Marrying frontier analysis-based benchmarking and user-tailored decision support

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Abstract

Benchmarking allows firms to identify possible sources of improvement in order to increase their performance. Production-theory based frontier methods support advanced benchmarking. While frontier analysis literature abounds, there are relatively few papers on the use of frontier methods in benchmarking efforts by managers. It seems that the enormous amount of frontier analysis knowledge insufficiently reaches its primarily intended beneficiaries, being actual decision makers. The objective of this paper is to investigate why frontier-analysis-based benchmarking techniques may insufficiently find their way into practice and to explore what can be done in order to make them being used by decision makers. We find that benchmarking and frontier analysis literature have mainly evolved as two separate streams. Benchmarking literature defines key issues that determine the willingness of managers to benchmark, including benchmarking relevance, required managerial skills, and required resources and time. We link these issues to the use of frontier analysis in benchmarking efforts by managers. Existing studies that consider this link mainly focus on increasing the relevance of frontier analysis for managers, by incorporating individual preference information in the identification of relevant targets. Although benchmarking literature mentions the necessity of deriving actual improvement actions for the relevance of benchmarking, we find only few studies that link the identification of actions to the mere frontier-analysis-based performance measurement. Combining frontier analysis with interactive decision procedures may be useful in this respect. Managerial skills are another key issue as managers must be able to provide the necessary preference information for target selection and detect actual improvement actions given the firm-specific decision environment. Required skills depend on the user-friendliness of the frontier analysis software, which is determined by its complexity and the language used. Required resources and time relate to the data of multiple firms needed to apply frontier analysis. It may be interesting to involve intermediaries in frontier-analysis-based benchmarking efforts, as it may be easier for them to gather data of multiple firms, to obtain the required skills and to identify improvement actions based on their experience with multiple firms.

Keywords: benchmarking, frontier analysis, decision support, user-tailored

1. Introduction

Benchmarking is the practice of determining the relative value of something by comparing it to a known standard. Methods of producing products, providing services, selling and marketing products and services, and managing internal business systems are compared with practices in other businesses (Camp, 1993). Benchmarking can be considered as a strategic tool that allows the firm to identify possible sources of improvement in order to increase its performance and competitiveness (Cassell et al., 2001). It is particularly valuable when no objective or engineered standard is available to define efficient and effective performance (Sherman and Zhu, 2006).

Frontier methods, like Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), are relative performance evaluation techniques that support advanced benchmarking. Originating from the work by Farrell (1957), frontier analysis considers the production function and optimizations based on price information. Since its origin, frontier analysis literature abounds. In 2001, DEA literature alone already recorded more than 1800 articles in refereed journals (Gattoufi et al., 2004). Emrouznejad et al. (2008) report an exponential growth of DEA-related articles between 1978 and 1995 up to a stabilized number of 226 publications per year from 1995 onwards. Between 2004 and 2006, the number again increased to approximately 360 publications per year.

Frontier analysis literature mainly consists of theory extending papers and so-called real-world applications. Application papers mainly report on work by researchers applying existing methods to real-world datasets (Emrouznejad et al., 2008). Literature about the use of frontier analysis in benchmarking efforts by managers is, however, relatively scarce. It seems that the enormous amount of production-function-based performance measurement knowledge insufficiently reaches its primarily intended beneficiaries, being actual decision makers. Numerous commercial and non-commercial software tools for frontier analysis exist (Barr (2004) provides an overview of DEA software), but it remains unclear to what extent these tools are actually being used for supporting decisions by managers. Specifically related to DEA, Lai et al. (2011a) report on the scarcity of studies about the link between DEA and decision support.

Despite the scarcity of literature about the link between frontier analysis and benchmarking efforts by managers, anchor points can be found in different streams of literature in order to explore this link. There is an extensive amount of benchmarking literature devoted to the added value of benchmarking perceived by managers and the efforts required to conduct a benchmarking process (see e.g. Elmuti and Kathawala, 1997; Anand and Kodali, 2008; Huq et al., 2008). Efficiency literature reports on strengths and limitations of using frontier methods for performance measurement in practice (see e.g. Epstein and Henderson, 1989; Charnes et al., 1994), on incorporating managerial preferences into frontier analysis (see e.g. Allen et al., 1997; Post and Spronk, 1999; Bogetoft and Nielsen, 2005) and on linking performance measurement with the identification of actual improvement actions (see e.g. Seol et al., 2007; Van Meensel et al., 2010a). Moreover, some studies can be found that integrate frontier analysis in a decision support framework (e.g. Athanassopoulos, 1998; Seol et al., 2011; Van Meensel et al., 2012).

