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Productivity development of Swedish distribution system operators in the 21st century

Application of the Malmquist index

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Abstract

Nowadays, Data Envelopment Analysis (DEA) is a well-established practice to apply in network regulation. More specifically, DEA can turn out to be a proper tool to evaluate the productivity development of an industry. From the Network Performance Assessment Model to the Revenue Cap Model and passing through a low-powered rate-of-return regime, Sweden experienced a broad range of regulatory scheme. This study is the opportunity to evaluate the impact on the industry of the two mentioned regulatory schemes. Through a Malmquist productivity index, our study encompasses a productivity analysis of the Swedish electricity distribution sector from 2002 to 2017. Besides, a Kruskal-Wallis test and a Tobit regression helped us evaluate if factors such as the ownership type or the customer density could have an influence on the performances of the operators. Among other results, we have demonstrated the low-robustness of the Network Performance Assessment Model and the stability of the industry from the establishment of the Revenue Cap Model onwards. Recommendations to the Swedish Energy Inspectorate are also given such as a revision of the general efficiency requirement imposed to the operators or the inclusion of environmental variables. Furthermore, the results have shown that it is likely that private operators present better performances than municipally-owned and cooperative operators.

Keywords – network regulation, electricity distribution data envelopment analysis, Malmquist productivity index

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Acronyms

COLS Corrected Ordinary Least Square. 22

CRS Constant Return to Scale. 25

CV Coefficient of Variation. 54

DEA Data Envelopment Analysis. 7

DRS Decreasing Return to Scale. 34

DSO Distribution System Operator. 1

HV High-voltage. 66

LV Low-voltage. 56

MPI Malmquist Productivity Index. 38

MPSS Most Productive Scale Size. 34

NPAM Network Performance Assessment Model. 15

OM Operation and Maintenance. 51

RAB Regulatory Asset Base. 19

SAIDI System Average Interruption Duration Index. 16

SAIFI System Average Interruption Frequency Index. 16

SD Standard Deviation. 54

SE Scale Efficiency. 55

SEC Scale Efficiency Change. 39

SEI Energy Inspectorate. 14

SFA Stochastic Frontier Analysis. 21

STEM Swedish Energy Authority. 14

StoNED Stochastic Non-parametric Envelopment of Data. 21

TC Technological Change. 38

TE Technical Efficiency. 54

TEC Efficiency Change. 38

TSO Transmission System Operator. 46

VRS Variable Return to Scale. 25

WACC Weighted Average Cost of Capital. 20

1 Introduction

Since the 1990's, the structure of the electricity supply industry has gone through major changes. Often called "deregulation" or, more fairly, "restructuring", this trend has resulted in the unbundling of the previous structure to create a more efficient market.

Introduced by authors such as Friedman and the so-called School of Chicago in the 1970's, the neo-liberal current empowered many governments to take up the mantle of deregulation. Among other sectors traditionally run by monopolies as telecommunication or gas, electricity was one of the main concerned network. Previously, utilities were concentrated in monopolistic positions in the areas in which they operated. There was usually no separation between the four different electricity sectors (generation, transmission, distribution and consumption), which were covered by the same public operator (Wangensteen, 2012). The restructuring triggered a global trend in the electricity market to unbundle these sectors in order to promote competition inside them. One of the main consequences of this restructuring was notably to introduce a competitive environment into the generation of the electricity market by allowing the different distribution system operators (DSOs) and major consumers to choose their supplier of electricity. According to this new scheme, the different generation companies competed through a wholesale commodity market, causing a reduction of the tariffs and more incentives for generators to optimize their operations. A major change has also taken place in electricity distribution. Given the existence of high fixed-costs, network utilities can be described as natural monopolies. Nevertheless, as highlighted in the neo-liberal literature, a distribution system operator is likely to abuse its market power, resulting in a lower total welfare than in a competitive situation. This typically results in effects such as a low cost-efficiency and high tariffs charged to the customer. In view of this, a regulatory change of network operators was needed. These regulations are nowadays mainly funded on incentive-based regulation such as depicted by Laffont and Tirole (1993).

This new type of regulation intends to offer proper incentives to operators to align their profit-maximizing goal with a total welfare-maximizing goal. To achieve this, different regimes have been tested with relative success throughout the world such as the common revenue cap.

Another way of viewing the issue is based on the information asymmetry between the regulator and the regulated operator, as underlined by the Agency Theory. In the case of a low-powered regulation, this would result in a company providing the regulator with wrong cost information in order to increase its allowed revenue. In the attempt of limiting this phenomenon, regulators resort to extensive use of freshly designed benchmarking methods such as Data Envelopment Analysis to capture the real performance of the operators and to determine a reasonable revenue cap according to the results.

Apart from providing useful informative tools for the regulation of a network, the benchmarking methods can as well offer a room for productivity research of the industry. Since performances of the different actors are reported every year by the regulator, they can be tracked over time in order to evaluate their productivity development related to several aspects. A productivity development evaluation can turn out to be particularly useful to address the health status of the distribution sector in a given country and more specifically, to evaluate the impact of a new regulation in the industry. This thesis will focus on this aspect of the benchmarking methods.

More precisely, we will concentrate on a country which can be seen as one of the precursors of the global restructuring trend: Sweden. To say a few words about its regulatory situation, Sweden recently switched to the more common revenue cap regime after having experienced three other regulatory schemes with limited success since its restructuring in 1998. This revenue cap is set for a regulatory period of four years and is revised at the end of it.

In light of the last two paragraphs, our research question is the following:

How did the productivity development of the Swedish distribution system operators evolve from 2002 until now?

To answer this question, *a productivity index based on a Malmquist approach* will be our main tool.

Such research is common and has been achieved in many countries. However, concerning Sweden, research of this kind dates back to the period 1970-1986 (Hjalmarsson and Veiderpass, 1992) or 2000-2006 (Agrell and Grifell-Tatjé, 2016). An updated analysis including recent data (2011-2017) or another model for 2002-2006 such as proposed in this thesis is relevant to complete these past studies. As evoked before, from a low-powered rate-of-return regime to a Revenue Cap Model and passing through the Network Performance Assessment Model, an engineering-driven model, Sweden experienced a broad range of regulatory schemes. Besides providing a clearer picture of the situation of the industry, this thesis is also the opportunity to evaluate the impact on the industry of the two main regulatory schemes: The Network Performance Assessment Model which was the model initially planned to regulate the industry; the Revenue Cap Model which was conceived in reaction to the fall of the latter scheme. Especially, this thesis can be the opportunity to provide the regulator with some relevant findings concerning the new regulatory scheme.

The next chapters of this thesis will be ordered as follows: Chapter 2 will aim at providing the first insights by exploring the literature that relates to benchmarking and productivity research in particular; Chapter 3 will set the regulatory framework through an introduction to the main families of regulatory regimes set up in electricity distribution followed by a glimpse of the regulation in Sweden; Chapter 4 will dig a bit deeper in the benchmarking techniques employed nowadays under the light of Data Envelopment Analysis and will then achieve a review of the existing literature concerning benchmarking research; Chapter 5 will develop more deeply the tools used to evaluate the productivity development, i.e. the Malmquist index and other statistics methods; Chapter 6 will follow with a quick summary of the data provided by the Swedish Energy Inspectorate and its formatting and model; Chapter 7 will analyze the results obtained by applying tools from Chapter 5 to data presented in Chapter 6; A conclusion with the main findings and recommendations will be given in Chapter 8.

2 Literature Review

The purpose of this section is to locate our thesis in comparison with the existing literature and to detect useful tools which might help us thereafter. We will first review the main benchmarking research for network operators in order to fill the gap between the regulatory setting of a country and its benchmarking method employed. By a second step, some of the main theoretical and practical studies about productivity development will be approached. Finally, a special attention will be devoted to benchmarking research concerning Scandinavian countries.

2.1 Benchmarking research for network operators

Directly inspired by the agency theory, economic regulation is now a well-established economical current to effectively regulate natural monopolies (Joskow, 2008). Combined with the introduction of new benchmarking techniques known as frontier-based methods by pioneers (Charnes et al. (1978); Banker et al. (1984); Banker et al. (1989)), the book written by Laffont and Tirolle (1993) set the outlines of the transition towards reformed regulations of network sectors such as telecommunication, electricity or natural gas transportation. To know more about economic regulation used in networks, a relevant reading that enlightens its main terms and concepts is provided by Agrell (2015). Regarding frontier-based methods, a non-exhaustive list of main findings in DEA until 2009, can be explored in Cook and Seiford (2009).

As said earlier, the electricity distribution sector can be seen as a good application for economic regulation. In this respect, Joskow (2008) examines developments of incentive regulation for electricity distribution and transmission network with a focus on price-cap regulation. A summary of regulation in electricity distribution through frontier-based method is exhibited by Agrell and Bogetoft (2017). Coelli et al. (2003) co-wrote a book to provide regulators with useful benchmarking tools to evaluate the efficiency of different actors in a regulated industry. More broadly, frontier-based methods turned out to be useful tools to evaluate the efficiency of the distribution sector. A cornerstone is the old but relevant review of existing studies of efficiency in the electricity distribution sector, using frontier-based methods proposed by Jamasb and Pollitt (2001). More research has been added in the last years. Many of them can be seen in the survey of DEA in energy and environmental studies by Zou and al. (2008).

2.2 Productivity development research for network operators

Productivity development research is nowadays a well-established application of frontier-based model. Total factor productivity index, which comprises the Malmquist productivity index (Caves et al. (1982)) or the Fisher index such as introduced by Coelli et al. (2005) appear to be the most common approach for assessing the productivity development of an industry. Nevertheless several variations have been proposed in the literature. Thus, Färe et al. (1994) proposed a decomposition of the index into a technological and a efficiency change component. A survey of some of the theoretical developments of the Malmquist index can be found in Färe et al. (1998). Ray and Desli (1997) suggested to complete the latter mentioned component of the Malmquist index by including a scale efficiency change component. Maniadakis and Thanassoulis (2004) proposed a cost-Malmquist index which allows to capture an allocative efficiency component. Pastor and Lovell (2006) conceived a global Malmquist productivity index in order to solve the circularity problem. The circularity problem stipulates that the productivity development of a firm between two periods cannot be deduced from the productivity development found for the periods in-between the two periods.

When looking more precisely at studies of productivity development through frontier-based methods, it appears that it can apply to a large range of situations. For instance, one of the first projects, proposed by Nishimizu and Page (1982), was a study of the productivity change in 23 social sectors in Yugoslavia between 1965 and 1978 thanks to a Malmquist index. Studies concerning productivity development of public sectors such as health care (Färe et al. (1992);Hollingsworth (2003)) or education (Parteka and Wolszczak-Derlacz (2013);Rahimiana and Soltanifar (2013)) are common practice. Concerning the electricity distribution sector, many studies have been performed to evaluate the productivity of network utilities. Inter alia, recent studies include Tovar et al. (2011) who examine the size and productivity of Brazilian distribution utilities from 1998 to 2005; Hattori et al. (2005) who compare the performance of distribution utilities in United Kingdom and Japan for 1985-1998; Çelen (2013) who performs a two-stage productivity development analysis of Turkish operators for 2002-2009; Amado et al. (2013) who measure the impact of a new technology on a group made of Portuguese operators from 2006 to 2008; Bishnoi and Gaur (2018) who measure productivity change among Indian distribution companies for 2006-2015.

2.3 Benchmarking research in Scandinavia

Scandinavian countries are some of the precursors of the electricity market restructuring. For this reason, a large literature focused on the efficiency and productivity of their electricity network. Agrell, Bogetoft and Tind (2005) introduce a regulation scheme based on a dynamic DEA yardstick as an alternative to the popular CPI-X revenue cap regulation. Førsund and Edvardsen (2003) use a fictive grid network based on distribution utilities from Denmark, Finland, Norway, Sweden and Netherlands to compare productivity of the different countries and their respective peer operators. More specifically, one of our datasets has already been used through the work of Agrell and Brea (2017) which underlined the need to capture heterogeneity in a sample by analyzing a sample compounded of 118 Swedish operators through a latent class model. Still using one of our datasets, Agrell and Niknazar (2014) investigated the robustness in applied best-practice regulation through the detection of three different types of outliers in the dataset.

One of the first studies of the electricity distribution in Scandinavia has been carried out by Hjalmarsson and Veiderpass (1992). The study intended to measure the productivity development in Sweden from 1970 to 1986. Through this study, it seems that the type of ownership of an operator does not affect its productivity, as opposed to the type of area with rural areas experiencing a higher productivity increase. Similar productivity research has been conducted in Norway for 1983-1989 (Førsund and Kittelsen (1998)), 2004-2007 (Miguéis et al. (2012)) and 2004-2013 (Cheng et al. (2014)) as well as in Finland (Korhonen and Syrjänen (2003)). More recently, productivity development research in Sweden has been carried out by Agrell and Grifell-Tatjé for the period 2000-2006 thanks to a Laspeyres index. This has been carried out in order to illustrate the failure of some regulation regimes to provide adequate incentives to firms, as was the case for the Network Performance Assessment Model used in Sweden before the Revenue Cap Model.

2.4 Landmark publications

Even though most of the latter mentioned papers directly relates to our thesis, there is no doubt that some studies influenced more our research than others. The table below summarizes the main studies and their contribution to our research.

Author(s)	Sample	Method used	Contribution
Färe, Grosskopf, Norris and Zhang	17 DEA countries 1979-1988	Decomposed Malmquist index	Decomposition of the Malmquist index into technological and efficiency change components
Ray and Desli (1997)	17 OECD countries 1979-1988	Revised Malmquist index	Addition of a scale efficiency change component
Miguéis, Camanho, Bjørndal E. and M.	177 Norwegian operators 2004-2007	Classical Malmquist index	Analysis of the most innovative operators
Hjalmarsson and Veiderplass (1992)	289 Swedish operators 1970-1986	Decomposed Malmquist index	Possibility to compare our results with previous results
Agrell and Grifell-Tatjé (2016)	218 Swedish operators 2000-2006	Fisher index	Possibility to compare our results with results from another model

Table 2.1: Relevant productivity studies

3 Regulatory framework

In this chapter, a first section will be dedicated to an introduction of the regulation of distribution network. This will be followed by a description of the main families of regimes established. Finally, an overview of the history of the regulatory scheme in Sweden will be given.

3.1 Network regulation

With very few exceptions, the distribution sector is always compounded of several distribution system operators (referred to as DSOs, operators or distribution utilities hereafter) operating under natural monopoly conditions. Due to large fixed costs and low marginal operating costs, the economies of scale constitute the main reason for the existence of these monopolies. The significant start-up costs also lead to high barriers for new entrants (Agrell and Bogetoft, 2017).

There will generally be several local monopolies within a country because of a trade-off between economies of scale and use of benchmarking methods. On the one hand, there is no doubt that economies of scale are exacerbated as the distribution company covers a wider area. On the other hand, a high number of DSOs facilitates the use of benchmarking methods such as described in Chapter 4. According to Wangensteen (1989), economies of scale fades as the number of customers is raising and the optimal size would be around a number of 10,000 customers.

As demonstrated by economic theory (Kahn (1971);Laffont and Tirole (1993);Armstrong and Sappington (2007)), pricing coming from a natural monopoly tends to be too high given the lack of competitiveness. This is even more amplified by the high market power of the operators, given the absence of substitutes translated into a relatively low elasticity of the electricity demand (Agrell and Bogetoft, 2017). This can lead to market-inefficiency. Secondly, given that the costs or bad performance (e.g weak quality supply) can be easily transferred to the consumers, there are low incentives to alleviate them. This can be called X-inefficiency.

As mentioned, the relationship between the regulator and the different distribution utilities is usually described as an application of the agency theory. The principal-agent problem can be defined as occurring when:

"The desires or goals of the principal and agent conflict and it is difficult or expensive for the principal to verify what the agent is actually doing" (Eisenhardt, 1989).

In other words, there will be an information asymmetry between the regulator and the firms holding the information about their cost technology needed by the former. This, however, is needed to implement an efficient policy limiting the abusive position of the operators in the market. The companies can take advantage of this situation to increase their profits at the expense of the social welfare (Laffont and Tirole, 1993), with two consequences:

1. *The market inefficiency* in the agency theory is referred to as the adverse selection problem which arises when there is a misrepresentation of the service provided by the agent (Eisenhardt, 1989). In the distribution sector, this will lead to the possibility for the better informed agent (the distribution utility) to increase consequently its tariffs by for instance, claiming too high costs.

2. *The X-inefficiency* will be described as a moral hazard problem, which is an issue occurring when the principal is not able to precisely monitor if an agent cheats in pursuing personal objectives (Bogetoft and Otto, 2011). In the distribution sector, this will induce the distribution utility to avoid taking action to be cost-efficient and to rely on a low-quality supply in order to minimize its costs.

Thus, regulatory authorities need to set the proper incentive measures in order to limit the aforementioned inefficiency issues and therefore, to ensure fair tariffs and a quality supply for the consumers by aligning the profit maximizing objectives of the the operators with those of the public interest (Hackett, 2010). In Europe, regulation regimes are mainly based on an incentives scheme, aiming to encourage the DSOs, whether state- or privately-owned, to take the right actions and to bypass the agency problem.

3.2 Classical regulatory regimes

Since the restructuring movement, various regimes have been tested to regulate the grid. Three main types of regulatory regimes can usually be identified in the literature: the cost-recovery, the fixed price and the yardstick regime.

3.2.1 Cost-recovery regime

Also referred to as cost of services, cost-plus or rate-of-return regulation (Agrell and Teusch), the first model is based on the reimbursement of the reported costs by the regulated firm. This will suppose the information provided by the firm as true and can be illustrated by the following formula (Agrell and Bogetoft, 2017):

$$R^k(t) = C^k_{Opex}(t) + D^k(t) + (r + \delta)K^k(t) \tag{3.1}$$

Where C^k_{Opex} is the operating expenses, D^k is the depreciation reflecting capital usage, r is the interest rate reflecting the credit costs of investments with similar risks, δ is a mark-up and K^k is the total investment for a firm k.

