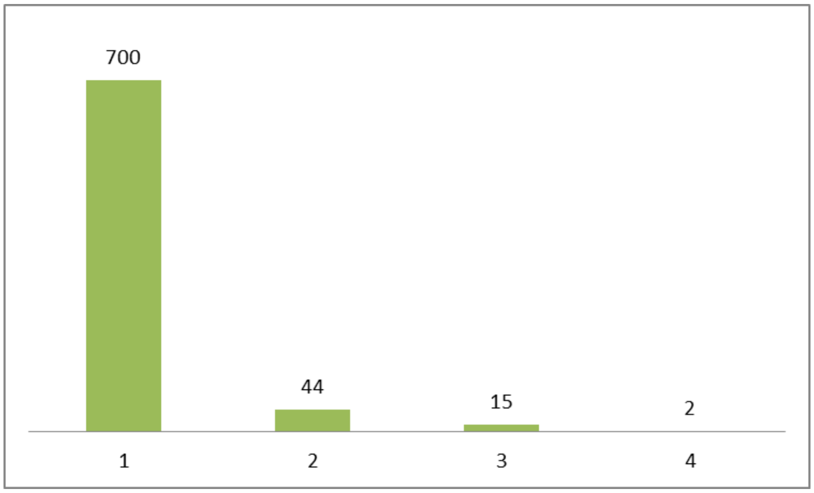
Criterion	#	%
geography	380	47.74%
ownership	46	5.78%
economic development	41	5.15%
legal structure	38	4.77%
treatment	36	4.52%
production system	29	3.64%
time	28	3.52%
size	26	3.27%
industry	23	2.89%
energy	22	2.76%
output	20	2.51%
strategy	11	1.38%
policy	10	1.26%
sector	10	1.26%
cluster	8	1.01%
management	5	0.63%
competitiveness	4	0.50%
channel	3	0.38%

Next, a crucial aspect is how to define the groups. We give the main criteria in Table 5.[5] Geography is the criterion used in almost one applied work over two. This may be explained as it is the criterion used in the founding papers (those in Table 1). We note that statistical methods are only used in 1.01% of the papers. Also, except for the criterion production system, used in 29% of the papers, the other criteria are

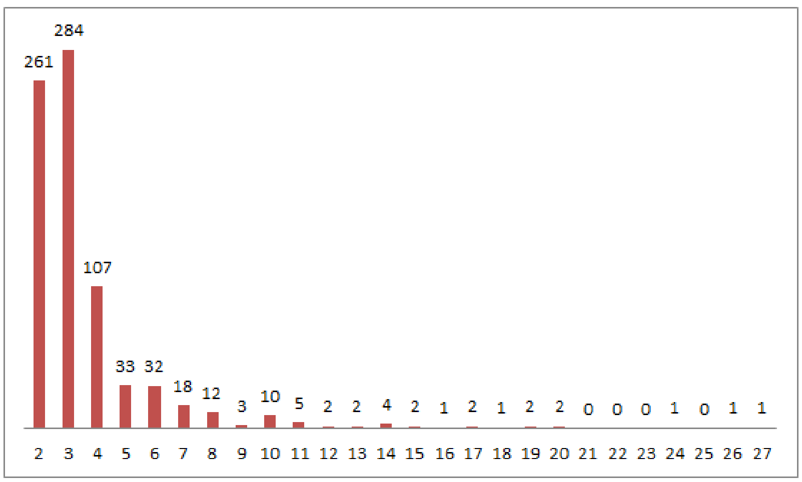
[4]The averages, 760.75 and 2954.05, respectively, are less informative in that case because of applications using very large samples.

[5]The following groups appear only in one paper: branch, career, collaboration, complexity, gene, playing position, risk, sex, star number, and water use.

Figure 2: Number of grouping procedures and groups



(a) Number of grouping procedures



(b) Number of groups

not directly related to technology but rather to environment heterogeneity, which is a more general definition of heterogeneity including technology heterogeneity. Finally, we note that a treatment effect, i.e. a causal effect of a category variable (here the groups) on an outcome variable (here efficiency score or technology gap), is used in more than 4% of the papers. It turns out that the meta-frontier modelling is an alternative way to consider binary or categorical variables for efficiency analysis. We give more details about the grouping procedure criteria in Tables 6, 7, and 8. Table 6 is only about geography as it is the main criterion and Table 7 presents more details for all other criteria except treatment that is discussed in Table 8. Examples for each criterion are also provided in these tables.