In this paper, we integrate the anchor points from existing literature and provide insights on marrying frontier analysis and benchmarking efforts by managers. The objective of this paper is to investigate why frontier-analysis-based benchmarking techniques may insufficiently find their way into practice and to explore what can be done in order to make them being used by decision makers. We review the literature to reconcile the demand by managers for benchmarking and the supply of production-function-based performance measurement methods.

The paper is structured as follows. In Section 2, we analyze the willingness of managers to benchmark. In Section 3, we give an overview of strengths and limitations of frontier methods for performance measurement. Section 4 then provides key issues for reconciling demand and supply. We focus on the link between frontier analysis and the benchmarking relevance for managers, the required managerial skills to adopt frontier-analysis-based benchmarking and the required resources and time. Section 5 concludes.

2. Demand side: manager's willingness to benchmark

Managers who are unwilling to perform a benchmarking process, will also be unwilling to use advanced performance measurement methods. Therefore, in this section, we analyze the willingness of managers to adopt benchmarking. There is an extensive amount of literature devoted to the benefits of benchmarking and the efforts required to conduct such process.

Since its initial development by Xerox in 1979, benchmarking as a total quality management tool has been widely adopted by firms around the world (Lai et al, 2011a), despite its complex and demanding nature. Multiple authors (e.g. Elmuti and Kathawala, 1997; Bhutta and Huq, 1999; Yasin, 2002; Anand and Kodali, 2008; Huq et al., 2008) give examples of organizations adopting benchmarking practices. Not only large companies, but also small and medium sized enterprises (SMEs) use benchmarking (Cassell et al., 2001).

Benchmarking will only be adopted as a management tool if managers attribute added value to the results of the process. The benchmarking benefits must exceed the efforts required to perform the process. Multiple authors report on the perceived benefits of benchmarking. Lai et al. (2011b), for example, state that benchmarking provides a better understanding for companies of their relative position in their industry. It works because it helps to understand own processes and enables to learn from others. Benchmarking equals innovation as real innovation comes from looking for the best examples outside one's industry. Benchmarking allows for evaluating and improving the quality of products, work processes and work procedures. Elmuti and Kathawala (1997) distinguish between benchmarking in order to assess relative performances, improve performances, increase productivity and improve an individual design, identify competitive strategies, enhance learning and identify potential areas of growth. Anand and Kodali (2008) state that benchmarking should be recognized as a catalyst for improvement and innovation, which is necessary for companies since global competition is rising, with more and more national economies becoming liberalized. Bhutta and Huq (1999) mention that benchmarking is a way to move away from tradition and establish the ground for creative breakthroughs.

Also the required efforts for benchmarking are described in literature. To start with, managers must be open to benchmarking (Huq et al., 2008). They have to be humble enough to admit that others are better at something, and wise enough to learn how to match and even surpass them at it (Lai et al., 2011b). One should be able to recognize one's shortcomings and acknowledge that someone is doing a better job. This attitude has to be inculcated in the organization (Elmuti and Kathawala, 1997). The willingness to benchmark also requires that managers do not feel that they give too much information to competitors (Dattakumar and Jagadeesh, 2003). When comparing performances between organizations, information inevitably becomes available for competitors (Bhutta and Huq, 1999). Finally, openness of managers to change and new ideas is also needed (Elmuti and Kathawala, 1997).

Hinton et al. (2000) mention the lack of time and available resources as reasons for entrepreneurs not to turn to benchmarking. For SMEs in particular, the resource requirement for benchmarking needs to be carefully established, because these organizations are normally tight on budget and cannot afford to venture investing sizeable resources (St-Pierre and Raymond, 2004). Benchmarking is a demanding process. It is not a one-time project but an ongoing process involving multiple steps. The Xerox benchmarking process in 1979, which addressed the production costs of photocopier machines and is considered as the first success in benchmarking history, involved ten steps (see e.g. Huq et al., 2008): (1) identify what is to be benchmarked, (2) identify comparative companies, (3) determine data collection methods and collect data, (4) determine the current performance gap, (5) project future performance levels, (6) communicate benchmark findings and gain acceptance, (7) establish functional goals, (8) develop action plans, (9) implement specific actions and monitor progress and (10) recalibrate the benchmarks. Bhutta and Huq (1999) incorporate the basic content of the benchmarking process in a benchmarking wheel, representing a continuous process involving the following steps: determine what to benchmark, form a benchmarking team, identify benchmarking partners, collect and analyze benchmarking information and take action. Completing the benchmarking steps is not always easy. Benchmarking exercises involve substantial organizational changes and so are typically of very difficult implementation (Zairi and Ahmed, 1999).