This model solves the market-inefficiency problem of the firm. Indeed, the regulated firm is ensured to be fully reimbursed for its additional costs. Providing the right amount of electricity to the demand and avoiding an overpricing will therefore be aligned with the profit maximization objective of the firm. However, this will usually result in poor performance:

"Firms have incentives to overinvest in capital and have no incentives to reduce operating expenditures since they just lower revenue" (Agrell and Bogetoft, 2017).

Without huge regulatory effort to extract the full information, the firms will be given the wrong incentives and the X-inefficiency will remain resulting in a low-powered regime (Agrell and Bogetoft, 2017). This is also often described as an ex-ante regime since the reimbursement will often occur prior to the concerned period on the contrary of an ex-post regime.

3.2.2 Fixed price regime

First proposed by Littlechild (1983) through a simple model, the second regime can be defined as more powered than cost-recovery while still operating ex-ante. This regime is currently broadly employed in European electricity grid regulation (Agrell, 2015). It consists of setting a cap on the revenue or the price of a company for a determined period. Through this model, the regulated firm will be reimbursed for its predetermined cost (revenue cap) or price (price cap) for a coming period and will allow it to maintain its additional efficiency gains during the period (Littlechild and Beesley, 1989). The revenue cap regime can be quickly illustrated by the following formula (Agrell and Bogetoft, 2017):

$$R^k(t) = C^k(0)(1 - x - x^k)^t, \quad t = 1, ..., T \tag{3.2}$$

Where $R^k(t)$ is the allowed revenue of the firm k in period t, $C^k(0)$ is the cost in period 0, x is the predicted productivity development and x^k, the individual requirement on the firm k reflecting the level of historical costs and the need to catch-up to best practices.

In the case of a price cap regime, the following formula will be appropriate (Joskow, 2008):

$$P^k(t) = P^k(0)(1 + RPI - x - x^k) \tag{3.3}$$

Where P^k is the allowed price for the firm k and RPI is the rate of input price accounting for changes in inflation.

These kind of regimes are supposed to prevent the grid from suffering from market-inefficiency and X-inefficiency (in other words, supposed to solve both the adverse selection and the moral hazard problem (Agrell, 2015)). Indeed, by setting this kind of regime, the regulator provides the right incentives so that the operator aims to minimize its costs in addition to providing the right amount of electricity supply.

The efficiency requirement is usually determined by some benchmarking methods as shown in Section 3. Techniques such as the Malmquist-index to analyze the productivity developments over the years will generally be helpful tools to determine the general requirement x and the individual efficiency requirement x^k. Thus, as said, this thesis can propose relevant content to the regulator in order to define general and individual requirement for the industry. Concerning the initial costs, according to the regulator, the total or operating cost will be used. However, if the initial cost is based on the operating cost, the regulator will have to take into account the risk of transferring some capital costs to operating costs (Agrell and Bogetoft, 2017).

Despite its theoretical efficiency and simplicity, the effective implementation of the regime can turn to an authentic challenge for the regulator. The need to predict the costs and individual and general efficiency requirements thanks to past data will have to be balanced with the realized costs and efficiency observed for the firm. On the one hand, if the cap is too ambitious, the firm will not cover its costs and the risk of bankruptcy or restructuring will affect the security of the electricity supply. This can provoke a bias to overestimate the cost of the regulated firms. On the other hand, if the decided revenue cap is too large, or too often reset by the regulator to reflect realized costs and efficiency gains, this will undermine the incentives provided to the regulated firms resulting in high informational rents. A ratchet effect can also be observed for agents increasing their cost in anticipation of resetting the initial cost in the next regulatory periods (Agrell et al., 2005). Finally, this kind of regime will be particularly favourable to regulatory capture (the firm will influence the revenue cap setting) since the firm can retain the realized profits (Agrell and Bogetoft, 2017).

3.2.3 Yardstick regime

The yardstick regime can also be characterized as a high-powered regime but will be set ex-post implying that the regime will be based on observations instead of predictions. Introduced by Shleifer (1985), the yardstick regime will induce a pseudo competition between the different DSOs by mimicking the market as closely as possible. For this purpose, a shadow firm will compete with the regulated firm. This shadow firm will be created thanks to the realized cost functions (which is the costs computed to produce a given output in light of input prices) of the other firms. In other words, a cost function will be estimated for the regulated firm based on the real observations of the other firms on the past regulatory period. Assuming a set of firm $N = \{1, ..., n\}$ the revenue of a firm k can be defined as follows (Agrell and Bogetoft, 2017).

$$R^k(t) = \frac{1}{n-1} \sum_{j \neq k}^{n} C^j(t) \tag{3.4}$$

Where $C^j(t)$ is the realized cost of the firm j in period t.

Alternative methods exist to aggregate the performance of the other firms. Instead of achieving an average, the allowed revenue can for instance just be the best practice realized performance (Agrell and Bogetoft, 2017).

As earlier implied, while still allowing the regulator to align incentives with profit maximization of the firms, the yardstick regime presents the advantage to rely upon observations instead of predictions, limiting the risk of bankruptcy or excessive informational rents (as it was the case for fixed price regimes) while still being relevant for the information asymmetry problem given the fact that the model is based on accurate components (Agrell et al., 2005). Besides, the revenue is not determined by the own cost of the DSO alone but by the performance of the other DSOs. This risk of regulatory capture is therefore greatly limited (Agrell and Bogetoft, 2017).

Even if this model seems to erase the flaws in the aforementioned regimes, there remain some risks of implementation. The first is the necessity to either find a set of comparable firms operating under similar conditions or to include the differences in the operating conditions into consideration through tedious computations (Agrell et al., 2005). In the case of a limited number of regulated companies, a risk of collusion can also appear (Agrell and Bogetoft, 2017).

3.2.4 Application in Europe

In light of what has been seen, it is worth mentioning that every regulation will present distinctive characteristics that can be related to the different regimes as said by Agrell and Bogetoft (2017). Reviewing the different regulation regimes in Europe, Agrell and Bogetoft proposed to link them to the most similar classical regulatory regime. This is summed up in Table 3.1.

Country	Regime
Austria	Revenue Cap
Belgium	Revenue Cap
Denmark	Revenue Cap
Finland	Revenue Cap
France	Cost recovery
Germany	Revenue Cap
Greece	Cost recovery
Hungary	Price Cap
Ireland	Price Cap
Italy	Revenue Cap (Operating costs only)
Netherlands	Yardstick
Norway	Yardstick
Portugal	Revenue Cap
Spain	Revenue Cap
Sweden	Revenue Cap
Switzerland	Cost recovery
United Kingdom	Revenue Cap

Table 3.1: European regulation regimes (Bogetoft and Otto, 2011)

We clearly see that, in European countries, including Sweden, the revenue cap approach presents a clear predominance nowadays.

3.3 Regulation in Sweden

Deregulated in 1996, Sweden can be quoted as one of the first countries to liberalize its electricity market. From this date, Sweden, through the Swedish Energy Authority (STEM) and more recently, through the Energy Inspectorate (SEI), implemented several regulations in order to ensure the electricity grid operators to comply with their obligations evoked in the Electricity Act of 1996.

This section aims to offer us with a glimpse of the regulation in Sweden since 1996. Given that our research aims to explore the effects of the Network Performance Assessment Model and the Revenue Cap Model, this will be followed by a more attentive look at their main components.

3.3.1 History

Following the restructuring in 1996, the STEM discovered evidence of excessive tariffs imposed by the operators to the customers. It quickly turned out that attempts to maintain the price at an acceptable level like price freezing were inefficient and that new regulatory tools were urgently needed (Wallnerström and Bertling, 2010).

Initially, the first idea was to use an existing model and to adapt it to the Swedish grid. Given the fact that models are designed directly in correspondence with an industry, the Swedish regulator finally decided to frame its own regulatory scheme: the Network Performance Assessment Model (NPAM). From 1998, it took 5 years for the scheme to come into force and 7 years to provide the first results. Rapidly, this model underwent fierce criticisms both from operators and higher institutions and was abandoned after only three years in 2006 (Jamasb and Pollitt, 2007). At this time, Sweden understood the non-feasibility of this model and changed to an intermediate ex-post cost-recovery scheme with rate-of-return regulation waiting for a higher-powered regime (Agrell and Grifell-Tatjé, 2016). Meanwhile, the Energy Inspectorate (SEI), freshly created in 2008 to monitor the tariffs and cost-efficiency of the distribution sector, began to conceive a regulatory program based on a revenue cap launched in 2012. This new regulation consists of an ex-ante revenue cap based on a period of four years. Given the recent nature of the revenue cap, the SEI undertook several adjustments at the end of the first regulatory period. Some other measures are also planned for the coming regulatory period but are still awaiting approval (Swedish Energy Inspectorate, 2018).

Nowadays, it can be said that even if many mergers occured, the distribution sector is characterized by a high number of operators mainly owned by municipalities with few cooperative and private actors. Even if most of the companies are publicly owned, some private operators such as E.ON or Elevio own consequent parts of the global Swedish network. Vattenfall, entirely state-owned, can also be seen as one of the main current actors (Council of European Energy Regulators, 2019).

3.3.2 The Network Performance Assessment Model

Applied from 2003 to 2006, the NPAM had the particularity of not relying on traditional benchmarking methods. On the contrary of a conventional incentive regulation, this model proposed an individual ex-post benchmark to the firm on a yearly basis. Figure 3.1 below provides an overview on the components of the NPAM.

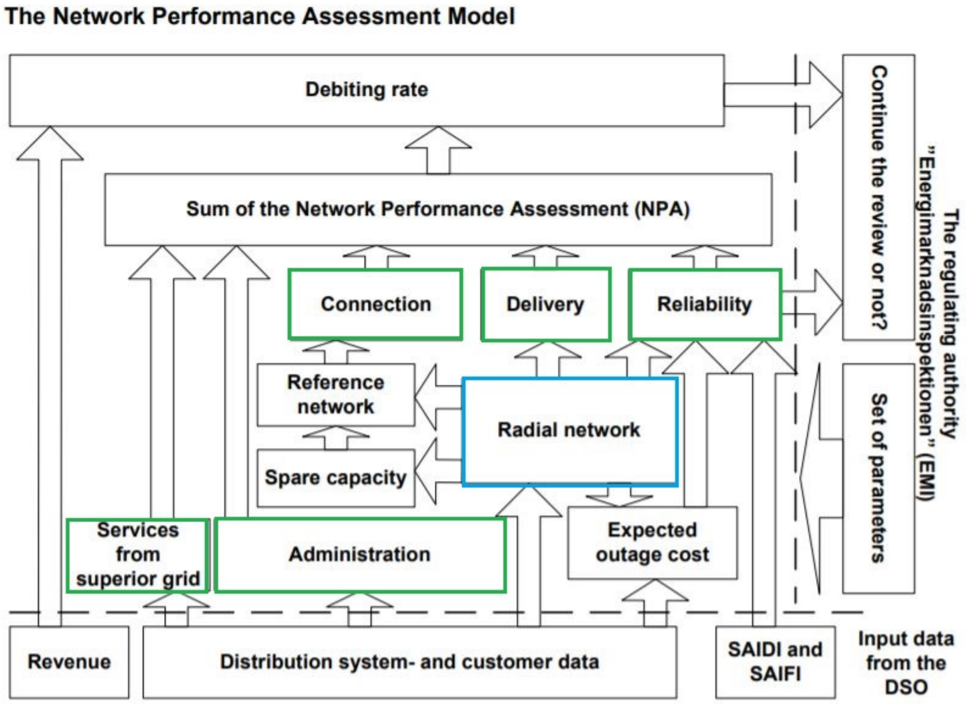

Figure 3.1: Elements of the NPAM regulation (Wallnerström and Bertling, 2008)

In short, a comparison was realized between the actual revenue of each operator and the results obtained through the NPAM, the supposed revenues of the operator, on a yearly basis. Those results were obtained through several computations based on geographic and technical information of all the low and high-voltage connections and supply points of each distribution company (Distribution system- and customer data in the figure). From these, a fictive *radial network* (in blue) could be estimated and used as reference to evaluate the efficiency of a company (Jamasb and Pollitt, 2007).

A major step of the NPAM was to deduce the cost norm of an operator from five main cost components (in green) thanks to the built radial network and other real inputs such as the System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI) of the operator. A summary is presented below (Wallnerström and Bertling, 2008):

1. *Cost of service* included mainly the fees paid by the operator to the superior grids. They were directly reported by the operator.

2. *Cost of administration* corresponds to the administrative cost for each customer. This cost was estimated by the STEM.

3. *The cost of connection* consists of the capital cost of the fictive radial network as well as the cost of spare capacity for redundant components.

4. *Cost of delivery* is cost related to the energy loss of a distribution company, given the customer density of the radial network. To obtain the cost, the energy loss was multiplied by the corresponding period price on Nord Pool.

5. *Cost of reliability* is deduced from the difference between the expected outage costs and the occured outage costs. Through an algorithm accounting for several characteristics of the radial network (mainly customer density and total energy delivered per voltage level for a year), the expected outage cost was computed. The occured outage cost is obtained through the System Average Interruption and Duration Frequency Indexes (SAIFI and SAIDI).

As mentioned, this system was welcomed with sharp criticism in 2004. A good time line of the situation has been described by Agrell and Grifell-Tatjé (2016). Impressively complex, the NPAM published first results for 2003 in June 2005. These results required twenty one operators to lower their tariffs. This was quickly followed by lawsuits by the concerned operators, which pointed out the lack of feasibility of the cost norm and procedural flaws. After two court sessions, STEM abdicated and set an upper bound on the revenue cut. However, despite the concessions, eight of the twenty one operators maintained their appeal and it became clear that the Swedish regulator would still not overcome the lawsuits. Finally, in 2008, a claim out of court between the Swedish regulator and the eight remaining operators was settled, leading to further decrease of the revenue cut. After four years of judicial troubles, the NPAM model was formally abandoned in Januray 2009 and an interim cost-recovery was implemented, waiting for the revenue cap to come into force.

Studies supported this decision and highlighted many flaws in the NPAM as again highlighted by Agrell and Grifell-Tatjé (2016). Lack of robustness in the model leading to disproportionate consequences of small parameters on the cost norm was raised by Wallnerström and Bertling (2008). Jamasb (2007) underlined the mitigated investment incentives of the scheme. According to him, it also appeared that customer density played a main role in the NPAM, while operators could not have influence on it. Lantz (2003) argued that the model did not take into consideration the differentiation between short and long-term perspective leading to wrong incentives on the long run. Besides, as underlined by Larsson (2005), the model required a lot of information, which made its effective application challenging. Other issues such as the lack of incentives for a reliable electricity or a reduction of the network losses were also raised (Wallnerström and Bertling (2010);Persson and Tornqvist (2006).

3.3.3 The Revenue Cap Model

The currently applied regulatory scheme in Sweden can be summarized by Figure 3.2

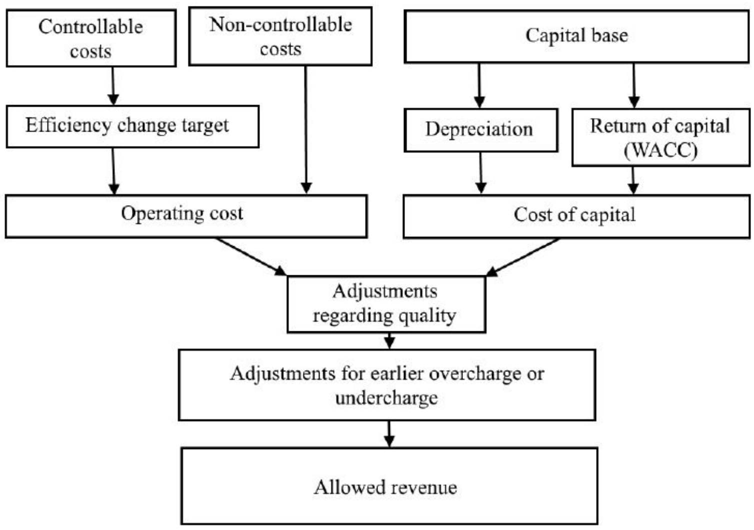

Figure 3.2: Elements of the Revenue Cap regulation. (Schweinsberg et al., 2011)

The determination of the revenue cap can be decomposed in three main operations: the determination of the operating costs (1), capital costs (2) and the subsequent adjustment realized (3) (Schweinsberg et al., 2011).

1. *The operating costs* are divided into two categories: the costs considered as non-controllable (33% of the revenue cap) and the cost considered as controllable (23%

of the revenue cap). The non-controllable costs are directly included in the revenue cap. Examples of these costs are the tariffs for feeding in electricity from generation plants or to be connected to the subtransmission level (Nordic Energy Regulators, 2011). Contrary to non-controllable costs, controllable costs can be influenced by the operation of the firm. They typically concern the operation and maintenance of the grid but will also include some capital expenditures not related to the grid such as vehicles or administration offices (Wallnerström et al., 2016). Until now, a general efficiency requirement of 1% has been judged as adequate by the regulator (Ek and Fredriksson, 2010). In addition, each operator is imposed an individual efficiency requirement varying between 0 and 7% to reach within two regulatory periods. The intuition is that the Swedish regulator estimated that a possible improvement of 30% over two regulatory periods could be seen as reasonable. Given that DSOs are allowed to keep half of these additional revenues,the global efficiency improvement amounts to 15%. Because of a yearly general requirement of 1%, this is equivalent to a maximum individual efficiency requirement equal to 7% in 8 years. To ensure the realization of these requirements, EI designed a benchmarking model based on DEA.