Table 6: Geography

Criterion	#	Average	Examples
agglomerations	2	12	Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta
areas	3	5.33	north, south
cities	7	4.29	Shangzhu Gangyan Farmland
continents	14	3.14	Europe Asia Latin America Eastern Europe
countries	70	6.14	Austria, Belgium, Denmark, France, Germany, Italy, Portugal
districts	1	3	Southern Gaborone, Central, Francistown, Maun and Western
regions	250	3.51	eastern, central, western
states	5	5.60	Gezira, Kassala, River Nile
zones	8	4.25	Key development zone, limited development zone

In Table 6, we give the number of times each sub-criterion has been used and the average number of groups. Regions and countries are the two main grouping procedures used for the geography criterion. More groups are usually considered for countries than for regions: averages of 6.14 against 3.51. Continents, that are used as an example in the original papers (see Table 1), are not popular for applications. Finally, other geographic grouping procedures have been considered but the number of applications is rather small. In Tables 7 and 8, we do not give the number of times each sub-criterion has been used as there is no sub-criterion in these cases. Instead, we provide the average and the median for the group numbers. For all criteria, except industry and sector, the median number of groups is three. Finally, in Table 8, we give some examples of the treatment criterion. We see that very different treatments have been considered.

4.2 DMUs

After the group selection, another important aspect is to choose the DMUs. Several types of DMUs have been used in combination with the meta-frontier. Before naming the DMUs, we give in Figure 3, the histogram for the number of DMUs. For better readability, we use intervals with different lengths in that figure.

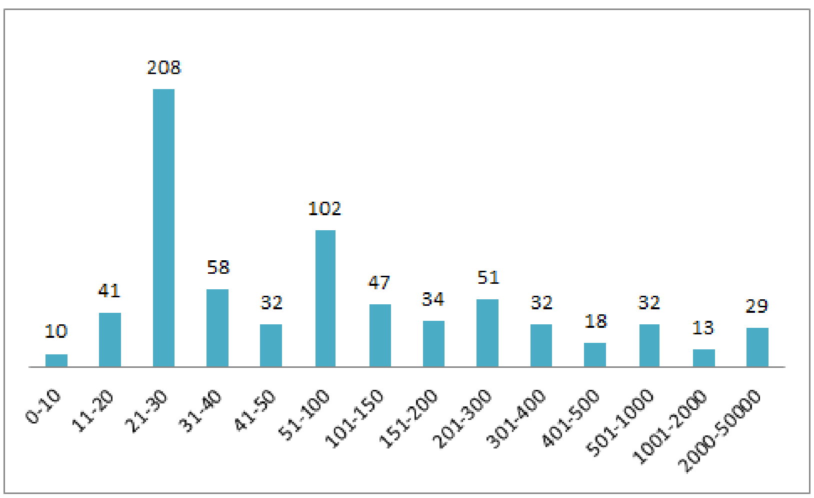
Table 7: Group criteria

Grouping	Average	Median	Examples
channels	3	3	supermarket, spot market, business, university, residential
competitiveness	3.50	3	first-tier, second-tier, third-tier, fourth-tier, high, upper, middle
economic development	2.82	3	developed, less developed, low income, high income, BRICS, OECD, advanced, followers, marginalized, developing, G7
energy	4.33	3	coal-intensive, oil-intensive, high-carbon, low-fossil, water stress, heavy-pollution, moderate-pollution , slight-pollution
industry	11.82	4	primary, secondary, tertiary,light, heavy, high-tech, textile, plastic products, fabricated metal product, machinery and equipment, electronics products, electrical equipment
legal structure	3.50	3	cooperative, labour society, islamic, conventional, private, international. local, senior, vocational, holding, academic
management	3.94	3	direct, indirect, mixed, inter-municipal cooperation, self-governing, franchise, independent
outputs	3.21	3	local, hybrid, OPV, rice, wheat, cash-crop, milk, crop, beef, water, online-game
ownership	2.86	3	state-owned, joint stock, city commercial, domestic, foreign, public, franchised, non-chain, local, central
policy	2	2	Project 211, key regions, host investment, Can Smart City Policy, 12th five year plan, Yangtze River Economic Belt, enterprise reforms
production system	3.32	3	organic, conventional, extensive, semi-intensive, intensive, traditional, monocroppers, intercroppers, pesticide-free, rain-fed, irrigated
sector	3.67	4	wholesale trade, hostelry, sanitary and social service, agriculture, mining, manufacturing, electricity, Gas and Water, Construction, Wholesale, transport, Public Administration, education
size	3.17	3	micro, micro-small, small, moderate-medium, large, big
strategies	3.30	3	traditional approach, performance-based approach, bidder, target, corporate, flagship, regional, world-class
time	3.22	3	periods, years, stages, intervals

Table 8: Treatment

Grouping	Average	Median	Examples
treatment	2	2	family or non-family, adopters or non-adopters, contract or non-contract, old or new members, listed or non-listed, organised or unorganised, independent or not independent, female or male, regulated or unregulated, specialist or non-specialist, market freedom or not

Figure 3: Number of DMUs



We see that most of the papers make use of less than 100 DMUs. In fact, the most frequent number of DMUs is between 21 and 30 with 208 occurrences. The average number of DMUs is 3,584.9 and the median is 54. There are no papers with less than five DMUs and with more than 555,000 DMUs. The most popular DMUs are given in Table 9.[6] There, we also give the number of apparitions of each DMU.