Managers also have to be convinced that benchmarking is relevant. The relevance of benchmarking mainly has to do with the selection of realistic targets to compare with. When choosing these targets, care must be taken to select a target that corresponds to the special characteristics of the particular organization: just because an entity differs from a target does not necessary mean that a problem exists or that an opportunity for improvement has occurred (Maleyeff, 2003). Best practices followed in a certain successful organization may not necessarily be the best when adopted by other organizations (Dattakumar and Jagadeesh, 2003). St-Pierre and Delisle (2006) mention that finding comparable enterprises is in particular difficult for SMEs, as they are often considered as unique.

Benchmarking is a huge undertaking and many companies become overwhelmed, ending up with an abundance of useless information (Huq et al., 2008). The complexity of the process requires the availability of sufficient management skills within an organization. Auluck (2002) mentions that managers should have a solid understanding of the organization's operations and requirements for improvement. Moreover, they should have the competence to effectively organize the implementation activities and cope with uncertainty and dynamic expectations that emerge in the benchmarking process (Amaral and Sousa, 2009). They must also support and give sufficient authority to benchmarking implementers.

Some authors (e.g. Elmuti and Kathawala, 1997; Bhutta and Huq, 1999; Amaral and Sousa, 2009) mention the importance of employees in the benchmarking process. After all, employees will be the ones to use the information and improve the processes. An increased focus by managers on better numbers but diminished focus on employees may cause resistance by some employees who are reluctant to changes inside the company. Reluctance may be due to the stress when required to move out of comfort zones, the challenge of learning new skills or the fear of exclusion. It is also important that employees have adequate and sufficient skills to implement benchmarking, which requires adequate training. Moreover, there has to be room, opportunity and incentives for employees to communicate with each other, within and across functions and among all levels of the organizational structure, both in a formal and informal manner.

Amaral and Sousa (2009) mention that benchmarking is only of benefit if it results in improvement actions that are actually implemented. Maire et al. (2005) state that benchmarking is not only about performance comparison, but also about implementing best practices in order to improve. Freytag and Hollensen (2001) distinguish between benchmarking, benchlearning and benchaction. It is, however, not always straightforward to implement best practices. Ungan (2004) states that although many companies are involved in benchmarking, adoption of best practices is not as high as might be expected. The main determinants of the adoption decision are the cost of adoption, external pressures such as competition, customer needs and government regulations, and satisfaction with the existing practice.

Although many authors describe the perceived benefits and required efforts of benchmarking, literature lacks approaches for quantifying these gains an costs. This shortcoming causes managerial hesitation with regard to the adoption of benchmarking (Yasin, 2002). The absence of economic evaluation approaches may be related to the lack of a standardized system for performance benchmarking. Multiple authors (e.g. Zairi and Ahmed, 1999; Maire, 2002; Dattakumar and Jagadeesh, 2003; Southard and Parente, 2007) state that there is no widely accepted process for conducting benchmarking exercises. One of the reasons is the difference among industries regarding the nature of the benchmarking process (Maleyeff, 2003). Another reason has to do with the origin of the benchmarking process. Anand and Kodali (2008) distinguish between (1) academic-based models, in which researchers use theoretical and conceptual aspects, which may or may not have been implemented and validated through real life applications, (2) consultant-based models developed from experience in providing consultancy and validated through implementation in the client's organization and (3) organization-based models developed by organizations themselves based on own experience and knowledge and therefore highly dissimilar.

Yasin (2002) and Kyrö (2004) mention that benchmarking at firm level has typically developed without the researcher's intervention. The position of the researcher is mainly the one of an outside observer and most of the benchmarking know-how available for managers is the result of practitioners' efforts. According to Kyrö (2004), benchmarking is in a very early stage when it comes to the interplay between scientific theories and practice and more focus should be put on applying explicitly scientific knowledge. In this context, an integrative synergetic cooperation between practician and academician is needed (Yasin, 2002). The absence of interplay between science and practice may explain the scarcity of literature about de demand and use of production-theory-based frontier methods by managers. Frontier methods, originating from the work by Farrell (1957), are a typical example of academic-based models. The lack of interplay between science and practice may have resulted in the fact that managers are not aware of the added value that the production function brings to the benchmarking process and therefore are not using frontier methods in their benchmarking efforts.