2. *The capital costs* (44% of the revenue cap) only concern assets which are part of the grid. Equipment such as vehicles are converted to controllable operating cost (Nordic Energy Regulators, 2011). These costs are constituted by two main elements: the depreciation and the return on capital. Their determination will first require the valuation of the regulatory asset base (RAB). Specifically, this valuation relies on the principle of replacement value. The value of each sort of grid equipment is computed based on the investment expenditures of an operator acting in a cost-effective manner. At the beginning of each regulatory period, each operator has to provide a list of the different grid materials used. Thanks to the replacement value and taking into consideration inflation, the Swedish authority is then able to compute the RAB for each operator and finally derive the depreciation and return on capital. A real annuity method was previously used to compute the depreciation for the first regulatory period (2012-2015). Since 2014, a new method taking into account the age of the assets and based on linear depreciation has been implemented. The goal was to provide companies with incentives to renew more frequently their grid materials. Concerning the return on capital, it is computed based on a common weighted average

cost of capital WACC imposed to the whole industry by the regulator following advice from consulting groups. The main challenge lies in the determination of a return which will provide proper incentives to invest in the industry, while avoiding companies from having too high revenue caps (Nordic Energy Regulators, 2011). This imposed WACC is often subject to legal debates. For instance, during the last period, the WACC changed from 5.85% to 5.92% after legal procedures from some operators (Council of European Energy Regulators, 2019).

3. *Adjustments* will be made to the revenue cap of a DSO. Those adjustments mainly account for the quality and reliability of the electricity supply proposed by the firm to its customers. Given the lack of relevance with the topic of the thesis, these mechanisms will not be discussed directly. Nevertheless, Appendix 1 provides us with an overview of them.

4 Benchmarking

As said in the introduction, benchmarking proved to be a useful tool for the regulator in the electricity distribution sector. Benchmarking can be characterized as “the systematic comparison of the performance of one firm against other firms”(Bogetoft and Otto, 2011). This chapter will help us be first acquainted with the frontier-based models used nowadays in benchmarking and secondly to introduce the reader to Data Envelopment Analysis.

4.1 Frontier-based methods

An initial intuition when it comes to benchmarking is that the efficiency of a firm increases as the firm produces more output with the same amount of input or will use less input to produce the same amount of output. Because a firm can be said efficient only if compared to others, benchmarking needs to define what is the best performance (Cooper et al., 2004).

Until recently, the main tools used to define the best possible performance were based on technical data from engineers. Only in recent years, benchmarking analysis has shifted to frontier-based models providing particularly useful tools for economic regulation. In a few words, "the idea is to model the frontier of the technology rather than to model the average use of the technological possibilities" (Bogetoft and Otto, 2011). Thus, a frontier based model will determine a technology set and a best-practice frontier. This function is defined on the basis of the performance of the most efficient actors, which will be the reference for the comparisons with the different firms of the panels. From this, the efficiency of a firm that is part of the panel will be derived. This kind of models provides reference to the operators by determining the most efficient ones. There exist four principal types of frontier-based models. Those models can be summed up by Table 4.1.

	Deterministic	Stochastic
Parametric	Corrected Ordinary Least Square (COLS)	Stochastic Frontier Analysis (SFA)
Non-parametric	Data Envelopment Analysis (DEA)	Stochastic Development analysis (SDEA,StoNED)

Table 4.1: Frontier models (Bogetoft and Otto, 2011)

As seen in this table, a model distinguishes from the others mainly by the way of two characteristics: parametric or non-parametric, and deterministic or stochastic. In short, it can be said that a model can be labelled as parametric as long as its frontier is defined a priori through several parameters. A non-parametric model will be much less restricted from the beginning. A deterministic model refers to one which does not include noise. The data will be considered as being exact and having no measurement error. On the contrary, a stochastic model will assume that the data has possibly been influenced by noise and will aim to account for it (Bogetoft and Otto, 2011).

DEA, introduced by Charnes et al. (1978), is characterized as deterministic and non-parametric. In order to estimate the technology, DEA uses the minimum extrapolation principle based on different assumptions to deduce the set containing all the data. SFA (Aigner et al. (1973);Battese and Coelli (1992)) includes the presence of noise and thus, draws a technology set which does not contain all the data. The technology set is computed a priori, in most cases thanks to the maximum-likelihood approximation. Regarding COLS (2016;Lovell (1993)), it can be summed up by the idea of adapting a regression model to enclose all the firms in the technology set through the shifting of the estimated line. The Stoned or SDEA is quite recent and aims at combining the relevant characteristics of DEA and SFA.

In spite of the equal relevance of the different approaches, only DEA will be used in this thesis. It is clearly a choice of convenience given that DEA is the method currently used by the Swedish regulator and appears to be easier to implement. On the one hand, the method will present qualities to provide a good representation of the industry, since the best-practice frontier being directly inspired from real observations without relying too much on strong assumptions. On the other hand, DEA will not take noise into consideration and results need to be interpreted with caution. This criticism is often addressed to regulation using DEA.

"If there is considerable noise in the data [...] firms may be evaluated against the hardest possible standards (possibly the most lucky firms) and not against a cautious standard"(Bogetoft, 2012).

4.2 Data Envelopment Analysis

Currently the dominant method used to benchmark firms part of the electricity grid is the so-called Data Envelopment Analysis (DEA).

DEA can be defined as:

"A mathematical programming method of estimating best practice production frontiers and evaluating the relative efficiency of different entities" (Bogetoft and Otto, 2011).

4.2.1 Production models and technology

Let us assume a firm i using m inputs and n outputs. The input vector x^i and the output vector y^i can respectively be defined as:

$$x_i = (x_{i,1}, x_{i,2}, ..., x_{i,m}) \in \mathbb{R}^m_+ \tag{4.1}$$

$$y_i = (y_{i,1}, y_{i,2}, ..., y_{i,n}) \in \mathbb{R}^n_+ \tag{4.2}$$

The presented vectors of each firm will allow us to define a technology set, which is "the set of combinations of input and output such that the input can actually produce the output". (Bogetoft and Otto, 2011)

The technology set will be defined as:

$$T = \{(x, y) \in R^m_+ \times R^n_+ |\, x\, can\, produce\, y\} \tag{4.3}$$

The firm will be generally compared to the best-practice frontier of the technology set, which is calculated from several reference firms.

In order to clearly determine the technology set from the performance of the firms, several assumptions need to be made (Daraio and Simar, 2007):

Assumption 1 – Free Disposability

This is a weak assumption (i.e. it does not restrict our model and can be seen as highly plausible) and can be defined as follow:

$$(x, y) \in T, x' \geq x,\ and\, y' \leq y \Rightarrow (x', y') \in T \tag{4.4}$$

If (x',y') produce less output with more input than the feasible combination (x,y), then it will be feasible too. The point (x',y') will be characterized as dominated by (x,y). In other words, this assumption gives to firms the possibility to waste their input and/or output.

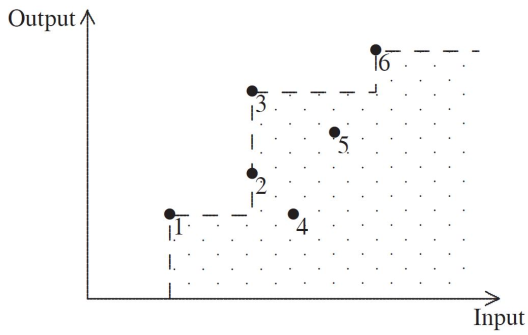

Figure 4.1: Free disposability (Bogetoft and Otto, 2011)

Assumption 2 – Convexity

The set is assumed to be convex and any weighted average of two feasible combinations (x_1, y_1) and (x_2, y_2), is feasible too. For α belonging to $[0; 1]$:

$$(x, y) \in T, (x', y') \in T, \alpha \in \left[0; 1\right] \Rightarrow \alpha(x, y) + (1 - \alpha)(x', y') \in T \tag{4.5}$$

The convexity is a stronger assumption, but presents the advantage of being analytically convenient and is often used in economics. Here below can be seen an illustration of the free disposability and convexity assumptions. By comparing this illustration to Figure 1, the representation of the convexity assumption can easily be deduced.

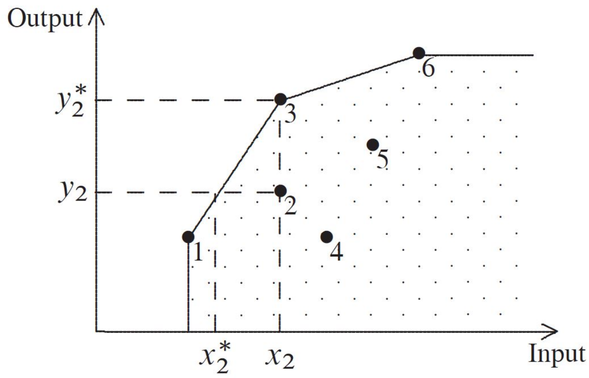

Figure 4.2: Free disposability and convexity (Bogetoft and Otto, 2011)

Assumption 3 – Scaling

While the implementation of the two first assumptions are conveniently admitted, the scaling assumption will usually be subject to debate for the regulator. The scaling assumption can be broadly defined as:

$$(x, y) \in T, \lambda \in \Lambda(\gamma) \Rightarrow \lambda(x, y) \in T \tag{4.6}$$

This states that the frontier can be achieved thanks to a rescaling of the data following different returns. Indeed, this assumption will often be decisive when evaluating the efficiency of the firms relatively to the best-practice frontier.

The table below sums up some of the most common assumptions. These assumptions are set up in an increasing order in view of the strength of their assumption.

Returns to scale	Assumption
Free disposability hull (FDH)	$\Lambda(fdh) = \{\lambda \in \mathbb{N}_+^K \mid \sum_{k=1}^K \lambda_k = 1\}$
Variable returns to scale (VRS)	$\Lambda(vrs) = \{\lambda \in \mathbb{R}_+^K \mid \sum_{k=1}^K \lambda_k = 1\}$
Decreasing returns to scale (DRS)	$\Lambda(drs) = \{\lambda \in \mathbb{R}_+^K \mid \sum_{k=1}^K \lambda_k \leq 1\}$
Increasing returns to scale (IRS)	$\Lambda(drs) = \{\lambda \in \mathbb{R}_+^K \mid \sum_{k=1}^K \lambda_k \geq 1\}$
Constant returns to scale (CRS)	$\Lambda(crs) = \{\lambda \in \mathbb{R}_+^K \mid \sum_{k=1}^K \lambda_k free\} = \mathbb{N}_+^K$

Table 4.2: Return to scale assumptions (Bogetoft and Otto, 2011)

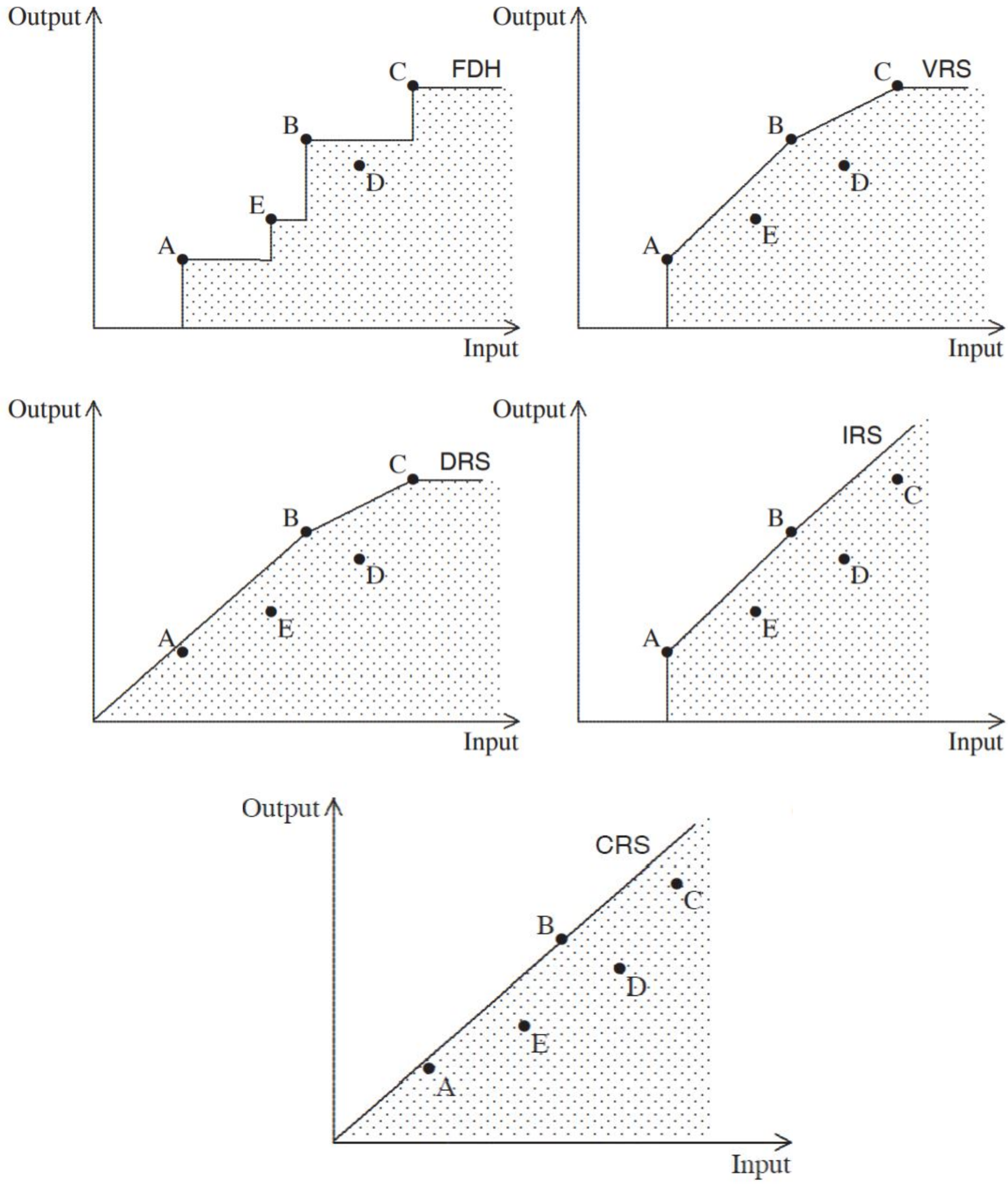

Figure 4.3: Technology set under different scaling assumptions (Bogetoft and Otto, 2011)

From a regulatory perspective, the scaling assumption plays a crucial role when determining the best-practice frontier and often directly affects the efficiency of a firm. A strong regulation uses , for example, a constant return to scale (CRS). Thus, a firm would prefer to see the best-practice frontier set under variables return to scale (VRS) rather than under CRS. Indeed, VRS is a softer assumption (two different-sized firms cannot be compared), which will result in higher efficiency score on average. Increasing return to scale will favour only small companies (because first presenting a VRS turning then to a CRS as the firm size will increase) and inversely, decreasing return to scale will favor big companies. Regarding the regulatory authority, the concern lies in finding a right trade-off between a scaling that would limit the firm information asymmetry and that would not be too tough to brake new investments or drive the companies into troubles (Bogetoft and Otto, 2011).

4.2.2 Efficiency measures

While we know that measures of the input and output used by a firm will be translated into a global efficiency score, there remains the question of how computing the efficiency score. The question is therefore: What are the common measures used to evaluate the efficiency of a firm relatively to a given input or output? Four different measures of efficiency are hereafter introduced.

4.2.2.1 Farell efficiency

The radial method designed by Farrell (1957) is certainly of the dominant approaches used in benchmarking literature. This efficiency can be divided into two sub-efficiencies: the input-oriented efficiency and the output-oriented efficiency.

The input-oriented efficiency will measure the proportional reduction of the inputs needed to reach the best-practice frontier while keeping the amount of outputs or other inputs constant. It can be defined as (Bogetoft and Otto, 2011):

$$E = min\{E > 0 \mid Ex \; can \; produce \; y\} = \frac{|x^*|}{|x_i|} = \frac{Minimal \; input \; (best \; practice)}{Actual \; input \; (firm \; i)} \tag{4.7}$$

The input-oriented efficiency will be characterized as:

$$E \leq 1 \tag{4.8}$$

However, it can happen that we are interested in deducing the firms that moved the frontier. To achieve this, we can resort to the super-efficiency. The principle is to compute the efficiency of a firm in comparison with a best-practice frontier which does not include the firm itself. In this case, a firm can be assigned a value superior to one. This is often used in regulation when it comes to detecting outliers in a sample or to evaluating firms located on the best-practice frontier.

The output-oriented efficiency will follow an opposite scheme that the input-oriented efficiency. We will measure the proportional augmentation of outputs needed to reach the best-practice frontier while keeping the amount of inputs constant.

$$F = max\{F > 0 \mid x\ can\ produce\ Fy\} = \frac{|y^*|}{|y_i|} = \frac{Maximal\ output\ (best\ practice)}{Actual\ output\ (firm\ i)} \tag{4.9}$$

The output-oriented efficiency will be characterized as:

$$F \geq 1 \tag{4.10}$$

Again, an output-based efficiency lower than 1 would not be logical.

Therefore, the higher the E or the lower the F, the more efficient the firm. All of this is illustrated below, where a firm is compared to a technology set under the assumptions of free-disposability, convexity and variable return to scale.