Provinces represent more than 20% of the applied works. This is mainly due to empirical papers investigating the efficiency performances of provinces in China. Next, we find firms, farms, and banks with more than 10% of the applied works each. In these cases, several DMUs over a large time period are, generally, observed making the technology heterogeneity a quite obvious choice. After, countries, a more macro-economic oriented DMU, are studied in more than 8% of the applications. Countries are the DMUs considered in the founding papers (Table 1). Next, cities and plants are quite popular DMUs with a bit more of 6% and 4%, respectively. The other DMUs represent less than 2% of the applications.

Next, to complete the overall overview of the grouping procedures given in Tables 5–8, we cross the DMUs and the grouping procedures in Table 10. This table represents a roadmap for practitioners.[7] While it is not a surprise to see geography as the most popular criterion for most DMUs, the grouping procedure popularity seems to be DMU-specific. First, geography is almost the only criterion used for the provinces (87.36%). For the farms, we find that, after geography, the production systems and the outputs are the most popular criteria. For banks, it is the legal structure and ownership that are the most often considered after geography. Economic development is the most used criterion for countries and cities after geography. Finally, for firms and plants, we do not see a clear pattern; several different criteria have been used after geography. We remark that it is more difficult to see a clear picture for the other DMUs given in Table 10 as the number of observations is rather small. This being said geography is again very often used for these DMUs.

[6] The following DMUs appear only in one paper: buildings, CEOs, chains, children, councils, departments, distributors, districts, equity funds, fisheries, franchises, greenhouses, management systems, meals, menus, owners, parcels, pharmacies, platforms, players, programs, projects, providers, regencies, responses, services, shops, smartphones, terminals, towns, vessels, villages, years, and zones.

[7] Note that we only present the group criteria that appear at least in three publications in Table 10, i.e. the group criteria of Table 5.

Table 9: Most popular DMUs

DMUs	#	**Percentage**
provinces	174	21.86%
firms	110	13.82%
farms	109	13.69%
banks	90	11.31%
countries	69	8.67%
cities	51	6.41%
plants	26	3.27%
regions	14	1.76%
hotels	13	1.63%
industries	13	
sectors	12	1.51%
airlines	6	0.75%
ports	6	
hospitals	5	0.63%
households	5	
institutions	5	
schools	5	
airports	4	0.50%
counties	4	
municipalities	4	
operators	4	
states	4	
universities	4	
facilities	3	0.8%
faculty members	2	0.25%
generators	2	
maintenance units	2	
mills	2	
restaurants	2	
traffic control centres	2	

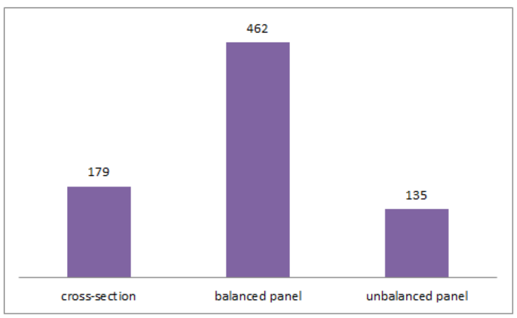
Table 10: DMUs and grouping procedure

DMUs	**Grouping procedures**
provinces	geography (152), economic development (8), energy (3), industry (3), policy (3), cluster (2), size (1), management (1)
firms	geography (38), industry (12), treatment (13), ownership (9), time (7), strategy (6), size (7), sector (5), output (4), legal structure (3), energy (2), policy (1), cluster (1)
farms	geography (46), production systems (26), output (13), treatment (9), size (3), ownership (2), channel (1), legal structure (1), cluster (1), management (1)
banks	geography (32), legal structure (24), ownership (18), time (5), size (3), treatment (3), strategy (1), cluster (1)
countries	geography (27), economic development (26), treatment (7), time (2), energy (2), competitiveness (2), sector (2), policy (1)
cities	geography (32), economic development (6), policy (5), industry (3), energy (1), time (1), size (1), competitiveness (1)
plants	geography (8), ownership (6), energy (5), size (2), legal status (1), industry (1)
regions	geography (7), time (2), treatment (1), production system (1), legal structure (1), cluster (1), competitiveness (1)
hotels	ownership (4), legal structure (3), management (2), size (1)
industries	geography (5), time (2), type (1), energy (1)
sectors	industry (3), energy (3), geography (1), ownership (1), time (1)
airlines	geography (2), ownership (1), time (1), strategy (1)
ports	size (2), geography (1), economic development (1), time (1)
hospitals	geography (1), ownership (1), legal structure (1), time (1), industry (1)
households	geography (3), size (1), treatment (1)
institutions	geography (1), legal structure (2), treatment (1), size (1)
schools	legal structure (1), treatment (1)
airports	geography (2), size (1), ownership (1)
counties	geography (3), strategy (1),
municipalities	size (1), output (1), management (1)
operators	geography (1), strategy (1),
states	geography (2), treatment (1), cluster (1)
universities	geography (2), strategy (1), policy (1)
facilities	legal structure (1), size (1), energy (1)
faculty members	geography (1)
generators	energy (2)
maintenance units	geography (2)
mills	geography (1), sector (1)
restaurants	channels (1)