3. Supply side: strengths and limitations of production function-based frontier methods for performance measurement

This section focuses on the reported added value and shortcomings of production function-based frontier methods for performance measurement. Frontier methods aim to identify inefficiency levels by comparing current performance levels of decision making units (DMUs) with their potential optimal performance levels. The analysis is based on production theory, which studies the process of converting input(s) into output(s). The relationship between the maximum amount of output(s) that can be achieved from a given set of input(s) with a certain production technology is called the production function. Output-oriented technical efficiency reflects the ability to produce maximal amounts of output(s) with a given amount of input(s). Input-oriented technical efficiency reflects the ability to use a minimal amount of input(s) to obtain (a) given amount of output(s). Cost allocative efficiency reflects the ability to use inputs in cost minimizing proportions, given their respective prices and the production technology. Input-oriented technical and cost allocative efficiency can be combined to provide a measure for cost efficiency (see Coelli et al. (2005) for an introduction to efficiency analysis).

To calculate efficiency scores, literature mainly distinguishes between nonparametric data envelopment analysis (DEA) and parametric stochastic frontier analysis (SFA). SFA was originally and independently described by Aigner et al. (1977) and Meeusen and van den Broeck (1977), and fits a parametric production function to given data, specifying a two-part error term that accounts for both random error and the degree of technical inefficiency. Detailed reviews of SFA can be found in Greene (1993), Kumbhakar and Lovell (2000) and Coelli et al. (2005). DEA involves linear programming methods to construct a nonparametric piece-wise frontier over the data. Efficiency measures are then calculated relative to this frontier (Coelli et al., 2005). An input-oriented model that assumes constant returns to scale (CRS) is proposed by Charnes et al. (1978). Subsequent papers consider alternative sets of assumptions, such as Banker et al. (1984), in which a variable returns to scale (VRS) model is proposed. Comprehensive reviews on the DEA methodology can be found in Charnes et al. (1994), Cooper et al. (2000) and Ray (2004).

In practice, single dimensional performance indicators are mainly used for comparing performances between DMUs (Maleyeff, 2003; Van Meensel et al., 2010a). Multiple authors report on the added value of using frontier methods for performance measurement. Frontier methods can bundle multiple inputs and, in case of DEA, multiple outputs into one comprehensive efficiency measure (Epstein and Henderson, 1989; Charnes et al., 1994; Easton et al., 2002; Bogetoft and Nielsen, 2005; Wang et al., 2008; Joo et al., 2009; Du et al., 2010; Van Meensel et al., 2010a; Akçay et al., 2012). Moreover, since overall efficiency is decomposable, the physical production analysis can be separated from price information, as technical efficiency is distinguished from allocative efficiencies (Van Meensel et al., 2010a). This also implies that frontier methods can be used from a controlling oriented viewpoint (efficiency measurement) as well as from a planning oriented viewpoint (resource allocation (Athanassopoulos, 1998).

Specifically related to DEA, literature mentions that by focusing on the observed operational practice in a sample of comparable units, DEA reference units may have greater practical appeal and higher perceived fairness than normative industrial engineering standards. In addition, since minimal assumptions are required regarding the production relationships, DEA reference units may be more defensible than performance standards based on estimating a parametric production frontier (Charnes et al., 1994; Post and Spronk, 1999; Bogetoft and Nielsen, 2005). Other advantages of DEA include the provision of insights into the effect of potential efficiency improvement on input use and output production (Charnes et al., 1994; Easton et al., 2002; Akçay et al., 2012), the possibility to include additional information about return-to-scale properties (Post and Spronk, 1999; Samoilenko and Osei-Bryson, 2013) and the possibility to include continuous, categorical and ordinal input-output variables (Charnes et al., 1994; Post and Spronk, 1999).

The requirement of minimal assumptions regarding the production relationships also entails shortcomings for DEA. The conventional DEA methodology implicitly makes a number of strong preference assumptions, that may not properly or fully reflect the decision maker's practical decision context (Epstein and Henderson, 1989; Post and Spronk, 1999). The standard DEA model is pareto optimal (Charnes et al., 1994), assumes linear input substitutability (Epstein and Henderson, 1989) and assigns equal priority to all input and output variables, freely allowing weights to be estimated in order to maximize the efficiency rating of the assessed DMU (Allen et al., 1997). A number of refinements has been proposed to incorporate additional preference information. For example, DEA has been adapted to include linear or non-linear input substitutability and output transformability (Post and

Spronk, 1999). Moreover, methods for incorporating weight restrictions and value judgments in DEA have been developed by several researchers (Allen and Thanassoulis, 2004).