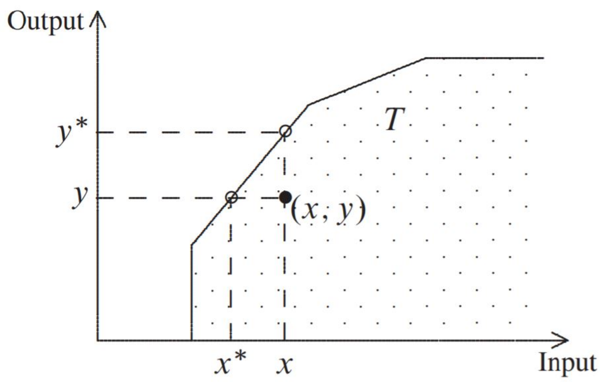

Figure 4.4: Farrell efficiency(Bogetoft and Otto, 2011)

It is worth to note that the regulator of electricity networks will adopt benchmarking methods based on input-based efficiency. The reason for this lies in the fact that DSOs will only have an influence on their inputs, the outputs being considered as given by the market demand (Bogetoft and Otto, 2011).

In case of multiple inputs and outputs, the hand computation can quickly become tedious and will require the use of models which can only be solved by computers (Bogetoft and Otto, 2011). The CCR model proposed by Charnes et al. (1978) was the first model using the term *DEA*. The model proposed is input-oriented, and assumes free-disposability, convexity and CRS assumptions such as:

$$min_{E,\lambda}(E)$$

$$s.t \quad Ex \geq \sum_{k=1}^{K} \lambda_k x_k \tag{4.11}$$

$$y \leq \sum_{k=1}^{K} \lambda_k y_k \tag{4.12}$$

$$\lambda_k \geq 0 \quad \forall k \in K \tag{4.13}$$

Quickly summed up, the first constraint on the inputs tells us that the firm k has to use at least as much input as the reference firm (a firm created from the combinations of the peer firms, i.e the firms lying on the best-practice frontier). The next constraint tells us that the reference firm has to produce at least as much as the firm k. The ultimate constraint will assign positive value to the weight vector and reflect the CRS assumption (Bjørndal, 2018).

In addition of the CRS assumptions, several other scaling assumptions can be applied according to the technology of the sample such as the VRS premise applied in the well-known BCC model (Banker et al., 1984). As a reminder, even though the return to scale employed presents a regulatory involvment, it is also needed to account for the nature of the industry:

"The CRS assumption is appropriate when all the firms are operating at an optimal scale. However, imperfect competition, government regulations, constraints on finance etc., may cause a firm to be not operating at optimal scale." (Coelli et al., 2005)

Thus, the input-based efficiency of a firm belonging to a set of K firms with a technology set $T(\gamma)$ can be summarized as the previously presented models but taking into account the constraint of the scaling assumption $\lambda \in \Lambda_K(\gamma)$. $\Lambda_K(\gamma)$ will typically be one of the assumptions mentioned in Section 4.2.1 (Bogetoft and Otto, 2011).

4.2.2.2 Cost efficiency

Although providing a good way of measuring input and output efficiency, the methodology described in the previous section disregards the possible preference regarding the different inputs and outputs typically expressed through a cost information. Nonetheless, in many situations, the preference among the different inputs or outputs is provided. This will typically be reflected through cost and price information and allows the regulator to elaborate further evaluation (Bogetoft and Otto, 2011). Farell proposed to account for this additional information through the concept of cost-efficiency Farrell (1957). In order to allow a good understanding of the concept, a simple illustration will be provided by Coelli et al. (2005).

Let us assume a firm represented by the point P and producing a single output y from two inputs x_1 and x_2 with known prices w_1 and w_2 such as first proposed by Farrell (1957).

The total cost is therefore given by the formula:

$$c = w_1 x_1 + w_2 x_2 \tag{4.14}$$

Since the input-price and the quantity needed of each input to produce an output are known, the cost preference function of the two inputs and the isoquant representing the possible combinations of the two inputs to produce a given output y can be drawn.

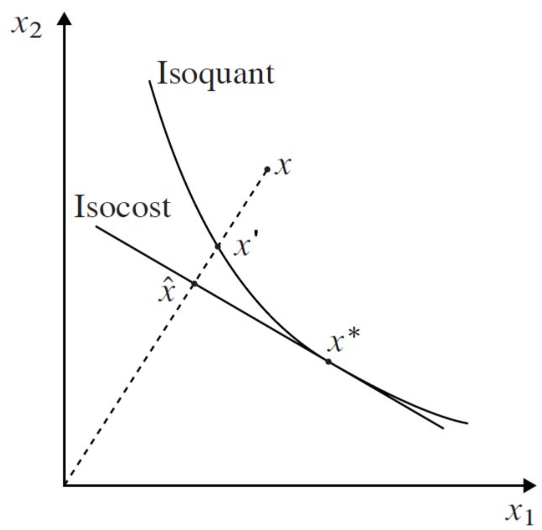

Figure 4.5: Cost efficiency(Bogetoft and Otto, 2011)

It seems clear that this new model will create more difficulty to be efficient since a firm will need to select a point which is technically efficient while allocating correctly its resource in order to minimize the cost as this can be illustrated above. Let us decompose the efficiency into three factors: technical, cost and allocative efficiency.

As demonstrated, technical efficiency can be easily computed by looking at the distance between the firm and the input-based efficient frontier represented by the isoquant. This efficiency will relate to the input-based efficiency.

$$TE = \frac{Minimal\ input}{Actual\ input} = \frac{x'}{x} \tag{4.15}$$

Where $\hat{x}$ is the best-practice input vector associated with the technically efficient point Q and x the input vector associated with the point P.

The firm will be efficient on a technical perspective if located on the best-practice frontier.

Since we also have access to the input prices, the cost efficiency can also be measured. Let x^* represent the cost-minimizing vector of Q'. The cost efficiency is defined as the ratio between the cost-minimizing input combination x" and the input cost of the firm.

$$CE = \frac{Minimal\ cost}{Actual\ cost} = \frac{wx^*}{wx} \tag{4.16}$$

Finally, the allocative efficiency mentioned before consists of having selected the efficient point x' instead of the point x* presenting the same efficiency but at a least expensive cost.

$$AE = \frac{Cost\ of\ x''}{Cost\ of\ x*} = \frac{wx^*}{wx'} \tag{4.17}$$

On this basis, the technical efficiency can be rewritten as

$$TE = \frac{Cost\ of\ x*}{Cost\ of\ x} = \frac{wx'}{wx} \tag{4.18}$$

A relationship can be derived between the three forms efficiency.

$$CE = AE \times TE \tag{4.19}$$

"This decomposition emphasized our initial intuition. To be cost efficient, the firm must be able to select the correct mix of inputs and use them in a technically efficient manner. It must use the right resources, and it must use them in the right way" (Bogetoft and Otto, 2011).

Thus, from these two components, cost efficiency can be derived, that is the ability of a firm to choose the right input-mix and to use them in the most efficient way.

Given K observations, m inputs with an input cost vector w and n outputs, the cost efficiency for the i-th firm is (Agrell et al., 2005):

$$CE_i = \frac{C(y_i, w_i)}{w_i * x_i} \tag{4.20}$$

where $C(y_i, w_i)$ is the cost function representing the minimal cost to produce an output y^i and can be defined as:

$$C(y_i, w_i) = min\{w_i x_i | (x_i, y_i) \in T(r)\} \tag{4.21}$$

Using the DEA approach, computing the cost function for the firm i can result in the following model:

$$min\ _{x,\lambda} w_i x_i \tag{4.22}$$

$$s.t. \quad x_i \geq \sum_{k=1}^{K} \lambda_k x_k \tag{4.23}$$

$$y_i \leq \sum_{k=1}^{K} \lambda_k y_k \tag{4.24}$$

$$\lambda_k \in \Lambda_k(\gamma) \quad \forall k \in K \tag{4.25}$$

Where x represent the vector of inputs optimally used for a firm producing an output y. This model will aim to minimize the costs by finding the best input-mix so that the evaluated firm use at least as much input as the reference firm and the reference firm produce at least as much output as the evaluated firm as represented by the first and second constraints, respectively.

Besides, we know that the cost efficiency of a firm i can be seen as a relation between the technical efficiency and the allocative efficiency. Therefore, the allocative efficiency is defined as:

$$AE_i = \frac{C(y_i, w_i)}{w_i x_i E(x_i, y_i)} \tag{4.26}$$

It can be seen that the allocative efficiency will be the ratio between the optimal cost found by the cost function and the product of the technical efficiency and the real cost of the companies.

4.2.2.3 Scale efficiency

In order to compare DEA programs under CRS and VRS assumption, Figure 4.6 is relevant.

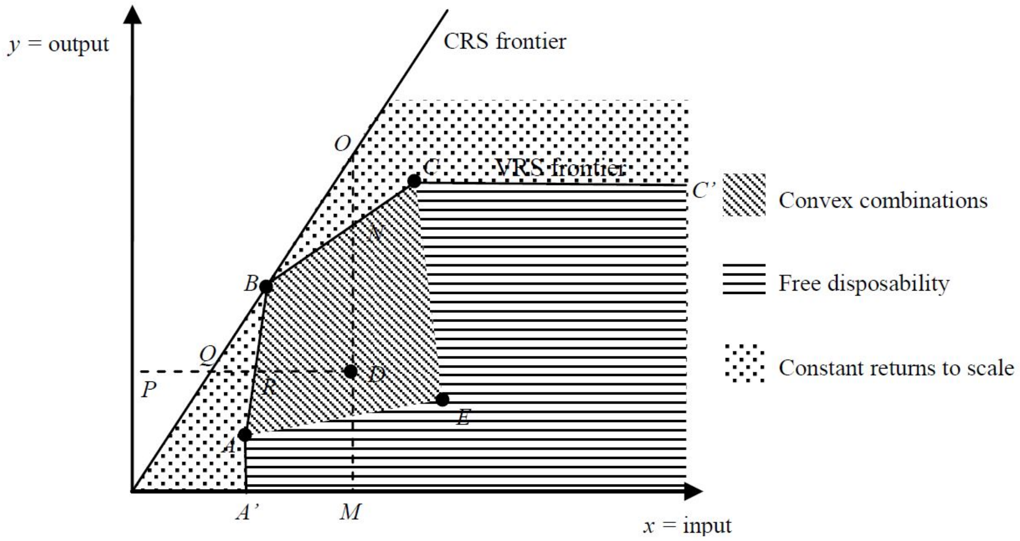

Figure 4.6: Scale efficiency(Bjørndal et al., 2010)

Figure 4.6 shows the best-practice frontier determined under convexity and free disposability assumption with a VRS and CRS technology. As demonstrated, the input-oriented technical efficiency for the point D under VRS and CRS assumption will be the following (Cooper et al., 2007):

$$E_{vrs} = \frac{PR}{PD} \geq E_{crs} = \frac{PQ}{PD} \tag{4.27}$$

Because of the stronger assumption (adding a constraint make the convex hull tighter), it can be easily derived that the technical efficiency of the point D will globally decrease if switching from a CRS to a VRS assumption. As a matter of fact, since the frontier is linearly increasing from the origin, the input-based efficiency will simply be the inverse of the output-based efficiency under a CRS technology assumption (Bjørndal et al., 2010).

It can be seen that all the firms will suffer from switching from a VRS assumption to a CRS assumption with the exception of the firm B The input level at the firm B will be called the most productive scale size (MPSS) such as suggested by Banker et al. (1984). Hence, all the firms should aim to adapt their size to be closer to B since its average output and average input are maximal and minimal respectively. The scale efficiency will express how close is a firm from the MPSS (Bogetoft, 2012) and can be written as:

$$SE = \frac{TE\ (crs)}{TE\ (vrs)} = \frac{PQ}{PD} / \frac{PR}{PD} = \frac{PQ}{PR} = \frac{Minimal\ input\ (crs)}{Minimal\ input\ (vrs)} \tag{4.28}$$

However, the scale efficiency does not tell us if a firm is above or below the optimal size, an easy way to deduce it is to compute the efficiency score under the DRS assumption (translated by the constraint $\sum_l^z \lambda_l \leq 1$). If the efficiency score under the CRS assumption and the DRS assumption is the same for a firm, then the firm will be above the MPSS and oppositely (Bogetoft and Otto, 2011).

4.2.2.4 Dynamic Efficiency

A primordial aspect when it comes to analyzing the efficiency of a firm is to locate it through time. For example, due to a global technological change or by a catch-up to best practice, a firm can increase its efficiency. The most popular way to assess the efficiency of a firm across the time is the Malmquist Productivity Index (1953), namely popularized by Caves et al. (1982) and extended by Färe et al. (1994).

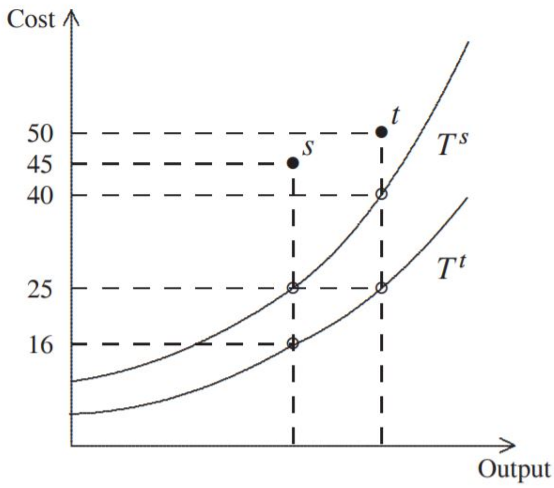

Figure 4.7: Dynamic efficiency (Bogetoft and Otto, 2011)

Following the illustration from Bogetoft and Otto (2011), the Figure 4.7 represents the firm and a best-practice frontier from the period s to the period t. Let $E(s,t)$ be a measure of the performance of a firm in period s against best-practice frontier in period t. If we want to measure the evolution of the performance of a firm between the two periods, we can alternatively write it as:

$$M^s = \frac{E(t,s)}{E(s,s)} \qquad M^s = \frac{E(t,t)}{E(s,t)} \tag{4.29}$$

The first equation expresses the progress of a company from the period s to t in light of the best-practice frontier in s. Same reasoning applies to the second equation but in light of the best-practice frontier in t. Because there is no reason to choose one to the other, the Malmquist productivity index will be the geometric average of the two.

$$MPI(s,t) = \sqrt{M^s M^t} = \sqrt{\frac{E(t,s)}{E(s,s)}\frac{E(t,t)}{E(s,t)}} \tag{4.30}$$

4.2.3 Non-discretionary variables

Until now, we considered that a firm could exercise influence over all of its different variables. However, in many cases, this turns out to be wrong and some components affecting the performance of a firm are beyond its control. For instance, an operator will see its operations affected by climatic components or the density of its customers. A response proposed by Banker and Morey 1986 was to include these variables, called non-discretionary variables, in the technical efficiency input-oriented model through an additional equation such as:

$$z \geq \sum_{k=1}^{K} \lambda_k z_k \tag{4.31}$$

Where z depicts the additional variables. As it can be seen, a special constraint is added which stipulates that they are fixed. Thus, the efficiency will be adjusted by reducing inputs considered as discretionary. Another manner to write the constraint is the following:

$$-z \leq \sum_{k=1}^{K} \lambda_k (-z_k) \tag{4.32}$$

Thus, in this case, the DEA program will interpret a non-discretionary input as a negative output. This transformation can appear to be useful since it allows us to take include these non-discretionary variables in a usual DEA model (Bogetoft and Otto, 2011).

A concern often raised is that this model supposes non-discretionary variables to be convex. To solve this issue, several other alternatives have been proposed to account for non-discretionary variables.

Introduced by Ray (1991), a first alternative was to apply a second stage to a classical DEA model through regression modelling in order to account for the non-discretionary inputs. This second stage aimed to adjust the efficiency scores by controlling the effect of the non-discretionary variables on them.

Another alternative suggested by Ruggiero (1996) was to establish a model which would assign no weight to peer-firms evolving in an advantageous environment. The formulation of the model is similar to the technical efficiency model presented in Section 3.2.2.1 with exception that the following constraint is included:

$$\lambda_k z = 0 \quad \forall l, j \in z_k > z_o; k \in K \tag{4.33}$$

This additional constraint sets a weight equal to zero if a firm has a higher level of non-discretionary input z than a given treshold z_0 so that these firms are not included in the reference set (Ruggiero, 2004).

Nevertheless, Ruggiero (1998) demonstrated that as the number of non-discretionary variables becomes bigger, the probability of identifying a firm as efficient increases. The reason is that firms are not compared with a firm who has a more advantageous environment. To account for this problem, Ruggiero suggested a revised three-stage model which would combine the Ray's two-stage model (1991) to the first Ruggerio's model (1996) by applying a regression of the non-discretionary variables to create a fictive non-discretionary variable included in the no-weight model.

5 Methodology

After a review of the literature, the regulatory setting and its main benchmarking tools, let us now focus on the tools that will be used to support our productivity research. This chapter will be divided into two main parts. First, we will explain the Malmquist index and its components proposed for evaluating the productivity change related to the Swedish DSOs for the period 2011-2017. A few limitations of the index will also be underlined. Secondly, second stage analysis techniques used to assess if non-discretionary variables are affecting the efficiency scores of the operators.

5.1 Malmquist productivity index

In Chapter 4, the Malmquist productivity index was introduced. This Malmquist index allows the regulator to assess the health and the competitiveness of an industry by determining if firms of an industry are improving throughout time. This measure can also turn to be effective when evaluating the effect of a regulation. Assuming an input-oriented model with CRS assumption, the Malmquist productivity index MPI between the period t and t+1 can be rewritten as:

$$MPI(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{E^t_{crs}(x^{t+1}, y^{t+1})}{E^t_{crs}(x^t, y^t)} \frac{E^{t+1}_{crs}(x^{t+1}, y^{t+1})}{E^{t+1}_{crs}(x^t, y^t)} \right]^{1/2} \tag{5.1}$$

Where $E^{t+1}_{crs}(x^t, y^t)$ is the efficiency score of a firm presenting inputs x and outputs y in period t in comparison with a best practice frontier in t+1 under CRS assumption. In case of productivity growth, the MPI will be greater than one. On the contrary, a productivity decline will lead to an MPI inferior to one.