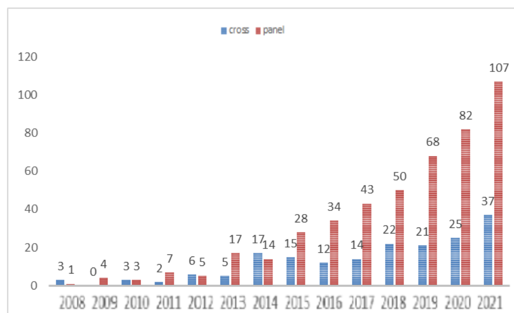
4.3 Data

Several features of the data are of interest such as their type, the number of observations, and the number of time periods. We provide graphical representations of these aspects in Figure 4. Panel data are the most popular for applied works; amongst them 77.39% are balanced. Note that such popularity increases with time. At this point, we remark that dealing with panel data may require making some extra technical choices; more discussion is made in Section 5. Next, the number of observations goes from 6 to 2,022,264 with an average of 13,141.82 and a median of 392. Finally, the minimal and maximal number of time periods are 1 and 55, respectively. The average time period is 9.78 and the median is 9.

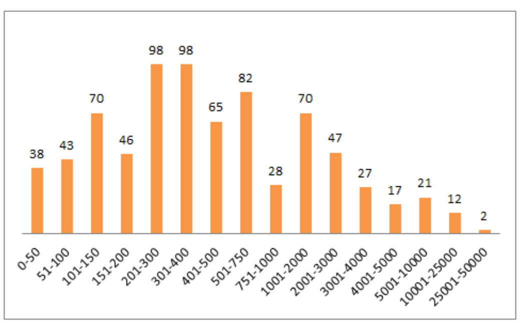
Figure 4: Data



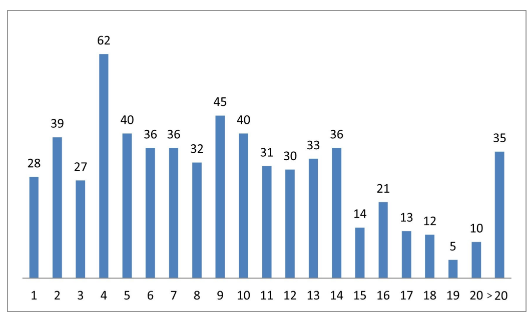
(a) Type of data



(b) Type of data over time



(c) Number of observations



(d) Number of time periods

We cross the data with the DMUs by focussing our investigation on the type of data and the average number of DMUs, time periods, and observations. We give such statistics in Table 11. Three remarks have to be made about this table. First, each column of Table 11 has to be interpreted separately. Second, there is probably an overlap between the three last columns as DEA is more popular when dealing with panel data and indexes. This is not a particular feature of the meta-frontier but it is rather true for efficiency analysis. Finally, the two last columns of Table 11 will be discussed later in Section 5.

Usually, large panel data are used when conducting an efficiency analysis for firms. This probably explains why the average number of observations is so high for this DMU. A similar argument holds true, but to a lesser extent, for banks and plants. For farms, it is usually the opposite situation: questionnaires for one or a couple of time periods are used. This explains the small share of panel data for this DMU type. The average number of DMUs is almost 30 for provinces; simply because the number of provinces in China is 31 (data for Tibet are generally difficult to get or to rely on). All applications for industries, sectors, and airlines are based on panel datasets.

5 Technical considerations

When using meta-frontier, practitioners have to make some important choices. The two major ones are probably selecting a measurement and an estimation method. Next, over time, several other aspects of the meta-frontier techniques have been highlighted. We, first, present which measurements and indexes are the most popular. Our second focus is the estimation method. Finally, we present a general discussion of other technical considerations.

5.1 Measurements and indexes

In Figure 5, we highlight some important features of the measurement and index selection process. Except in 25 papers, the applications involve one measurement. The three most popular measurements are output-oriented technical efficiency (almost 30%), the directional distance function (a bit more than 20%), and slacks-based measurements (a bit more than 16%). Note that their popularity remains true and even stronger over time. The input-oriented technical efficiency measurement only reaches 10%, and the same is true for the output distance. The popularity of the output-oriented technical efficiency measurement is partly explained as it is the most popular measurement when using SFA as an estimation method. Indeed, the output technical measurement is used in almost 70% of the cases while the cost measurement is almost 20% for SFA. For DEA, we have that almost 30% of the papers use the