Another frequently reported limitation of DEA is its sensitiveness to outliers. The non-robustness of the DEA measure with respect to measurement error and outliers places great demands on the accuracy of the DEA and on the choice of DMUs to include in the field (Epstein and Henderson, 1989; Donthu et al., 2005). SFA deals with these outliers by distinguishing between random error and inefficiency. The main strength of SFA is that it considers stochastic noise in data and allows for the statistical testing of hypotheses concerning production structure and degree of inefficiency. Its main weaknesses are that it requires an explicit imposition of a particular parametric functional form representing the underlying technology and also an explicit distributional assumption for the inefficiency terms (Coelli et al., 2005). Moreover, if the aim is to exploit duality characteristics in order to derive cost or environmental functions that are consistent with the estimated production function, a restrictive functional form is required (Van Meensel et al., 2010b).

Another important issue when using frontier methods for performance measurement concerns the comparativeness of the DMUs. Frontier methods work better in case of more comparative units. Measuring efficiency and productivity of large organizations is a non-trivial exercise, involving a complex input-output structure, requiring a large number of variables to reflect the operations of the companies and a large number of companies to discriminate on their relative efficiency (Thanassoulis, 2000; Emrouznejad et al., 2008). The number of comparator units can be increased by the use of panel data, treating each unit as a distinct comparative entity in each unit of time (but requiring a relatively stable technology to make comparisons across time meaningful), or by dividing the complex entities which are few in number into self contained homogeneous parts and make the parts the units of assessment (Thanassoulis, 2000).

The comparativeness of the DMUs also depends on the degree of homogeneity of the technology that is used. Frontier methods typically assume that the underlying production technology is the same for all DMUs (Coelli et al., 2005). There might, however, be unobserved differences in technologies, as is illustrated by Van Meensel et al. (2010b) who use a mechanistic approach to assess farm-specific production functions for a sample of homogeneous pig-finishing farms. Orea and Kumbhakar (2004) state that these differences in technology might be inappropriately labeled as inefficiency. They address this issue by estimating a latent class stochastic frontier model in a panel data framework and illustrate with Spanish banking data that bank-heterogeneity can be fully controlled when a model with four classes is estimated.

4. Reconciling demand and supply: key issues for using frontier-method based performance measurement in benchmarking efforts by managers

In this section, we explore how frontier-method based performance measurement can contribute to benchmarking efforts in practice. The analysis of the willingness to benchmark

(Section 2) reveals the importance for managers of a number of criteria in order to adopt benchmarking. Section 3 reveals the strengths of frontier methods for performance measurement as such, but also shows some shortcomings that have to be addressed. Based on these insights, we now focus on the reconciliation between demand and supply. We analyze how the use of frontier methods is related to criteria that determine manager's willingness to benchmark. We link frontier methods to, respectively, benchmarking relevance, required skills, and required resources and time.

4.1 Benchmarking relevance

The analysis of the willingness to benchmark shows that the benchmarking relevance is mainly determined by two factors. First, benchmarking can only be relevant if relevant targets are identified. Second, the relevance of benchmarking depends on the possibility to detect and implement actual improvement actions. In the following sections, we discuss the link between frontier methods and these two factors.

4.1.1. Identifying relevant targets

We start with the identification of relevant targets for individual DMUs. In Section 3, we already focused on determining a realistic frontier and corresponding efficiency scores. We mentioned that the choice of data set is important for representing a homogeneous technology and allowing for sufficient discrimination between DMUs. Also the curvature of the production frontier has to be carefully considered, especially when resource allocation problems are addressed. Particularly when using DEA, one has to be careful with outliers that may influence the established frontier.

Post and Spronk (1999) argue that the selection of realistic targets is not only a matter of technical production possibilities, but also of organizational policy considerations, managerial preferences and external restrictions. The incorporation of value judgments by managers regarding inputs and outputs may lead to more realistic efficiency scores. Different methods exist for incorporating these value judgments. Allen et al. (1997) provide an overview of value judgment methods for DEA, distinguishing between direct restrictions on the weights, adjustments of the observed input-output levels and restricting the virtual inputs and outputs. More recently, extensions and alternatives for these methods have been published. Allen and Thanassoulis (2004), for example, present an approach where unobserved DMUs are created by adjusting the output levels of certain observed relatively efficient DMUs, reflecting a combination of technical information of feasible production levels and value judgments of the individual decision maker. The main advantage of this approach is that 'local' value judgments, specific for only part of the production possibility set, can be incorporated into the analysis, instead of including 'global' preferences valid for all the DMUs. Also value efficiency analysis (see Halme et al., 1999; Halme and Korhonen, 2000; Korhonen et al., 2002) includes 'local' individual preference information, through letting the decision maker choose the most preferred solution, being the preferred input-output vector on the efficient frontier.