5.1.1 Decomposition of the Malmquist index

According to the Malmquist index, the progress of a firm can be due to two different factors according to Färe et al. (1994): the technological change (TC) capturing the global technological progress of the industry and the technical efficiency change (TEC) measuring the catch-up of a firm compared to the other companies between two periods. Besides, the scale efficiency change (SEC) proposed by Ray and Desli (1997) is also introduced as a third term. As hinted in Chapter 4, the scale efficiency change measures if a company has been able to come closer to the MPSS to gain cost-efficiency. Thus, the MPI can be decomposed in three main terms such as:

$$TC = \left[\frac{E^{t}_{\text{vrs}}(x^{t+1}, y^{t+1})}{E^{t+1}_{\text{vrs}}(x^{t+1}, y^{t+1})} \frac{E^{t}_{\text{vrs}}(x^{t}, y^{t})}{E^{t+1}_{\text{vrs}}(x^{t}, y^{t})} \right]^{1/2} \tag{5.2}$$

$$TEC = \frac{E^{t+1}_{\text{vrs}}(x^{t+1}, y^{t+1})}{E^{t}_{\text{vrs}}(x^{t}, y^{t})} \tag{5.3}$$

$$SEC = \left[\frac{\frac{E^{t}_{\text{crs}}(x^{t+1}, y^{t+1})}{E^{t}_{\text{vrs}}(x^{t+1}, y^{t+1})}}{\frac{E^{t}_{\text{crs}}(x^{t}, y^{t})}{E^{t}_{\text{vrs}}(x^{t}, y^{t})}} \frac{\frac{E^{t+1}_{\text{crs}}(x^{t+1}, y^{t+1})}{E^{t+1}_{\text{vrs}}(x^{t+1}, y^{t+1})}}{\frac{E^{t+1}_{\text{crs}}(x^{t}, y^{t})}{E^{t+1}_{\text{vrs}}(x^{t}, y^{t})}} \right]^{1/2} \tag{5.4}$$

Made from a geometric average between two relevant ratios like the MPI, a positive average TC translates a shift of the best-practice frontier under VRS technology. That term will often tend to be on a global average superior to 1 seeing that the TC is a measure of the technology progress of an operator and it would be uncommon to have technologies in an industry globally regressing. However, companies can have positive TC even if not located on the best-practice frontier. In order to detect if a firm moved the best-practice frontier, the operator need to fulfill two conditions underlined by Färe et al. (1994): to have an efficiency scores equal to one in period t+1; to have a positive TC from the period t to t+1.

The TEC term compares the evolution of a firm between two periods under VRS technology. If a company caught up the best-practice frontier, the TEC will be superior to 1. On the contrary of the TC, it is not rare to see a negative average TEC. Intuitively, this situation would mean that the industry has become more heterogeneous. In other words,few firms have stretched the best-practice frontier while others have not taken advantage of it. Thus, it can happen that even if the global technology is progressing, this only benefits the companies located on the best-practice frontier. The TEC term is therefore important to understand the dynamic of the operators between each other.

Finally, the scale efficiency change will be superior to 1 if the company is getting closer to the MPSS. A SEC superior to 1 is the sign of an industry with companies tending to become same-sized and adopting a more suited field of operation. This is often the hardest way for a firm to increase its productivity since it depends directly on the fixed asset of a company, which cannot be easily adapted. For instance, investments in capital expenditures cannot be easily converted into operating expenditures.

As components of the MPI, it can be derived that the product of the three previously mentioned terms will provide us with the MPI as a result:

$$MPI = TEC \times TC \times SEC \tag{5.5}$$

Concerning the DEA model, an example of the manner of computing the efficiency score of a firm k in period t+1 and a best-practice frontier in t under CRS technology can be illustrated as follows (Cheng et al., 2014):

$$min_{E,\lambda}(E) \tag{5.6}$$

$$s.t \quad Ex_{t+1} \geq \sum_{k=1}^{K} \lambda_k x_{k,t} \tag{5.7}$$

$$y_{t+1} \leq \sum_{k=1}^{K} \lambda_k y_{k,t} \tag{5.8}$$

$$\lambda_k \geq 0 \tag{5.9}$$

$$x \geq 0 \tag{5.10}$$

In order to compute accurate results, some precautions have to be taken regarding the the TC and SEC components. Since some efficiency scores are computed in comparison with the best-practice frontier from the previous period under VRS assumption in an input-oriented model, it can happen that for extreme operators (the major operators usually) located on the best-practice frontier, no feasible solution will be found. The logic is that if a firm increased its output between two periods and there is no reference firms from the past period with which the firm can be compared (in other words, no other firms has reached that level of output in the previous period), the efficiency found for the firm will amount to infinity. To quantify their removal, the MPI scores (which are under CRS assumption and still valid even with the concerned companies) are compared with and without the included companies.

5.1.2 Limitation of the Malmquist index

The Malmquist index is not beyond any reproach. As briefly explained, a first criticism which can be addressed to the Malmquist index is its lack of circularity. The circularity condition is the following (Pastor and Lovell, 2006):

$$MPI(t, t+2) \neq MPI(t, t+1) + MPI(t+1, t+2) \tag{5.11}$$

According to this equation, the Malmquist index of two periods cannot be derived from the index referring to those periods and the periods in-between.

This can be paraphrased by:

"If we have an index for the comparison of productivity between periods k and f, and between l and f, we can establish a productivity comparison between units k and l via the arbitrary third unit, f, that is independent of which third unit, f, that is chosen" (Førsund, 2002).

Secondly, besides its absence of circularity, the Malmquist index suffers from another flaw. Relying only on the technical efficiency based on the work of Farell (1957), the Malmquist index is not able to relate the global cost efficiency change since the allocative efficiency component is not considered by the index.

"The Malmquist index may not give a full picture of the sources of productivity change such as those resulting from a unit aligning its input mix better with the prevailing input prices." (Maniadakis and Thanassoulis, 2004)

Yet, it is a common sense that the more information a regulator owns the more he will be able to take effective decisions and propose an effective regulatory framework.

However, as mentioned by Coelli (2005), it is often harder for a firm to improve on an allocative than on a technical perspective:

"Allocative efficiency changes may result from distortions in factor markets not really under the control of the operator. Limited access to capital markets and national agreements with unions unrelated to the operator's specialized employment needs are two common examples of sources of allocative inefficiency for which the operator should not necessarily be blamed. " (Coelli et al., 2003)

This reason simply lies in the nature of the network capital which is often long-lived and not easily substituted, limiting even more the access to capital markets. Secondly, a distribution company can face quite different environment resulting in restrictions on its network capital.

Thus, although using Malmquist index incorporating an allocative component is more suited theoretically, it will often lead up to limited results since companies have only a limited control over their allocative efficiency. A clear productivity development will not be often observed.

5.2 Second stage analysis

Once our efficiency analysis done, it is relevant to understand how to explain the difference of productivity between the different actors by completing a second stage analysis. Thus, the second stage analysis will consist of evaluating the environmental or structural differences. This will be achieved by two main tools: the Tobit regression for the continuous variables and the Kruskal-Wallis test for the categorial variables.

5.2.1 Tobit regression

Proposed by James Tobin (1958), A Tobit regression can be related to a simple linear regression which is censored and where noise is truncated. The use of a Tobit regression can be justified by the following quote:

"Linear regression do not take into account that efficiencies are greather than 0 and less than or equal to 1 and that many efficiencies are typically at the upper boundary of 1" (Bogetoft and Otto, 2011).

Thus, the Tobit regression will be defined as:

$$E = \begin{cases} 0 & \text{if } az + \epsilon \leq 0 \\ az + \epsilon & \text{if } 0 < az + \epsilon < 1 \\ 1 & \text{if } az + \epsilon \geq 1 \end{cases} \tag{5.12}$$

Like a linear regression, the goal is to estimate the coefficient a, which will relate to the marginal effect that the continuous variable z has on the efficiency score. A random error term is expressed through ϵ since the model does not entirely explain the efficiency thanks to the continuous variables (Bogetoft and Otto, 2011).

5.2.2 Kruskal-Wallis test

Concerning the categorial variables, the Kruskal-Wallis test proposed by Bogetoft and Otto (2011) can be used. Established by Kruskal and Wallis (1952), this test aims to decide if significant differences can be found in the results of two or more samples according to a specific variable. This test aims to answer the following statement:

"The question is whether the differences signify differences among the populations, or are merely the chance variations to be expected among random samples from the same population" (Kruskal and Wallis, 1952).

In our case, our population will be the three main different type of ownerships among the Swedish operators (cooperative, public or private) and the variable tested will be the efficiency score of the three groups. The idea of the test is to rank all the observations on a common scale in order to detect if a sample is systematically ranked higher than the others. After the ranking, the following statistical test can be used:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{c} \frac{R_i^2}{n_i} - 3(N+1) \tag{5.13}$$

Where C is the number of samples, n_i the number of observation in the ith sample, N the number of observations in all samples combined and R_i the sum of the ranks in the ith sample. This test is based on a chi-squared law such as $\chi^2(C-1)$ and a high statistical value leads to confirming the hypothesis of a significant differences among the samples.

6 Data

In this chapter, the reader will get acquainted with the dataset analyzed through our productivity research. As mentioned in Chapter 1.4, the Swedish undertook many reforms concerning its regulatory scheme of the electricity distribution sector and proceeded to the collection of a diversified range of information during different periods. One of the main challenges was therefore to collect data allowing us to compare the different years in order to reach some conclusions about the state of the industry. Two distinct sets of data provided by the Swedish Energy Agency (STEM) and the Swedish Energy Inspectorate (SEI) are analyzed throughout this thesis. The first consists of relatively exhaustive information on Swedish distribution utilities for the period 2002-2006 while the second provided the same type of information for the period 2011-2017.

For each dataset, a model has been designed. The first model concerns the period 2002-2006 (Model 1) and the second refers to the period 2011-2017 (Model 2). In order to maintain a semblance of continuity in our research, Model 1 and Model 2 are as similar as possible even if some variables were removed because they were not significant. These two models are mimicking as closely as possible the current model applied by the EI. One of the strengths of these models is to include the main costs faced by operators. This gives a response to the critics addressed to the MPI concerning its lack of consideration of the whole cost-efficiency (Maniadakis and Thanassoulis (2004),Coelli et al. (2003)).

6.1 Dataset 2002-2006

6.1.1 Data collection and preparation

This data, collected by the Swedish regulator, provides precise information on the assets and costs of the different Swedish distribution companies for the period 2002-2006. Since we need to have the same sample of distribution companies for each year, a first step was to balance the panel, namely, through completing the mergers which took place for 2002-2006 within the sample. These mergers have been realized by consolidating the different inputs and outputs of the merged companies together to create fictive merged companies for the years before the merger. Besides, operators which were not represented in all years or with unrealistic information have been removed. A third step was to take into account the outliers. They were detected using both super-efficiency and data cloud methods even if the data cloud method was only applied to get some additional intuition. Results can be found in Appendix 2.

At the end of the data preparation, the dataset consisted of a sample of 825 observations depicting the main characteristics of 165 operators for 2002-2006.

6.1.2 Model 1

The selection of the variables of the benchmarking model is not a trivial exercise. Different models of past research mentioned in Chapter 2 which used the same dataset were reviewed (Agrell and Niknazar (2014);Agrell and Brea-Solís (2017);Agrell and Grifell-Tatjé (2016)). Nevertheless, it has been decided to follow as closely as possible the current model used by the Swedish authority in order to facilitate the comparison with the second model presented hereafter. This model, based on the main costs faced by an operator as input, is a good response to the criticism that the Malmquist index only takes the technical and not the whole cost-efficiency into account. In addition, given the presence of environmental information, some non-discretionary variables were included to provide us with a better analysis of the difference of efficiency existing between the DSOs. Nevertheless, the significance of these initial variables needed to be investigated. This has been done thanks to the Kolmogorov-Smirnov's test for discretionary variables and Tobit regression for non-discretionary variables in Appendix 3. The variables that were not significant according to the test were removed.

6.1.2.1 Candidate inputs

As said, the inputs initially chosen aim to depict the main costs that a distribution company has to face.

Input 1: The operating costs represents the different costs associated with the operation and maintenance of the company activity on a yearly basis. They are expressed in real terms. We can write them as:

$$\text{Operating costs} = \text{Cost of personnel} + \text{Cost of metering} + \text{Other costs} \tag{6.1}$$

Input 2: The capital costs represents the different costs occurring to the asset base expressed on a yearly basis. They comprise the cost of finance (return on capital) and the cost of depreciation.

$$\text{Capital costs} = \text{Cost of finance} + \text{Cost of depreciation} \tag{6.2}$$

6.1.2.2 Candidate outputs

We included five different outputs in our first version of this benchmarking model. As mentioned, the choice of these variables is directly related to the investigation led by the Swedish authority. According to the EI, they can be seen as the main cost drivers of the distribution utilities in Sweden. Nonetheless, given that the output depicting the number of network stations of a DSO being not represented for this period, a variable depicting the number of transformer substations was chosen as the best proxy.

Output 1: Energy delivered through high-voltage is the amount of energy provided by the DSO to customers by lines between 40 and 130kV. This electricity is typically transmitted to the industry sector

Output 2: Energy delivered through low-voltage is the amount of energy provided by the DSO to customers by lines less than 40kV. This energy will often be intended to provide the residential sector.

Output 3: The peak load corresponds to the highest power demand delivered by the company within a year.

Output 4: The number of sub-transformers refers to the number of transformer substations which transfer electricity from the TSO to the DSO with a reduction of the voltage level.

Output 5: The number of connections corresponds to the number of customers subscribed to the DSO (one customer typically represents one household).

6.1.2.3 Candidate non-discretionary variables

We have chosen to follow the model proposed by Banker and Morey (1986) in order to include the non-discretionary variables in our model. These non-discretionary variables will be included as negative outputs as proposed by Bogetoft and Otto (2011).

Non-discretionary variable 1: Operator size depicts the relative size of an operators through its total network length (TNL) as the sum of the high-voltage lines (HVL), low-voltage lines (LVL), high-voltage cables (HVC) and low-voltage cables (LVC) lengths. Indeed, we can assume that operators with a larger network can benefit from economies of scale. The total network length of an operator was deduced as the sum of the kilometers of cables and lines in both high and low-voltage.

$$\text{TNL} = HVL + LVL + HVC + LVC \tag{6.3}$$

Non-discretionary variable 2: Proportion of cable in the network depicts the ratio of cables in the network of an operator.

$$\text{Cable proportion(\%)} = \frac{\text{Cable network length (km)}}{\text{Network length (km)}} \tag{6.4}$$

On the one hand, since cables are harder to settle than lines and their maintenance cost is also higher, a high ratio would suggest more important costs for an operator. On the other hand, this ratio can also offer a proper proxy to estimate if the operator is located in a urban or rural area or in other words, if the distributor is facing a higher customer density since cables will be preferred to lines in a urban area with space constraint. In this configuration, a high ratio would suggest lower costs for an operator since a less large network is needed to provide electricity to the customers. After performing a Tobit regression (Appendix 3), it seems that the cost saving due to the higher customer density overcomes the higher cost of the cable material. Thus, a high ratio corresponds to lower-costs and operators operating in urban areas are advantaged.

Non-discretionary variable 3: Proportion of network at low-voltage accounts for the ratio between the low-voltage network length and the total network length. Knowing that low-voltage electricity is mainly destined to small consumers (households, public infrastructures,...) and high-voltage to industrial consumers, the profile of the consumers for each operator is addressed through this ratio. A large ratio implies that the operator mainly provides electricity to small consumers while a small ratio that the main consumers of the operator are industrial companies. It is known that low-voltage lines or cable suffer from more energy losses than high-voltage ones. Thus, a high ratio is supposed to affect negatively the efficiency scores as it would reflect the high share of the network that is made of low-voltage lines or cables.

$$\text{Low-voltage proportion}(\%) = \frac{\text{Low-voltage network length (km)}}{\text{Network length (km)}} \tag{6.5}$$

6.1.2.4 Final model

In light of the investigation summarized in Appendix 3, only six of the mentioned variables appeared to be significant and have been retained in Model 1.

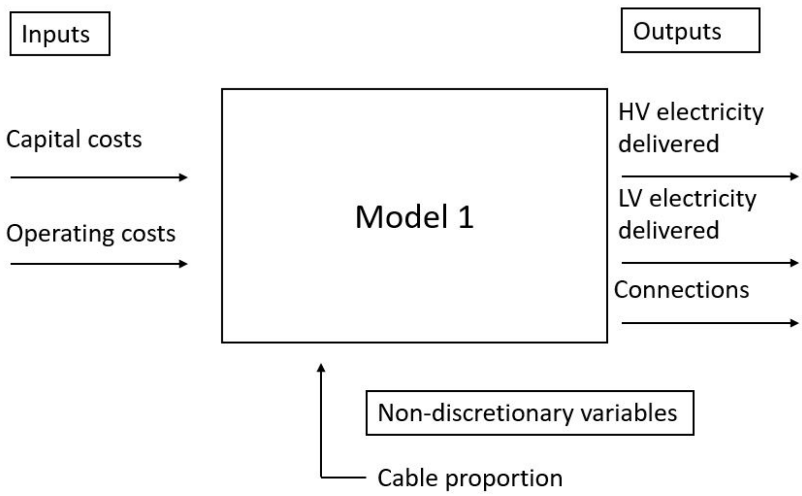

Figure 6.1: Overview of Model 1

6.1.2.5 Descriptive statistics

After having performed the Kolmogorov-Smirnov's test and the Tobit regression, our final model can be represented as follows:

A quick overview of the median, mean and standard deviation of each variable for Model 1 can be found below.