Table 11: DMUs and data

DMUs	Averages			Shares		
	DMU	Time	Observation	Panel	Index	DEA
provinces	29.54	11.38	337.16	94.86%	40.36%	92.57%
firms	24305.58	8.65	78247.6	78.89%	25.58%	57.79%
farms	1590.42	6.05	7978.87	28.70%	9.68%	32.41%
banks	176.61	9.43	3833.10	87.36%	22.37%	58.62%
countries	62.41	14.12	879.36	97.10%	31.34%	76.12%
cities	167.53	8.27	1561.78	88.24%	40%	90.20%
plants	200.91	5.76	4309.46	69.23%	61.11%	65.38%
regions	153.36	13	931.23	78.57%	9.09%	85.71%
hotels	738.33	5	1091.83	53.84%	16.67%	84.62%
industries	134.62	10	1797.69	100%	46.15%	100%
sectors	34.91	13.18	442.17	100%	33.33%	83.33%
airlines	21.33	3.67	92.3	100%	16.67%	100%
ports	58	10.4	295.83	83.33%	20%	66.67%
hospitals	112.2	6.33	464.6	60%	66.67%	80%
households	2141.25	9	6856.6	40%	50%	60%
institutions	260.6	5	1337.2	80%	25%	80%
schools	176.25	2.2	577.6	80%	60%	100%
airports	60.25	8.5	166	50%	50%	66.67%
counties	534.5	4.33	689.25	66.67%	33.33%	75%
municipalities	2104.5	3	5759.75	50%	0%	100%
operators	58.67	6.67	344	66.67%	0%	75%
states	22.75	9.33	149.25	75%	66.67%	100%
universities	236	4	889	100%	50%	100%
facilities	386	7	743.67	33.33%	0%	100%
faculty members	31	47	407	50%	0%	100%
generators	1655.5	18	1655.5	50%	0%	100%
maintenance units	48.5	2	69	50%	100%	100%
mills	197	16	2812	100%	0%	100%
restaurants	81	1	81	0%	0%	100%
traffic control centres	3950	1	3950	0%	0%	100%

directional distance function, and almost 25% use a slacks-based measurement. The output technical, output distance, and input distance are all around 12-13%.

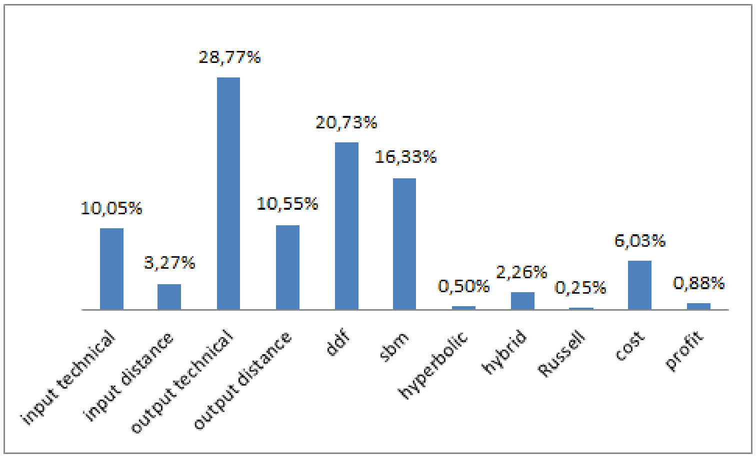
Amongst the 462 papers using a balanced panel dataset, a bit more than 40% are based on an index. Note that this percentage goes down to 10% for unbalanced panels. The most popular index is clearly the Malmquist index (almost 30%) followed by the Malmquist-Luenberger (8%) and the Luenberger (3%) indexes. In Table 11 (fifth column), we give the shares of index used for balanced panel data for each DMU type. Using indexes is more popular for plants, provinces, and industries. There is also an important use of indexes for states, schools, airports, households, and hospitals but these shares are less reliable as these DMUs have been selected less than five times in applied works. On the contrary, indexes are not so popular for farms, regions, and hostels. This is probably due to the structure of the data (cross-sectional or unbalanced panel).

5.2 Estimation methods

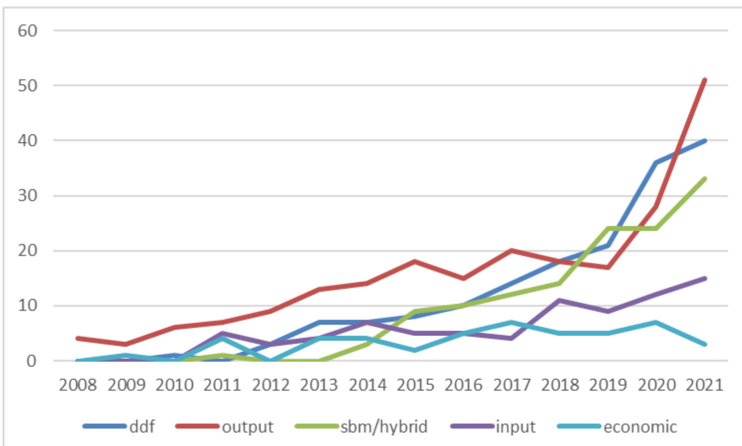
The second important aspect of all empirical applications is the selection of an estimation method. Several features of the estimation methods are provided in Figure 6. A first observation is that DEA is the most popular estimation method with a more nit more than 70% of the applications. SFA reaches a bit more than 27%. We highlight the (minor) use of alternative methodologies such as FDH and Stoned. We also point out that initially the meta-frontier was designed using econometric and SFA estimation methods, DEA was only introduced in 2008 (see Table 1). Finally, the translog function is clearly the most popular functional form when using SFA (more than 80 %).