There are also attempts to combine frontier methods with interactive procedures from Multiple Criteria Decision Making (MCDM) theory. Belton and Vickers (1993), for example, incorporated DEA in a visual interactive software called Visual Interactive Data Envelopment Analysis (VIDEA), displaying the implications of different weight restrictions on the efficient frontier and obtained efficiency scores. Post and Spronk (1999) introduce the Interactive Data Envelopment Analysis (IDEA) procedure, combining DEA with Interactive Multiple Goal Programming (IMGP). This procedure is helpful in case when complex decision problems with multiple decision alternatives and goal variables make it difficult to elicit preference information from decision makers. An additional advantage of their approach is that the decision maker can select targets, not only from the production frontier, but also from the production possibility set interior, in order to include some degree of organizational slack. More recently, Bogetoft and Nielsen (2005) also consider the identification of realistic targets as an interactive choice problem. They propose an internet based benchmarking design, letting the user decide in which direction to move and how far to move. Van Meensel et al. (2012) present a Decision Support System (DSS) for farrow-to-finish pig farms based on frontier analysis, allowing the user to select targets to compare with, based on the preferred direction and extent of improvement. During the development of this DSS, possible users explicitly stated that their aim was not to become fully efficient in one step, but to conduct stepwise improvements. Therefore, the DSS allows users to select targets that perform better, but are not necessarily fully efficient.

The interactive articulation of preference information by confronting the decision maker with well-defined and feasible decision alternatives provides flexibility to the decision maker in deriving realistic targets. An additional advantage is that the decision maker obtains more insights in the decision situation, through becoming more involved in the process of solving the decision problem. This embedded learning effect can shape and alter his preferences and may improve the incorporation of value judgments (Post and Spronk, 1999).

Another issue in determining relevant targets is that they can only be realistic if the process to be benchmarked is relevant. After all, this process determines the choice of inputs and outputs that are included in the benchmarking effort. Easton et al. (2002) mention that the aim of firms is not necessarily to become more efficient, but for example to improve the quality of the delivered product or service. Sherman and Zhu (2006) state that most benchmarking studies do not include quality and propose a quality-adjusted DEA (Q-DEA) that deals with quality measures in benchmarking. They express the need for further research on incorporating quality in frontier approaches, in order to improve their practical value.

A final issue related to the relevance of targets concerns their dynamic nature. While frontier methods assume a static situation in which performance targets are identified, the decision environment in practice can be considered as dynamic. Samoilenko and Osei-Bryson (2013) therefore propose a DSS that combines DEA with other data analytic and data mining techniques, in order to evaluate the external competitive environment of a productivity-driven organization, as well as to identify the differences between the current state of the organization and the states of its competitors. The need for incorporating the dynamic nature of the decision environment into a single performance measurement depends on the type of decision that has to result from the benchmarking effort. For a strategic decision based on a one-time use of frontier analysis, it is obviously required to include expected changes of the decision environment in the analysis. For operational decisions, it is probably more useful to repeat the analysis more frequently, and incorporate in subsequent applications changes in the decision environment as they occur.

4.1.2. Deriving actual improvement actions

The second factor that influences the benchmarking relevance is the possibility to derive improvement actions to be implemented. While the added value of benchmarking reported in literature ranges from assessing relative performance to identifying improvement measures (Elmuti and Kathawala, 1997), multiple authors (e.g. Maire et al., 2005; Amaral and Sousa, 2009) argue that benchmarking only becomes relevant when improvement measures are actually implemented.

In literature, some examples can be found of approaches combining frontier methods and other methods in order to derive actual improvement measures. Seol et al. (2007), for example, argue that DEA as such does not identify the process that preferentially has to be improved in order to approach the benchmark. They use an integrated approach of DEA and decision tree (DT) analysis in order to allow managers to select the process to be improved first and provide an illustrative example for the service industry. Lai et al. (2011b) present a DSS for public university libraries that integrates the steps of the benchmarking wheel, using DEA for performance measurement and incorporating guidelines for the identification of actual improvement measures. Akçay et al. (2012) analyze the solutions of DEA with information visualization and data mining techniques, stating that structuring results in this way contributes to the detection of actual improvement measures by managers. Van Meensel et al. (2010a, 2012) determine the position of pig farms in an efficiency framework, but use key performance indicators (KPIs) pig farmers are familiar with (e.g. feed conversion, average daily weight gain) to communicate the assessed improvement margins. Using these KPIs may facilitate the detection of actual improvement actions by farmers.