Category	Unit	Variable	Median	Mean	SD
Input x	SEK	Operating costs	24,019	53,438	157,227
Input x	SEK	Capital costs	7,118	25,211	93,553
Output y	No	Number of connections	11,664	30,767	91,350
Output y	MWh	Energy delivered HV	49,411	163,413	445,851
Output y	MWh	Energy delivered LV	159,954	407,543	1,137,159
Dis. var. z	%	Cable network proportion	0.6935	0.6879	0.216

Table 6.1: Descriptive statistics 2002-2006 model

As it will also be seen later, the operators present sensitively variable sizes. The choice of not removing the most important DSOs from the dataset can partly explain the significant standard deviation and the gap between the mean and the median.

6.2 Dataset 2011-2017

6.2.1 Collection and formatting

The second dataset provided by the EI consists in information related to cost and physical characteristics of the Swedish distribution operators for the period 2011-2017. This data contains the most recent information and will be used to set the different requirements of the next regulatory period (2020-2023).

It can be argued that 2014-2017 does not correspond with the regulatory period set by the EI for the revenue cap (2016-201). This time lag is simply related to the access to data. As a matter of fact, the individual and general efficiency requirements applying to each DSO have to be set before summer 2019 for the time period 2020-2023. However, the last reported output information by the operators are from 2017 and back. Regarding the capital costs, they are reported once in the beginning of a regulatory period with forecasting for the next years.

A major difficulty is that the SEI switched in 2014 from a real annuity to a linear depreciation method to assess the depreciation. Given that the depreciation is a major component of the capital costs, it was required to conduct two different studies of the dataset for both the period 2011-2015 and 2014-2017. The reason of the overlapping is that, even if the linear depreciation method has been used from 2014, capital cost computed by the way of the real annuity method were still provided until 2015.

Like the model for 2002-2006, several adjustments were made to the dataset in order to balance the panel and account for the mergers. The treatment of the outliers based on the same methods as previously mentioned can again be referred to Appendix 2. The final result was samples compounded of 142 and 152 operators with complete information for the period 2011-2015 and 2014-2017 respectively. The reduced number of observations for 2011-2015 can be explained by the fact that some operators have been removed since no information on their capital costs was provided. This sample can nevertheless be considered as representative of the electricity distribution industry in Sweden. As an indicator of this, the total amount of connections ranged between 4,392,896 in 2011 and 4,455,802 in 2015.

6.2.2 Model 2

As mentioned, Model 2 is directly inspired from the current model used by the Swedish authority. Model 2 initially tested the two inputs and five outputs presented hereafter. Just as for Model 1, statistical tests were conducted to evaluate the significance of the variables (Appendix 3). From the test, it has been concluded that the peak load could not be considered as significant and was removed from Model 2. As a reminder, note that, due to different valuation of the capital costs, Model 2 has been performed on two samples: one from 2011 to 2015 with the capital costs evaluated through a real annuity depreciation method and one from 2014 to 2017 with the capital costs evaluated through a linear depreciation method.

6.2.2.1 Candidate inputs

As said, the inputs will aim to relate to the costs of the DSO. Although closely related, those inputs will not correspond exactly to the inputs previously introduced since they will not consist of the total operating costs but only the controllable operating and capital costs have been computed based on a linear depreciation according to the model proposed by the SEI (cfr. Chapter 3.3.3).

Input 1: The controllable operating costs relates to the operating costs that the operator can influence and at least, partially avoid. Those operating costs are reported on a yearly basis by the distribution companies concerning the previous exercise. Among others, they mainly comprises:

- Labour cost
- OM cost
- Overhead cost
- Converted capital cost (cf. Chapter 3.3.3)

Note that the controllable operating costs are expressed in real value and account for the inflation. They have been indexed to the price level of the year 2014.

Input 2: The capital costs is compounded of the depreciation and return of the regulatory asset base incurred during the year. As said, there has been a change in the methodology of computing these and the capital costs based on a real annuity method are displayed for 2011-2015 while those based on linear depreciation applies for the model for 2014-2017.

The previously used real annuity method was achieved by applying a constant depreciation rate according to the type of materials. Thus, materials related to metering had a rate of 6,9% a year while materials related to the network stations and the distribution lines had a rate of 3,5%

The new evaluation of the grid assets is based on a more elaborated depreciation method based on the capital costs provided by the distribution companies at the beginning of the new regulatory period. It can be described as follows (Wallnerström et al., 2016):

$$\text{Capital costs} = \begin{cases} (\frac{1}{DT} + \frac{DT+1-age}{DT} * \text{WACC}) * \text{PPV} & \text{if age} \leq DT \\ (\frac{1}{age} + \frac{1}{age}.\text{WACC}) * \text{PPV} & \text{if DT} < \text{age} \leq \text{DT} + \alpha \\ 0 & \text{if } age > DT + \alpha \end{cases} \tag{6.6}$$

Where DT is the estimated depreciation time,age is the age of the asset, WACC is the weighted average cost of capital,PPV is the present purchase value of the asset, alpha is a constant for providing some capital costs more years after the DT.

6.2.2.2 Candidate outputs

As explained, only the variable referring to the peak load can be considered as insignificant both for 2011-2015 and 2014-2017. The only variation with Model 1 refers to the inclusion of the number of network stations instead of the number of sub transformers.

Output 4: The number of network stations accounts for the number of transformers and exit points in the grid of the DSO.

It can be noticed that this model does not include non-discretionary variable. Even though geographical variables would certainly be relevant, they have not been included yet in the Swedish regulatory model. However, the variable depicting the number of network stations aims to include the structural difference between the different DSOs and works as a proxy for the customer density when coupled with the number of connections. For instance, a distribution utility with a small customer density will have a more consequent number of network stations than the same company in a high-density environment. There is also a differentiation between low and high-voltage electricity delivered since it leads to different costs (Council of European Energy Regulators, 2019).

6.2.2.3 Final model

After conducting the tests in Appendix 3, six of the presented variables are considered as significant and included in Model 2.

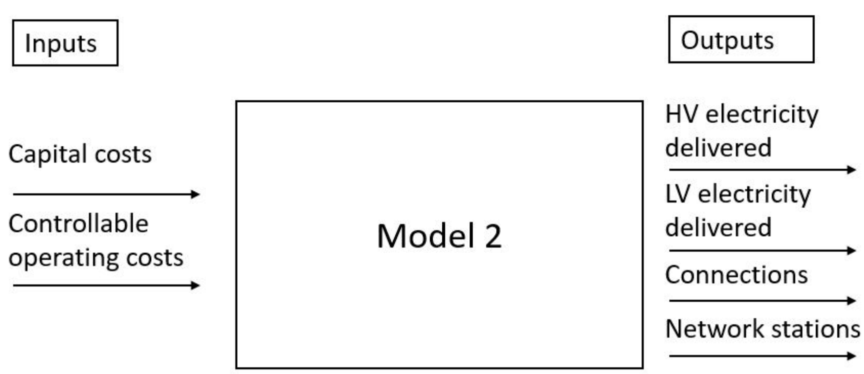

Figure 6.2: Overview of Model 2

6.2.2.4 Descriptive statistics

As explained, Model 2 is divided into two periods: a period going from 2011 to 2015 with capital costs based on real annuity and a period going from 2014 to 2017 based on linear depreciation. Descriptive statistics of the retained variables for the respective periods are displayed below.

Category	Unit	Variable	Median	Mean	SD
Input x	SEK	Capital costs	44,769	117,666	357,058
Input x	SEK	Controllable Operating costs	18,709	47,281	127,836
Output y	No	Number of connections	12,163	31,367	98,048
Output y	MWh	Energy delivered through high-voltage lines	47,314	154,514	468,631
Output y	MWh	Energy delivered through low-voltage lines	156,947	390,685	1,151,931
Output y	No	Number of network stations	279.0	960.8	3,433.4

Table 6.2: Descriptive statistics 2011-2015

Category	Unit	Variable	Median	Mean	SD
Input x	SEK	Capital costs	32,752	103,362	333,339
Input x	SEK	Controllable costs	20,632	53,411	143,230
Output y	No	Number of connections	11,822	35,749	112,283
Output y	MWh	Energy delivered through high-voltage lines	47,168	164,561	482,037
Output y	MWh	Energy delivered through low-voltage lines	156,125	442,830	1,340,547
Output y	No	Number of network stations	290.9	1157.6	4231.6

Table 6.3: Descriptive statistics 2014-2017

7 Analysis

In this chapter, the different tools presented in Chapter 4 and 5 will be applied on the sets of data presented in Chapter 6. One section will be devoted to assess and analyze the productivity development through a Malmquist productivity index in each period. Second stage analysis will also be performed for the two periods, aiming to verify if the type of ownership (public, private or cooperative) but also if environmental factors for 2011-2017 can influence the efficiency scores. A special attention will be dedicated to the 2011-2017 period given its more recent nature.

7.1 Productivity development for 2002-2006

7.1.1 Efficiency scores

Even though the efficiency scores cannot be associated with a productivity development, it is useful to get a first impression of those for the 165 operators for 2002-2006. As a reminder, variables from Model 1 have been used to evaluate the efficiency scores for each year. Table 7.1 presents the average efficiency score (TE) and the corresponding, standard deviation (SD) and coefficient of variation (CV), for each year. The number of peer firms and the minimum technical efficiency score within the year are also included. Note that the results are expressed in percentage except for the number of peer firms.

Year	Unit	TE	SD	CV	Peer firms	Minimum
2002	%	68.00	20.00	29.40	22	16.01
2003	%	67.09	18.97	28.27	15	27.73
2004	%	65.46	19.19	29.31	21	30.70
2005	%	62.79	19.33	30.80	16	16.22
2006	%	62.86	18.59	29.58	13	29.68

Table 7.1: Efficiency scores 2002-2006

Given that the model is input-oriented, we first see through these results that firms could, on average, decrease their costs between 32% and 36% for each of the years. Secondly, it can be concluded that the industry is quite heterogeneous. We deduce it when focusing on the average efficiency scores. As said, the average efficiency score can be considered as a measure of the heterogeneity of an industry since they show how close the operators are to the best-practice frontier. As an illustration, an average efficiency score of one would depict the fact that all the companies are located on the best-practice frontier, demonstrating that the industry is using the same technology. On the other side, an average efficiency score close to zero would indicate that few firms are outperforming and putting the best-practice frontier away from other operators. Having a look at the large number of peer firms and the low minimum scores confirm that the operators present particularly different efficiency scores.

Sweden was one of the first countries to restructure its electricity market. Therefore, it can be supposed that the distribution sector is quite mature. Having a look at the scale efficiency scores (SE) depicted in Table 7.2 confirms this intuition.

Year	SE
2002	97.04
2003	97.41
2004	98.06
2005	96.41
2006	96.18

Table 7.2: Scale efficiency scores 2002-2006

The averages per year are particularly high with scale efficiencies ranging from 96.39% to 98.41%. It seems that most of the firms have an optimal size according to Model 1.

7.1.2 Productivity change

7.1.2.1 General scores

After a brief overview of the efficiency scores, let us now dig deeper into the productivity measurement for 2002-2006. However, before proceeding to any computation, the removal of some operators as suggested in Chapter 5.2 is taken into account. These operators are: *E.ON Elnaet Sverige* and *Vattenfall Eldistribution*. They represent the two largest of the industry. Besides, the fact of including a negative output generated the reverse problem. Two operators are removed: *Blaasjoen Naet AB* and *Hamra Besparingsskog*. They present a relatively moderate size. The effect of the removal of those four operators can be seen in Appendix 4.

The results after removal are summed up in Table 7.3. The distribution of the scores of the different components can be found in Appendix 5 for a better review of the industry productivity development.

Year	MPI	TEC	TC	SEC
2002-2003	1.0344	0.9995	1.0395	1.0017
2003-2004	0.9762	0.9711	1.0061	1.0017
2004-2005	0.9919	0.9820	1.0109	1.0024
2005-2006	1.0008	1.0192	0.9828	1.0030
2002-2006	0.9576	0.9587	1.0006	1.0072

Table 7.3: Malmquist index 2002-2006

It can be seen that the MPI recorded a noticeable of the productivity enhanced by a positive TC for the period prior the implementation of the NPAM. Afterwards, the operators endured an important decline of their productivity from 2003 to 2005 and stabilized in 2006. All these results together give us a negative MPI for the period 2002-2006. This fall is due to a decrease of the TEC. Through this component, we see that the industry became less competitive and that the gap widened between the operators from 2002 to 2006. The TC and the SEC remained stable during this period. Concerning the SEC, this can be explained by the fact that most of the operators already have an optimal size. Therefore, the improvement of the scale efficiency is limited.

In view of our results, it seems that the NPAM provided wrong incentives to stimulate the productivity development of the whole industry. As an illustration, let us have a look at Figure 7.1. Note that the capital costs are depicted in brown and the operating costs in blue

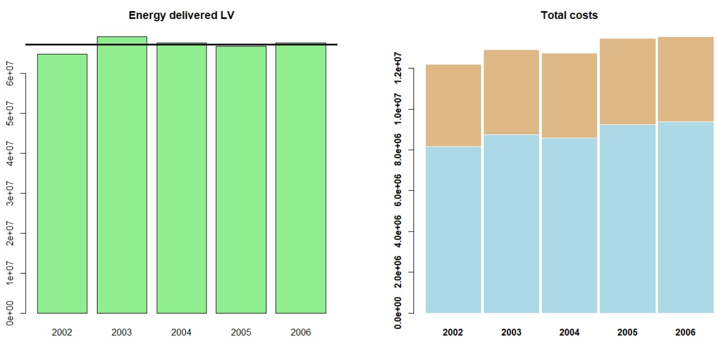

Figure 7.1: Evolution of the cost and the low-voltage electricity delivered 2002-2006

Through this illustration, we can conclude that an increased supply in LV electricity drove the raise of additional investments for 2002-2003. However, this was followed by a decrease in the electricity delivered. Even though it cannot be undoubtedly said that the inauguration of the NPAM is the cause (a conjonctural decrease of the demand could also explain it), it seems a credible hypothesis.

7.1.3 Second stage analysis

Does the type of ownership of an operator has an influence on the cost-efficiency scores? We will try to explain this question through the application of the Kruskal-Wallis test explained in Section 5.3.2. As a reminder, this test consists mainly of detecting possible differences among the results of different samples. A high statistical value (and de facto a low p-value) expresses divergences among the samples. Three different samples have been created according to the legal status of the operator: one sample with 32 private operators, one with 30 operators categorized as cooperatives and one gathering 103 operators owned by the municipality. The results of the test are displayed below.

Year	Statistical value	P-value
2002	8.107	0.0173
2003	15.949	0.0003
2004	17.025	0.0002
2005	15.695	0.0004
2006	19.620	0.0000

Table 7.4: Kruskal-Wallis test 2002-2006

We see that the p-values are all significantly low and coupled to a high statistical value. As a matter of fact, it can be concluded that a significant difference in performance is detected according to the ownership.

However, the test does not tell us which type of ownership is performing better. A good way of assessing it is to compute the average of the efficiency scores per type of ownership for each year and to compare them. These scores are not weighted. If it was the case, given that few large private operators are located on the best-practice frontier (Vattenfall, E.ON Elnaet Sverige and Fortum), the results presented in Figure 7.2 could even be intensified.

Figure 7.2: Efficiency scores per type of ownership 2002-2006

The efficiency scores indicate that private operators perform better than operators under municipal or cooperative ownership. It also seems that cooperative are performing at a far lower level than municipally and privately owned utilities.

It could be argued that large economies of scale is the reason of their high efficiency scores and that municipally owned operators of a similar size would obtain similar results. However, the Tobit regression displayed in Appendix 3 shows that the network length has a low impact on the efficiency scores. Secondly, environmental factors such as the weather or the topological conditions would need to be taken into account to confirm that a difference does exist between private operators, cooperatives and municipally-owned operators.

7.2 Productivity development 2011-2017

As said before, due to different methods of valuation of the capital costs (real annuity and linear depreciation), the period 2011-2017 will be divided into two periods: one from 2011 to 2015 and one from 2014 to 2017.

7.2.1 Efficiency scores

The average results of 142 operators for 2011-2015 and 152 operators for 2014-2017 are summarized in the table below. The average technical efficiency (TE), the standard deviation (SD), the coefficient of variation (CV), the peer firms and the minimum efficiency score are displayed. These results are expressed in percentage. The peer firms, expressed in number, are the only exception.

Year	TE	SD	CV	Peer firms	Minimum
2011-2015					
2011	84.43	10.87	13.74	19	61.19
2012	84.53	11.18	13.22	23	59.58
2013	83.86	11.19	13.34	20	58.94
2014	83.86	11.05	13.16	19	60.32
2015	85.09	11.18	13.14	23	61.00
2014-2017					
2014	80.45	11.73	14.57	14	49.49
2015	81.51	11.90	14.6	21	52.21
2016	81.84	11.55	14.08	17	55.12
2017	82.36	11.55	13.99	20	58.63

Table 7.5: Efficiency scores 2011-2017

Given that the inputs depict the main expenditures faced by an operator, a first interpretation of the table is that the operators could on average decrease their cost by about 15% and 20% if performing as the best operators for 2011-2015 and 2014-2017 respectively.

The average efficiency scores are slightly lower for the period 2014-2017 than for the period 2011-2015. Given the stability of the results and the difference also observed in 2014 and 2015, it can be concluded that the linear depreciation method certainly allows the model to discriminate better the different operators than a simple annuity method. Nevertheless, a bias can also be caused by the linear depreciation. The operators owning old networks infrastructures have lower capital costs than others companies with more recent networks infrastructures and therefore, will appear more efficient. The variation of the score seems to be quite stable with only non-significant variations for both 2011-2015 and 2014-2017.