We cross the DMUs with the estimation methods in Table 11 (last column). DEA is the most used estimation method for all DMUs except farms (32%). The lower percentage for farms is probably explained by the historical use of SFA (and econometric techniques) for agriculture as is the case in the initial papers (see Table 1). DEA is more popular for DMUs observed at an aggregated level such as provinces, cities, countries, regions, industries, counties, and sectors. Probably because it is more difficult to find convincing arguments for selecting a particular production function at that level. On the contrary, it is probably easier to find such arguments for smaller and microeconomic levels. This is probably why we observe lower percentages of DEA

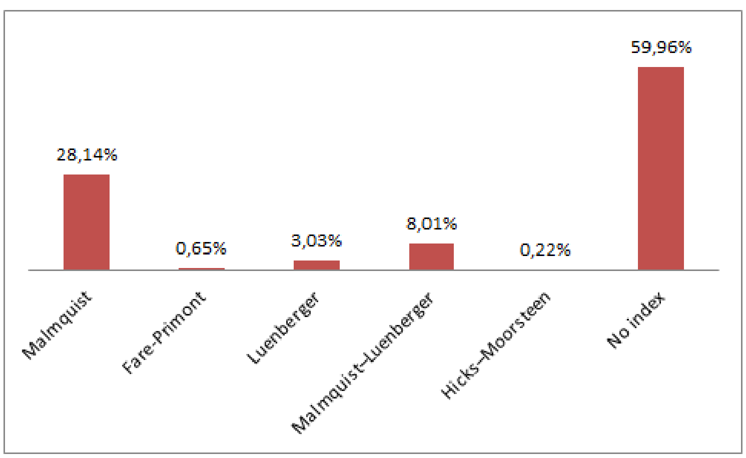
Figure 5: Measurements and indexes



(a) Measurements in percentage

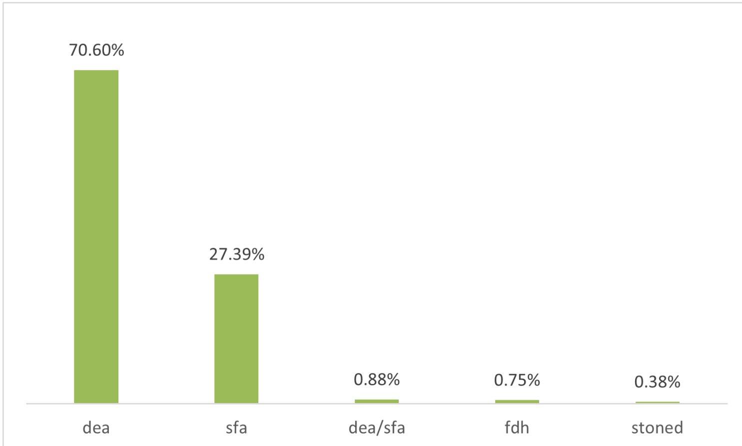


(b) Measurements over time

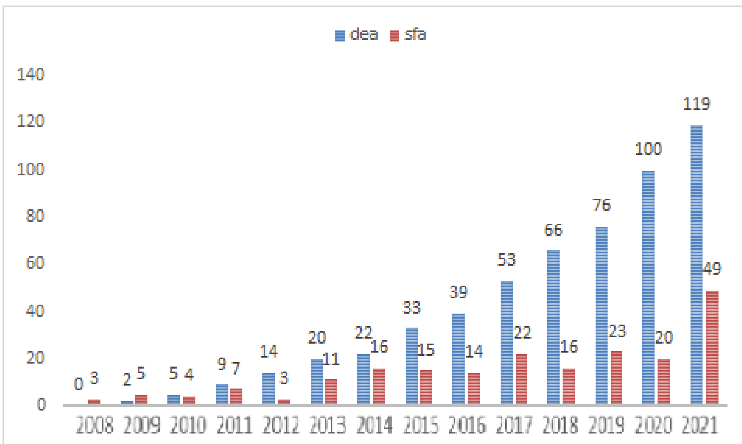


(c) Indexes for balanced panel (462)

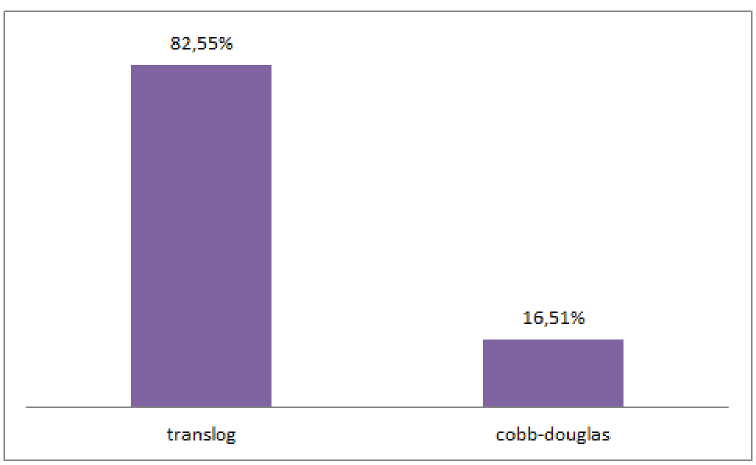
Figure 6: Estimation methods



(a) Estimation methods



(b) Estimation methods over time



(c) Production functions for SFA (212)

use for firms, banks, and plants. Finally, note that when the DMUs are not really producers (e.g. faculty members, traffic control centers), the use of DEA is very high and can even reach 100%.