Performance measurement as such using frontier methods can thus only be considered as a part of the benchmarking effort. When it comes to identifying actual improvement actions, combinations with other methods become appropriate. The idea of using frontier methods in an interactive target identification setting (see section 4.1.1.) may also be promising in this respect, as the learning effect for the decision maker may contribute to the ability to detect improvement actions. This ability also highly depends on the skills of the manager, which will be discussed in the following section.

4.2. Required skills

Conducting a benchmarking process requires appropriate skills. Although the use of frontier methods may contribute to a better benchmarking process, it also requires additional skills from the decision maker. Multiple software packages for frontier analysis are available, so decision makers must not do the mathematical computation of the performance measurement by themselves. However, in literature, we did not find any information on the use of these software packages by actual decision makers. Therefore, in the following paragraphs, we provide some reflections about the compatibility between frontier analysis software and the skills of managers conducting a benchmarking effort.

We start with required skills for using frontier methods to identify relevant targets. As value judgments prove to be important for relevant target selection, decision makers must be able to provide such information to the frontier analysis software. Value judgments that are incorporated in frontier methods through weight restrictions or related approaches, require substantial amounts of a priori articulated general preference information (Post and Spronk, 1999; Allen and Thanassoulis, 2004). It may be difficult for individual decision makers to provide this information. Using Multiple Criteria Decision Making (MCDM) procedures in combination with frontier methods may help, as they do not require substantial amounts of a priori articulated general preference information, because they rely on the interactive articulation of local preference information (Post and Spronk, 1999).

Skills are also required for identifying actual improvement actions, based on the obtained performance scores. Here also, the interactive involvement of decision makers in the performance measurement effort may help, as the decision maker obtains more and more insights about the decision situation. Methods like Decision Tree (DT) analysis can also help in this respect (see section 4.1.2), but their generic nature still has to be combined with appropriate management skills to detect actions tailored to the specific decision environment.

Necessary skills for using frontier analysis software also depend on the user-friendliness of the software. An important aspect for user-friendliness is the complexity of the software. The question is: should individual decision makers become familiar with the complexity of frontier methods or should the inclusion of frontier methods in user-friendly software keep decision makers away from the complexity? The answer lies probably somewhere in the middle. Epstein and Henderson (1989) mention the need for managers to understand the measurement system by which they are evaluated. If manages do not understand the complexity and behavior of the measure, they cannot control it effectively and it may be perceived as unfair. A high degree of managerial understanding of the measure would therefore appear essential for its use as an established performance measure. Van Meensel et al. (2012) mention that managers cannot be expected to become familiar with the complexity of frontier methods. Nevertheless, they should be able to interpret the obtained results. This requires some effort from the manager but can also be influenced by the way the software is provided. For a case of performance measurement of pig farms, Van Meensel et al. (2012) mention that, on the one hand, pig farmers need to get used to input-output reasoning to analyze adequately performances. On the other hand, partial productivity KPIs are used to explain why a certain performance level is achieved, as pig farmers are familiar with these KPIs.

Another aspect of user-friendliness of a software is the language or jargon that is used. Frontier analysis involves a specific jargon decision makers may not be familiar with (Van Meensel et al., 2010a; Van Meensel et al., 2012). It may be appropriate to use a simple language in frontier analysis software and to avoid as much as possible specific jargon. This improves the accessibility for users and avoids that the software is not being used by decision makers due to language complexity.

Given the skills required to conduct a benchmarking process using frontier methods, it is appropriate to wonder who will perform the benchmarking process and use the frontier analysis software. While the decision maker himself should necessarily be involved in the benchmarking process, it may also be appropriate to collaborate with intermediaries, like consultants. Intermediaries can use frontier analysis software in their advisory tasks for multiple firms and therefore, it may be more appropriate for them to become familiar with the software. Since intermediaries have contact with multiple firms, it may be also easier for them to find relevant targets for a particular firm and to identify relevant improvement actions. The frontier analysis software then facilitates the interaction between intermediary and firm manager.

4.3. Required resources and time

The use of frontier analysis in benchmarking efforts requires resources and time. An important issue in this respect is the availability of sufficient data. When using generic frontier analysis software, a sample of data consisting of multiple firms has to be introduced. Individual managers usually do not dispose of data of other firms. This may again plead for involving intermediaries, for whom it may be easier to have data from multiple firms. Different managers can also use frontier analysis together, each providing their own data. This may facilitate mutual discussions and learning processes that can contribute to the identification of firm-specific improvement actions. Another option is to provide case-specific instead of generic software that already contains a standard data set. Individual managers can then upload their own data that can be compared with the items of the standard data set in the software.