Drawing the attention on the coefficient of variation (CV), it can be seen that the variation of the efficiency score is quite limited with standard deviation representing between 13.14% and 14.57% of the average efficiency score all the years confounded. Combined with high minimum efficiency score, this strengthens our belief that the two samples analyzed are quite homogeneous. Besides, the operators seem to tend to catch-up the best-practice frontier as shown by a slight global increase in the efficiency score of 1.5% and 2% for 2011-2015 and 2014-2017 respectively. However, let us remember that this catch up only accounts for one component of a productivity change. Indeed, the best-practice frontier can also evolve from year to year (depicted by the TC).

These results denote a mature industry. As an illustration, the average scale efficiency scores for each year is depicted in Table 7.6:

Year	SE
2011-2015	
2011	96.98
2012	97.80
2013	97.17
2014	97.76
2015	98.04
2014-2017	
2014	94.6
2015	95.1
2016	95.6
2017	95.9

Table 7.6: Scale efficiency scores 2011-2017

A slight difference can be noticed in the average efficiency scores for 2011-2015 and 2014-2017. As explained earlier, the change of capital costs valuation method induced a clearer distinction among the operators. Apart from this, no major changes have happened in the industry and most of the operators present a convenient size. A limited amount of mergers is expected in the industry for the years to come.

7.2.2 Productivity change

7.2.2.1 General scores

Let us now turn to the productivity measures for 2011-2017. Like in 2002-2006, it is important to underline that those results do not take into consideration the following companies as they are the largest companies and they divert of the technology set of the previous period as explained in Chapter 5.2:

- In 2011-2015: *E.ON Energi Distribution* and *Ellevio AB*
- In 2014-2017: *E.ON Elnät Sverige AB*,*Vattenfall Eldistribution AB* and *Ellevio AB*

Results shows that this removal does not influence the MPI as it can be seen in Appendix 4. Once these operators are removed, let us have a look at Table 7.7 below.

Year	MPI	TEC	TC	SEC
2011-2012	1.0318	0.9925	1.0413	0.9993
2012-2013	1.0015	0.9996	1.0018	1.0015
2013-2014	0.9939	0.9947	0.9921	1.0016
2014-2015	1.0024	1.0129	0.9922	0.9983
2011-2015	1.0024	0.9980	1.0230	0.9993
2014-2015	1.0066	1.0089	1.0040	0.995
2015-2016	0.9752	1.0001	0.9677	1.0066
2016-2017	1.0061	1.0040	1.0033	0.9996
2014-2017	0.9857	1.0123	0.9739	1.0005

Table 7.7: Malmquist index 2011-2017

Between 2011 and 2015, it can be noticed that most of the years with exception of 2012-2013 presents a positive productivity development. However, with exception of the year 2011-2012, the productivity development is marginal and at the end of the day, the productivity development for the period 2011-2015 appears quite stable. The small increase is due to the TC that is globally positive for 2011-2015. Concerning the TEC and SEC, they have undergone small declines but can be considered as stable for 2011-2015 (this even more when having in memory that the TEC and SEC deduced from efficiency scores presented Chapter 7.2.1 would have been positive). It would be in any case difficult to imagine other results for the SEC given the high scale efficiency scores obtained previously (Chapter 7.2.1) and the limited influence of the operators on the size of their operations as mentioned in Chapter 6.2.1.

It seems somewhat surprising that the period 2011-2012, the last year prior the revenue cap that was characterized with a low-powered regime, present the best productivity development. Turning to the cause of this upturn, the development of the productivity comes mainly from the TC with an augmentation of more than four percent between 2011 and 2012. This results in a positive TC for 2011-2015. A plausible hypothesis can explain this by the ratchet effect. This effect indicate that before the introduction of the Revenue Cap Model, the operators could have purposely increased their costs to benefit from an increased revenue cap for the next regulatory period and to meet more easily the general efficiency requirement imposed by the SEI.

Concerning the productivity measurements for 2014-2017, the results reveal that the global productivity development have been plateauing with slight increases between the years 2014-2015 and 2016-2017. However, a significant fall of the productivity is observed for 2015-2016, which corresponds to the transition between the two regulatory periods. This is essentially due to the TC component. One reason might be the change in reporting the capital costs or controllable operating costs by the regulator. For example, some categories of operating costs might have been transferred from non-controllable to controllable or the common capital rate of return imposed by the SEI could have been adjusted, resulting in an increase tinhe global input quantity for the same amount of output and affecting badly the best-practice frontier. If this hypothesis is retained, this would greatly change our results and the productivity development of the industry could be considered as increasing in light of the productivity development for 2014-2015 and 2016-2017. Looking deeper at the TEC, as hinted by the efficiency score reported before, it is slightly progressing on average, showing a tendency of homogenization in the distribution sector concerning the best-practice usage. This contrasts with the period 2011-2015. A pertinent hypothesis of the increase of the homogeneity in the sample can be attributed to the successful introduction of the individual efficiency requirement in addition to the general requirement forcing poor-performing operators to catch-up with best practices. The SEC presents insignificant fluctuations and can be considered as stable. This appears quite reasonable for the same reason as the one mentioned before for the period 2011-2015.

Even if we retain the hypothesis that some changes in reporting occured between the two regulatory periods (which would alleviate or even remove the productivity decrease in 2015-2016), those results depict a slightly better industry with a productivity development inferior to 1%. As said, this is not surprising given the maturity of the industry. Nonetheless, when comparing with the efficiency requirements imposed by the regulation, it suggests that the general efficiency requirement imposed to the operators by the regulator could be overestimated. As a reminder, the regulator imposes a general efficiency improvement of 1% for any operator. This requirement had been proposed from a research achieved in 2010 (Ek and Fredriksson) based on productivity results from Sweden for 2000-2008. The findings are, among others, that the productivity development of the industry using a MPI is estimated to 3.6% for the period 2000-2006. The report relies on other benchmarking techniques and finally concludes that the productivity development of the Swedish distribution sector is equal to about 2%. Accentuated by the fact that the regulator explicitly wanted to set a low efficiency requirement in order to allow the operators to retain some efficiency gains, a revision of the general efficiency requirement would certainly be relevant for the Swedish authority. However, note that additional research based on other tools (SFA, Stoned, engineering models) would add consistence to the evaluation of a plausible general efficiency requirement.

7.2.2.2 Scores distributions

To get a broader picture of the situation, a look at the distribution of the results as illustrated in Section 7.1 might be relevant. The distributions of the MPI, TC, TEC and SEC scores between 2011 and 2015 are illustrated in Figure 7.3.

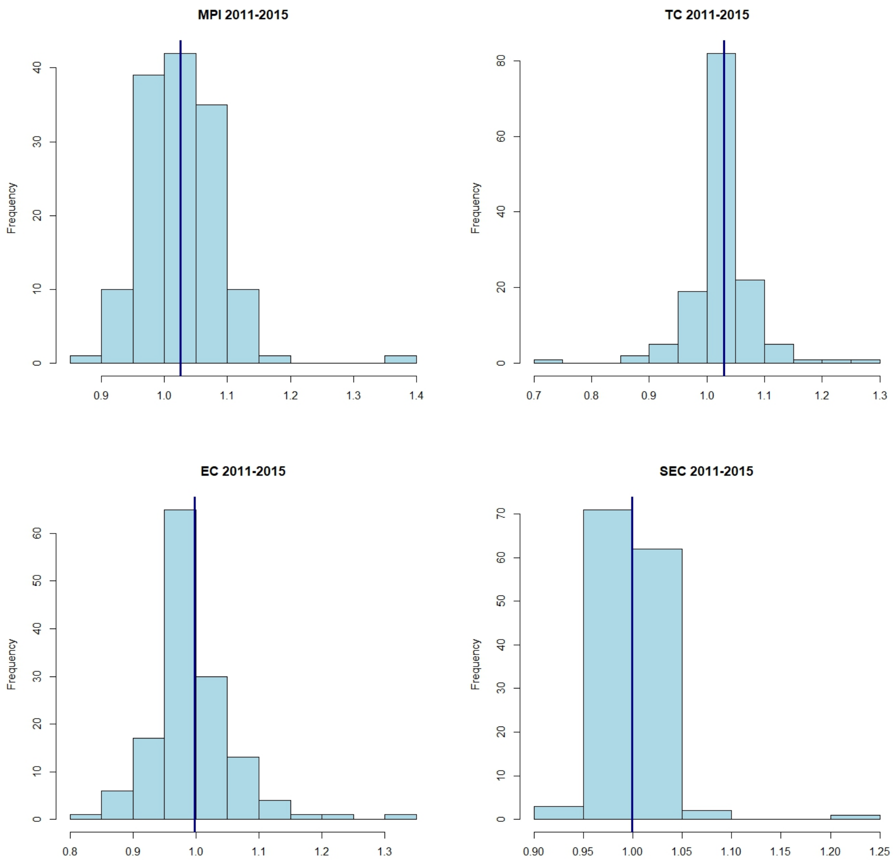

Figure 7.3: Histograms of the Malmquist index and components 2011-2015

Observing the histogram of the MPI, the distribution seems to follow a normal law characterized by a low standard deviation. Only Bodens Energi Nät AB delivers exceptional results with a 27 percent increase of its productivity. This is mainly due to a dramatic catch up to best-practice with EC increasing between 7 and 16 percent every year from 2012. A case study exploring the reasons which allowed Bodens Energi Nät AB to operate such a catch-up could be worthwhile.

Concerning the TC and EC components, they follow normal distributions, even more concentrated than for the MPI. The SEC has unsurprisingly nearly all its results concentrated between 0.95 and 1.05.

Histograms can be observed in Figure 7.4 concerning the distribution of the productivity of the different components scores for 2014-2017.

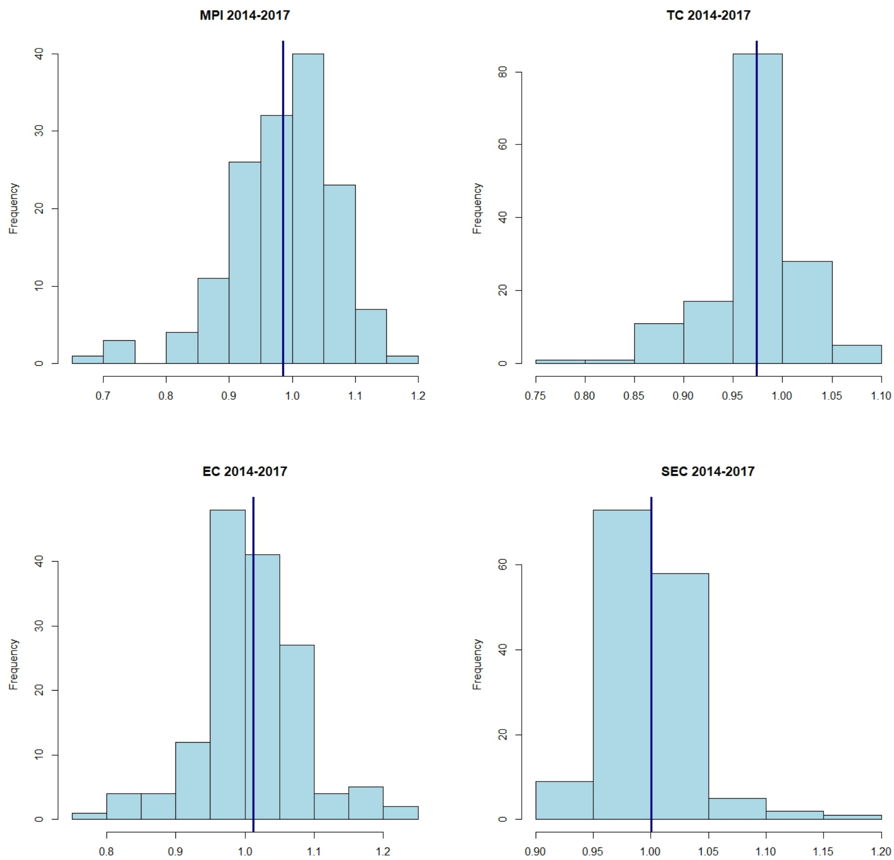

Figure 7.4: Histograms of the Malmquist index and components 2014-2017

Through these histograms, it can first be noticed that the MPI and its components also display what seems to be normal and concentrated distributions. However, some operators stand out with MPI inferior to 0.75. A special attention will be given to them later.

Regarding the components of the productivity, the TC seems also to present few companies having experienced a recoil of their technology. As mentioned, this can be due to a change in reporting. Concerning the TEC measures, they are concentrated around 1 with few operators presenting a higher number than 1.2. This seems to indicate us that a catch-up to best practice dictated by an individual efficiency requirement of 0.082% as asked by the regulator could be reachable. Again, most of the SEC measures concentrate between 0.95 and 1.05.

7.2.2.3 Causes of the productivity change

It can appear to be hard to know the dynamic of the distribution sector in view of the MPI and its components. In order to have a better understanding of the results presented in Table 7.7, Figures 7.5 and 7.6 depicts the evolution of the total levels of input and output used by the industry between 2011 and 2015 and 2014 and 2017.

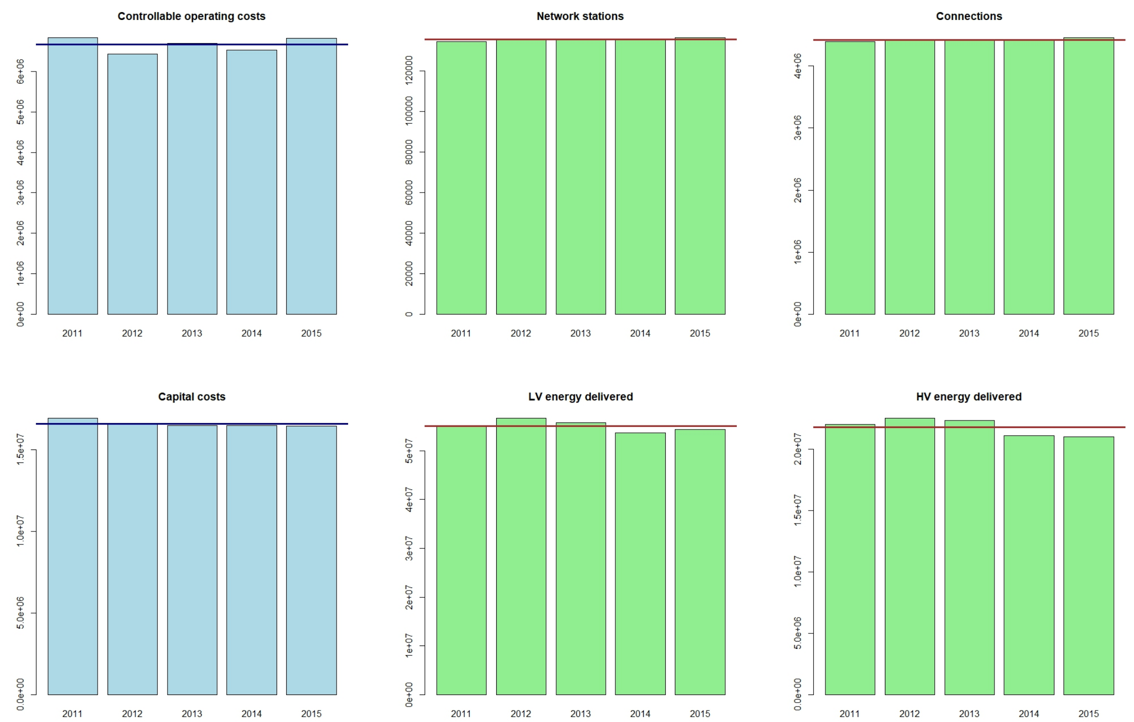

Figure 7.5: Variables evolution 2011-2015

Regarding the controllable operating costs, they seem to vary from one year to the next but seem quite stable on the long run. On the other side, the capital costs seem to be constantly decreasing from 2011 to 2015. Note that both the controllable operating costs and capital costs substantially declined from 2011 to 2012. This fact supports the hypothesis of a ratchet effect prior to the establishment of the Revenue Cap Model.

Concerning the outputs, while the number of connections can be considered as steady, an increased followed by a drop in energy delivered through low and high-voltage is noticed. Therefore, it appears that, apart from the reduction of the costs, the raise in LV and HV electricity delivered for the period 2011-2012 can also partly explain the significant productivity development for this period. On the contrary, the fall in 2012-2015 is likely to have limited the productivity improvement of the industry in our model. Nevertheless, this drop cannot be imputed to a reduced supply. According to the International Energy Agency (2019) in a recent report, this drop in consumption was conjectural and an increase followed during the next years.