We end this section with an important remark. We do not distinguish the different types and features of DEA and SFA in our literature review. Instead, we regroup all DEA and SFA estimation methods together. Most of the empirical papers make use of standard DEA and SFA but some rely on more advanced techniques. Several extensions have been suggested for DEA and SFA such as bootstrapping, bias correction, inference, instrumental variables, and true fixed effect. Those features are not specific to the meta-frontier

5.3 Extensions

While the concept of meta-frontier has not changed since its initial definition, several theoretical extensions and combinations with existing methods have been pointed out in the literature. We propose an overall overview in Table 12.[8]

The first aspect that has been pointed out in the literature is whether the meta-frontier should be defined as a convex or non-convex envelopment of the group-specific frontiers. As assuming convexity is a stronger assumption and because it creates fictive areas based on fictive DMUs, it is important to justify such a choice. Nevertheless, most of the applications rely on a convex envelopment; in fact, only 3% use a non-convex envelopment. This is probably due to the popularity of DEA against FDH, the difficulty of the computation when a non-convex envelopment is chosen, and the initial definition of the DEA estimator for the meta-frontier of O'Donnell et al. (2008).

The computation of the efficiency scores and technology gaps has been defined in the initial papers of O'Donnell et al. (2008) for SFA and DEA, but not when a non-convex envelopment is considered. In the latter case, mixed integer programmings are needed making the non-convex meta-frontier less attractive for practitioners. Fortunately, work has been made to come up with linear programming even when a non-convex meta-frontier is considered. This latter technical aspect represents, in fact, the second extension in Table 12.

[8]Note that Table 12 covers technical aspects from 2009 to 2022. Technical aspects before 2008 are discussed in Section 3.1.

Table 12: Extensions

Contribution	Authors
envelopment	
non-convex meta-frontier	De Witte and Marques (2009) Sala-Garrido et al. (2011) Tiedemann et al. (2011) Thieme et al. (2013) Kerstens et al. (2019)
computation	
linear programming	Huang et al. (2013) Afsharian and Podinovski (2018)
aggregation	
geometric average	Mazumdar and Rajeev (2010) Bhandari and Maiti (2012) Bhandari an Ray (2012)
economics-based	Walheer (2020)
frontier	
inter-temporal frontier	Tulkens and Vanden Eeckaut (1995)
global frontier	Pastor and Lovell (2005) Oh (2010)
overall frontier	Afsharian and Ahn (2014)
index	
Malmquist	Chen et al. (2009) Vaughn Aiken et al. (2009) Oh and Lee (2010) Chen and Yang (2010)
Malmquist-Luenberger	Oh (2010)
Luenberger	Zhang and Wei (2010) Chen (2015)
network	
series	Chiu et al. (2013) Halkos et al. (2015)
dynamic	Yan and Jie (2016)

Another aspect is the computation of group-level measurements. Indeed, while all measurements are defined at the DMU level, it is natural to present results for the groups. Historically, the arithmetic averages were used. This is an obvious naive candidate. Next, using the geometric average has been suggested. Again, this is a natural candidate. This being said, no theoretical justifications are given either for the arithmetic or geometric averages. The first attempt to come up with a theoretical aggregation is the concept of an economics-based aggregation scheme. In short, the weights are linked to economic optimization behaviour but, generally, require observing such behaviour and some prices. Only 1.62% of the publications use the geometric average and 0.65% use the economics-based one.

Next, other types of meta-frontier have been suggested. The meta-frontier is defined by the founders as the envelopment of the group-specific frontiers. There is therefore one meta-frontier per time period. It turns out that the meta-frontier is designed for static settings. The inter-temporal frontier is a natural extension of the meta-frontier when panel data are considered. It is defined as the envelopment of the static group-specific frontiers. That is, there is one inter-temporal frontier for each group. Next, the global and overall frontiers are defined as enveloping the inter-temporal frontiers. The distinction between the global and the overall frontier is that the global is based on a convex envelopment while it is a non-convex one for the overall frontier. Note that the global frontier has gained popularity as almost 10% of papers that consider indexes have used that definition. This is not the case for the inter-temporal and overall frontiers with less than 10 applications.

Once dynamic meta-frontiers are defined, it is natural to use indexes to capture what is happening over time. This is a common way to proceed when conducting an efficiency analysis. The most popular indexes have been used and decomposed in the meta-frontier context, such as the Malmquist, Malmquist-Luenberger, and Luenberger indexes. A particularity here is that when decomposing such indexes into several parts, we obtain specific components related to the technology gap, i.e. components that relate the meta- to the group-frontiers. In a similar vein, the concept of meta-frontier has been combined with network production structure; an important topic in efficiency analysis. Nevertheless, it represents only 3.52% of the published works.