Van Meensel et al. (2012) provide a number of attention points that have to be taken into account when a standard data set is used or individual managers can upload their own data. These include a uniform and clear definition and registration of the required variables for all firms, which is necessary for a correct comparison between firms, the necessity of a regular update of the standard dataset, to capture for example technological progress over time, and the degree to which anonymity can be assured to the managers involved. The extent of anonymity that is required depends on the openness of the managers to conduct a benchmarking process, which is one of the factors affecting the willingness to benchmark (see section 2). When frontier analysis software is used by a group of managers, they have to be open to share information of their own firm with the other participants. When a standard dataset is used, it may be useful to incorporate typical but fictive firms that represent the required variation in a sample of firms.

Benchmarking using frontier methods also requires preference data. Value judgments approaches usually require a substantial amount of a priori articulated general preference information (Allen and Thanassoulis, 2004). Interactive approaches, combining for example frontier analysis with MCDM procedures, require less a priori formulated information, because they rely on the interactive articulation of preference information by confronting the decision maker with decision alternatives (Post and Spronk, 1999).

The use of frontier methods by managers also requires time. Time is for example needed to gather the necessary data, both firm data and preference information. Value judgments approaches are mentioned in literature (e.g. Allen and Thanassoulis, 2004) to be often time demanding. Here again, it may be more useful to spend time to interactive approaches, as they provide a learning process for the decision maker that may improve insights about the decision problem and may lead to a better result of the benchmarking process.

5. Conclusion

In this paper, we investigate why frontier-analysis-based benchmarking techniques may insufficiently find their way into practice and we explore what can be done in order to make them being used by decision makers.

We find that there are two streams of literature that have evolved mainly separately from each other. On the one hand, benchmarking literature reports on the perceived added value by managers, required efforts and steps that need to be undertaken in order to successfully conduct a benchmarking process. On the other hand, literature on using frontier analysis for performance measurement mainly consists of theory extending papers and application papers on work by researchers applying existing methods to real-world datasets. The added value of this paper is that we bridge the two streams of literature in order to explore key issues for using frontier analysis in benchmarking efforts by managers.

Existing studies on linking frontier analysis to benchmarking in practice are relatively scarce. Most of the work done focuses on increasing the relevance for managers of using frontier analysis. Approaches for incorporating individual preference information of the decision maker in frontier methods have been developed in order to allow for selecting more relevant targets. To a much lesser extent, efforts have been undertaken to link the mere performance measurement using frontier analysis to the identification of actual improvement actions. Further research may focus on this issue, since benchmarking literature highlights the importance of deriving improvement actions for the relevance of benchmarking. Mere performance measurement can then only be considered as a part of the benchmarking process. In order to identify relevant improvement actions, frontier analysis may be combined with other approaches, like the interactive setting of relevant targets using Multiple Criteria Decision Making procedures, as it provides a learning effect for the decision maker getting gradually more insights in the decision problem.

Besides the contribution of frontier analysis to the benchmarking relevance, there are also other key issues that affect the use of this method for benchmarking by managers. These key issues are hardly touched upon in existing frontier analysis literature. Managerial skills are a key issue, as they are required to provide the necessary preference information and to detect improvement actions given the specific decision environment. Required skills also depend on the user-friendliness of the frontier analysis software that is provided for the manager. This user-friendliness is determined by the complexity of the software and by the use of a simple language and the avoidance of specific frontier analysis jargon in the communication between software and manager. Required resources and time are another key issue. Multiple data are needed as frontier methods use data of multiple firms to allow for comparison. Important is also the choice of user of the frontier method in the benchmarking process. It may be interesting to involve intermediaries, as it may be easier for them to gather data of multiple firms, to obtain the required skills for using frontier analysis software and to identify improvement actions based on their experiences with different firms.

Key issues like relevance, user-friendliness, managerial skills and choice of user also appear in another stream of literature, being decision support literature. They are considered as critical success factors for decision support systems (see e.g. Hartono et al., 2007). Marrying frontier analysis and benchmarking literature therefore may profit from a third partner, being decision support literature. Decision support literature also mentions the benefit of a participatory approach involving stakeholders for the successful development of decision support systems (e.g. Lynch and Gregor, 2004). Participatory processes involving managers, intermediaries and frontier analysis researchers may therefore be useful to develop adequate decision support systems for frontier-analysis-based benchmarking efforts by managers. After all, the various key issues that affect the marriage between frontier analysis and benchmarking, and the diversity of cases for which benchmarking can be applied, urge for a tailor-made and case-specific approach.

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