6 Discussion

We end this paper by pointing out potential issues (or, at least, warnings) when using the meta-frontier and presenting potential research directions.

Grouping procedure. As mentioned before, the grouping procedure is at the core of the meta-frontier technique. It implies that a wrong grouping procedure would immediately cancel the efficiency analysis reliability. We give below some lines of thought.

- For the moment, subjective and a-priori grouping procedures are used by practitioners. Few or no arguments are given to support such procedures. Efforts have to be made on that part.

- Partitioning DMUs in groups does not necessarily imply that technology heterogeneity is observed. In fact, technology heterogeneity is usually not observed. Other available information can be used to define the groups but they might not be related to technology. An option is therefore to consider heterogeneity in a more general (or vaguer) way by using the concept of environmental heterogeneity. This being said the previous remark about providing convincing arguments when defining the groups remains true.

- Statistical methods, such as cluster methods, can help when forming groups. Indeed, when no convincing a-pririo arguments are found, relying on statistical methods seems to be a safe option. Until now, such methods have only been used in 1.01% of the applied works. Another option is to run a statistical test a-posteriori (e.g. Kruskal-Wallis test or Mann–Whitney test). The underlying intuition is that if group-level technology gap distributions are found to be different, this reveals technology or environment differences. Such tests are only used in a minority of empirical applications.

- Also, the grouping procedure and the efficiency analysis are used as two independent techniques. First, practitioners use a certain criterion or method to define the groups, and, next, an efficiency analysis is run. As discussed before, the grouping procedure has a direct impact on the efficiency analysis results. Modifying the groups would give rise to different empirical results.

- Finally, practitioners have to decide the number of groups and allocate DMUs in each group. No guidelines are really available for both aspects. Usually, this is done once and for all even when dealing with large sample or panel data.

Practical importance of the extensions. The discussion made in Section 5.3 has revealed that some theoretical extensions and combinations with existing methods have been suggested in the literature. Nevertheless, the fact is that such extensions have received very little attention in the applied world. We discuss here two important aspects: convexity and aggregation.

- The meta-frontier has been defined as the envelopment of group-level frontiers. There is no particular reason for that envelopment to be convex. In fact, if a convex envelopment is used fictive areas based on fictive DMUs are created. From a mathematical point of view, assuming a convex envelopment is a stronger assumption. Two options are then available: use a non-convex envelopment or come with arguments to select a convex envelopment. In the past, a convex envelopment was selected since computations were much more difficult with the non-convex option. This is not the case anymore as linear programmings have been defined even when a non-convex envelopment is selected.

- In a group context, it is important for practitioners to obtain measurements at the group level. As measurements are given for DMUs when using the meta-frontier technique, a procedure has to be selected. As a rule, the arithmetic average is used. The issue is that, while an obvious naive first choice, no theoretical justification comes with it. This is probably why the geometric average has been used by others (to a very lesser extent). Recently, more coherent aggregation schemes have been suggested but they are more demanding (e.g. data and assumptions about the technology). There is therefore a trade-off between using a non-justified but less demanding aggregation scheme and using a more justified but more demanding aggregation scheme.

Some ideas for future works. Extending or combining the meta-frontier with existing concepts is clearly still possible. Nevertheless, we point out three more important extensions needed to convince practitioners to continue using the meta-frontier.

- A first feature is the lack of flexibility of the meta-frontier. Almost all applied works define the groups, the number of groups, and the DMU allocation in each group once and for all. When dealing with a small sample over a short time period, this makes sense, but for larger samples and panel data, it is less obvious. More flexibility is therefore needed. For instance, some groups may disappear or be created over time; new DMUs can be observed; DMUs can change their group belonging over time; etc. While some works have been made on these aspects (Walheer, 2023), much more has still to be discovered.

- As discussed before, statistical methods are not very popular when combined with the meta-frontier. While important efforts have been made to better understand the statistical properties of the efficiency analysis (DEA and SFA), the same cannot be said for the meta-frontier. The statistical properties of the technology gaps are unknown, the connection between the grouping procedure and the efficiency analysis has not been studied (a recent exception is Tsionas, 2023), and the statistical properties of the grouping procedure have not been studied.

- Finally, more and more practitioners make use of indexes in combination with the meta-frontier. An advantage is that such indexes can, generally, be decomposed into different parts allowing us to distinguish the group- from the meta-frontier impacts. Nevertheless, with several components, it is often difficult to know what each really measures. Much effort has to be made to come up with index decompositions that are clearer. Next, the previous discussion about the aggregation for measurements remains true for indexes as they are defined for the DMUs. It is thus important to come up with a coherent way to define the indexes and the components for the groups.

Declarations

Conflict of interest: The authors declare that they have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Appendix

References related to the literature review about the concept of meta-frontier for the period 1969–2021 are given per year in the attached Appendix.

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