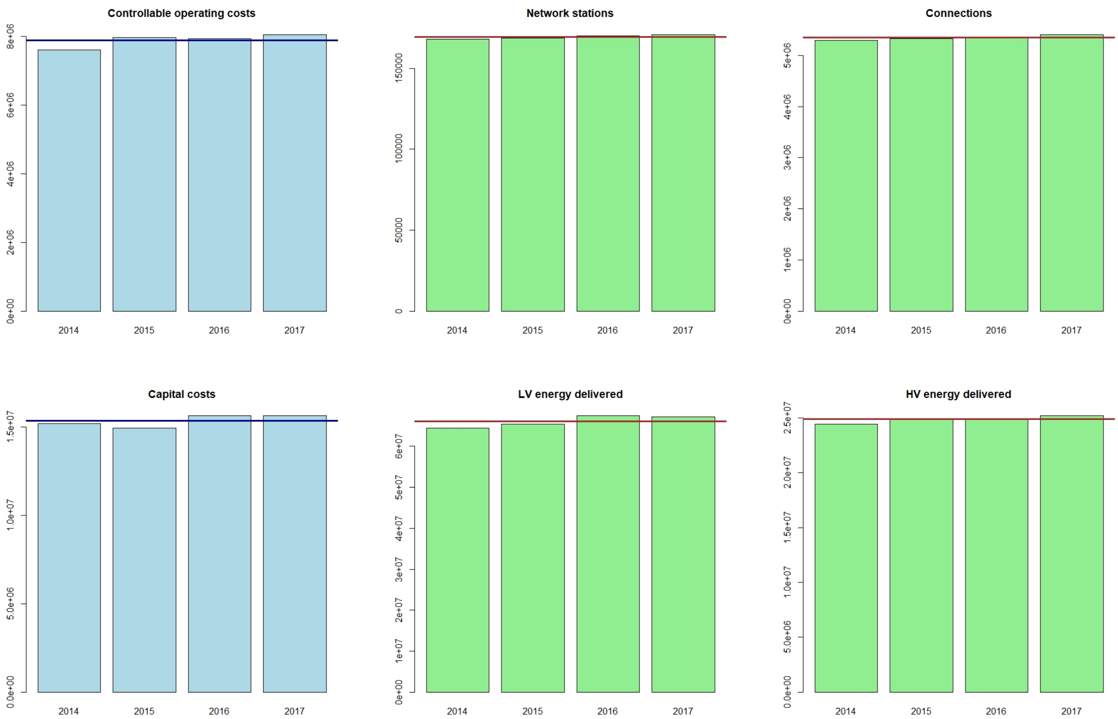

Figure 7.6: Variables evolution 2014-2017

As shown by 7.6, it seems highly likely that our intuition of a possible change in reporting effectively occured. As a matter of fact, both the capital costs and controllable operating costs have endured significant variations within the years 2014-2015 and 2015-2016. While the rise of controllable operating costs between 2014-2015 does not seem to affect the productivity (because compensated by a fall in capital costs and a rise in total LV energy delivered), the subsequent boom in capital costs for 2015-2016 reinforces the hypothesis of a change in reporting. In fact, an increase of 3.1% in total LV energy delivered is observed for the same year. We can therefore reach the conclusion that without this change in reporting, the productivity development of the sector would certainly be growing in the same way as 2014-2015 and 2016-2017.

7.2.3 Effect of the capital costs

As highlighted several times, the difference in the method of valuation of capital costs prevents us from comparing the productivity development of the period 2011-2015 and 2014-2017 together. However, by removing the capital costs from our variables, we could obtain a model depicting results for the two periods altogether. Nevertheless, an intuition suggested by the test of significance of our variables (Appendix 3) is that taking away the capital costs would lead to considerably different results. Besides, the limited number of variables would probably limit us to offer a proper analysis of the industry.

To convince ourselves of the impact that it would have on our productivity analysis, productivity development have been computed for each year with and without the capital cost in order to compare the impact of the removal of the capital costs on the productivity changes for the periods 2011-2015 and 2014-2017. The results are shown in Figure 7.7.

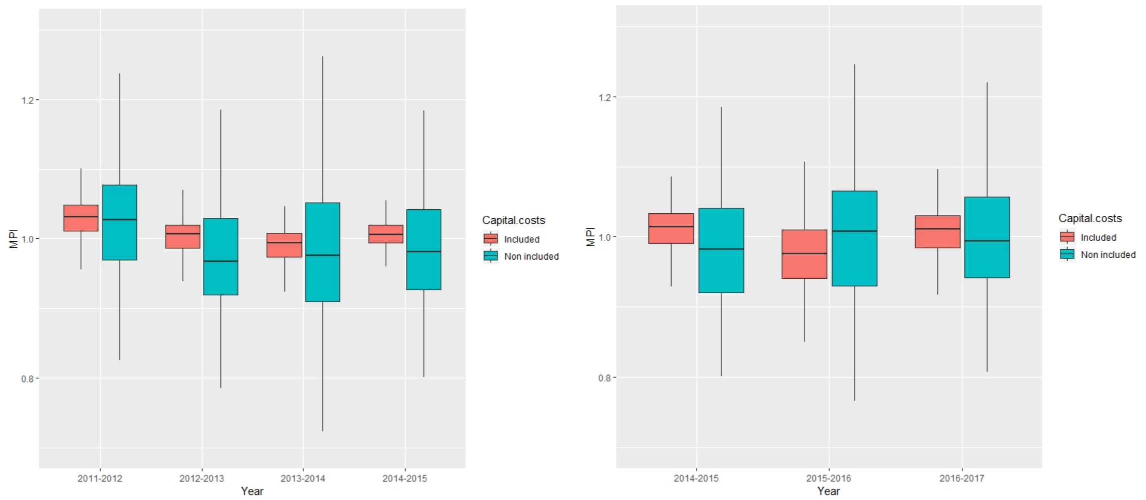

Figure 7.7: Malmquist index with and without capital costs 2011-2017

The figures underline unsurprisingly significant differences in the productivity development measures for the model with and without capital costs. This indicates us that removing the capital costs would give significantly different results. It can also be noticed that the variation of the productivity change measures would increase. Indeed, less variables allow the models to offer a better ranking of the different operators since based on less variables.

7.2.4 Analysis of the most innovative and underperforming companies for 2014-2017

After having reviewed the global tendency of the productivity, we found it relevant to analyze more deeply which companies have been showing the best improvements for the recent years. A sample composed of the 15 best performing operators according to the MPI between the year 2014 and 2017 has been retained. Those operators can be summed up in Table 7.8 in a descending order. There is no doubt that a distribution utility presenting a low efficiency score will have more potential to improve. For this reason, the last column representing the mean between the efficiency scores obtained in the last four years has also been added.

Operators	2014-2015	2015-2016	2016-2017	2014-2017	Average efficiency score
Njudung Vetlanda	1.2197	1.0096	0.9562	1.1626	0.7531
Falbygdens Energi	1.0332	1.0795	1.0271	1.1492	0.6810
Södra Hallands Kraft	1.0097	1.1754	0.9785	1.1466	0.6930
Vattenfall Elec.	0.9300	0.9686	1.3477	1.1455	0.7987
Ulricehamns Energi	1.0229	1.0198	1.0808	1.1329	0.8176
Hamra Besparingsskog	1.0570	0.9893	1.0491	1.1262	0.8620
Övertorneå Energi	1.0330	0.9710	1.1306	1.1262	0.8467
Vara Energi	1.0811	0.9988	1.0375	1.1258	0.8481
Härjeåns Nät	1.0679	0.9579	1.0387	1.0972	0.6310
Åsele Elnät	1.0386	1.0202	1.0387	1.0920	0.7403
C4 Elnät	1.0652	1.0698	0.9899	1.0920	0.8781
Olofströms Kraft	1.0258	1.0325	1.0255	1.0919	1
Brittedals Elnät	1.0108	1.0192	1.0548	1.0888	0.6920
E.ON Elnät Stockholm	1.0608	1.0651	0.9724	1.0879	0.9913
Ljusdal Elnät	1.0814	0.9652	1.0196	1.0779	0.6992

Table 7.8: Innovative operators 2014-2017

Above all, some precautions need to be taken with these results. It can be seen that according to our results, some operators sometimes present outstanding productivity improvement such as *Njudung Vetlanda*, *Södra Hallands Kraft* or *Vattenfall Electricity Distribution* with productivity improvement of 21%, 17% and 34% between two periods.

Those results seem highly unrealistic from a common sense perspective. As said earlier, the possibility of a change in reporting is a plausible hypothesis to explain at least partly the productivity development of those firms.

Nonetheless, constant productivity development for a company such as *Falbygdens Energi* cannot be denied. This company presents an average efficiency score significantly below average but has been able to work out how to make its operations more efficient. Other companies having high efficiency requirements could get inspired of this example to catch-up more quickly to best-practice.

Finally, in green is depicted the company *Olofströms Kraft*. In spite of being on the best-practice frontier, the operator seems to keep improving its productivity. According to Färe et al. (1994), this company can be considered as the most innovative operator since it contributes in moving the best-practice frontier. Specific research of that operator is certainly meaningful in order to detect the cause of the productivity development.

From an opposite perspective, it can be interesting to assess the underperforming operators of the industry over the last four years. The fifteen companies presenting the worst productivity development between 2014 and 2017 have been summed up in Table 7.9 in a descending order.

Operators	2014-2015	2015-2016	2016-2017	2014-2017	Average efficiency score
LKAB Nät	0.9938	0.9892	0.9055	0.8836	0.6592
Nacka Energi	1.0151	0.9762	0.9064	0.8827	0.8919
Mölndal Energi Nät	1.0105	0.8668	1.0155	0.8814	1
Trelleborgs kommun	1.0330	0.9521	0.9013	0.875	0.7584
Oxelö Energi	1.0041	0.8017	1.0677	0.8583	1
Landskrona Energi	1.0061	0.9547	0.9142	0.8566	0.9828
Blåsjön Nät	1.03317	0.6994	1.1381	0.8532	0.7210
Mellersta Skånes Kraft	1.0353	0.9204	0.9011	0.8537	0.7922
Bodens Energi Nät	1.0981	0.8818	0.8660	0.8354	0.832
Bergs Tinglsags Elec.	0.8147	1.0146	1.0092	0.8137	0.6390
Skövde Nät	0.8437	0.9577	0.9879	0.8118	1
Mälar Energi Elnät	0.8972	0.9064	0.9972	0.8090	0.8860
Gotlands Elnät	0.8945	0.8564	0.9671	0.7499	0.8275
Skyllbergs Bruks	0.7696	0.9044	0.9969	0.7391	0.9561
Sturefors Eldistri.	1.0349	0.6582	0.9301	0.6550	0.8885

Table 7.9: Underperforming operators 2014-2017

Again, these results should be taken cautiously given that some changes in reporting could have occured. However, for companies presenting constantly negative productivity improvement, it cannot be denied that some aspects of the operations should be questioned.

On the one hand, highlighted by the presence of three peer firms in the 15 underperforming operators, it can be supposed that peer firms will more often tend to rely too much on their high efficiency score. A lack of incentives could be the reason since fully efficient operators would have the same efficiency requirement even in case of negative productivity development because they are already entirely efficient. In other words, they would have no incentives to decrease their costs, since it will not affect their efficiency score. A system based on super-efficiency seems to be an option to solve, at least partially, this issue and to keep giving incentives to the best operators to reduce their costs.

On the other hand, two companies, *Bergs Tinglsags Elec.* and *LKAB Nät*, depicted in red, demonstrate relatively low efficiency score and are apparently struggling with catching-up to best-practice. These results show that a special care in the monitoring of these companies would certainly be needed. While *Bergs Tinglsags Elec* can be seen as a typical operator, the nature of *LKAB Nät* can certainly explain why the average efficiency score is so low. Indeed, *LKAB Nät* is an operator devoted only to providing electricity to the mining company of the same name. The company is characterized by a modest amount of customers and a higher energy consumption per capita. Thus, ceteris paribus, *LKAB Nät* will present lower efficiency scores due to less customers than a similar company operating in normal conditions.

7.2.5 Second stage analysis

7.2.5.1 Comparisons between the types of ownership

The Kruskal-Wallis test has again been applied in order to account for possible divergence in the efficiency scores according to the ownership type. For the period of 2011-2015, 90 of the 142 operators were classified as publicly-owned while 25 and 26 were respectively labelled as private and cooperative companies. The samples for 2014-2017 were compounded of 99, 25 and 27 operators for the samples with publicly-owned, private and cooperative firms respectively.

Table 7.10 summarizes the main results of the test.

Year	Statistical value	P-value
2011	4.658	0.0974
2012	7.471	0.0239
2013	6.173	0.0457
2014	5.800	0.0550
2015	2.707	0.2583
2014	0.118	0.9426
2015	0.308	0.8575
2016	0.734	0.6928
2017	1.935	0.3800

Table 7.10: Kruskal-Wallis test 2011-2017

These results appear to be a bit puzzling. Indeed, while the test indicates clearly no difference in performance according to the ownership structure for the period 2014-2017, the test conducted for the period 2011-2015 seems to indicate us the opposite. Even worse, the results for the year 2014 show two opposite things. If the capital costs are valued with the real annuity method, it seems that a difference does exist according to the structure of the ownership while no difference is detected when the capital costs are valued with a linear depreciation method.

As said earlier, the test only points that a difference between the samples exist but does not provide us with information concerning its nature. The different average efficiency scores per type of ownership allows us to understand the difference between the type of ownership.

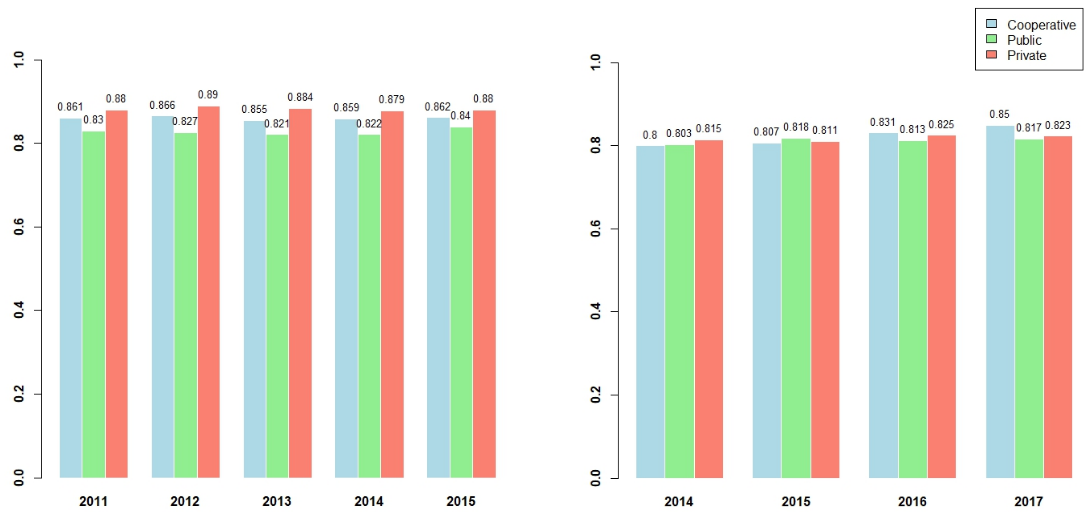

Figure 7.8: Efficiency scores per type of ownership 2011-2017

We see that operators with private ownerships perform better than municipally-owned and cooperative distribution utilities according to data collected for 2011-2015. On the contrary, no real difference can be distinguished for the period 2014-2017.

An explanation of the difference between the two sets of data can be found when remembering the reasons of the change from a real annuity method to a linear depreciation. As a reminder, the objective was to provide operators with additional incentives to invest in the renewal of their grids by rewarding the operators with a newer network by the means of a higher revenue cap. Since the real annuity method proposed a linear rate following the type of the assets without accounting for the age of them, it was in the interest of an operator to save its money and to maintain as long as possible its old grid, given that expenditures in a new grid would not result in an increase in the capital costs and therefore the revenue cap. On the contrary, with a linear depreciation valuation, the capital costs are higher for an operator with a recent grid, resulting in a higher revenue cap. Besides, reforms in 2016 concerning the incentive mechanism for a reliable supply also probably played a role in the renewal of the grid of the operators (cf. Appendix 1).

In our model, this effect leads to higher capital costs and a decreased efficiency for the operators with a recent grid if the capital costs are assessed through linear depreciation. In other words, a firm with an old grid will obtain higher efficiency scores than a similar firm with a more recent grid. This bias can be observed in Figure 7.8. The privately owned companies are not performing better than municipally owned and cooperative operators when capital costs are valued with a linear depreciation method unlike when the capital costs are valued with a real annuity value. In view of the results, we can reach the conclusion that there is probably a difference in the age-structure between private, cooperative and municipally-owned operators, which will lessen the average efficiency scores of the private companies in comparison with the cooperative and publicly-owned companies since having a newer grid. The reason of this more recent grid remains in the fact that private operators are more monitored than cooperative and publicly owned companies. Therefore, new investments will be realized regularly to optimize their operations. The private companies will notice the incentives faster and maximize their revenue cap. This is especially true given the fact that the operators are allowed to retain a part of their efficiency gains according to the SEI policy. On the contrary, municipalities and cooperatives will often feel less the need to renew their grid, their first goal being simply to ensure a decent supply of electricity and their financial results being less closely monitored.

7.2.5.2 Other environmental factors

Secondly, it can be interesting to have some insights on different environmental factors. Using a Tobit regression, the objective is to assess if some environmental factors can explain the efficiency scores of the operators.

Given the lack of environmental information, the factors were created thanks to the variables used in Model 2. This also explains why they have not been included in Model 2. The two environmental factors tested are (1) the customer density, approximated by dividing the amount of connections by the number of network stations and (2) the high-voltage network proportion that refers to the ratio of high-voltage electricity on the total electricity delivered by an operator.

Regarding (1), it appears likely that some economies of scale would allow operators in urban areas to be more efficient than operators in rural areas. The intuition is that the capital costs are highly correlated to the number of network stations and a firm operating in a low-density area will therefore have more network stations and more costs than a firm providing electricity in a urban area, which will counter balance its high costs in comparison with its number of connections. Another way of estimating the customer density would have been to relate the number of customers with the network length of an operator. Nevertheless, it has not been set up by the SEI which estimated that only including the two variables in the model would be sufficient.

Regarding (2), operators can have higher efficiency scores when providing mainly high-voltage since it implies fewer losses for the same amount of electricity delivered. Once again, EI tried to account for this difference by discerning low and high-voltage electricity delivered in the outputs. This implies that a company with a large proportion of high-voltage electricity delivered can still be considered as efficient even if having higher costs than a company delivering the same amount of energy but through low-voltage lines.

As underlined in the previous paragraph, these environmental factors are supposed to be taken into consideration by the model of SEI. However, results obtained summed up in Table 7.11 below offer us another perspective. For each year is written the environmental factor coefficient while the p-value is depicted in parenthesis. As a reminder, the smaller the p-value, the higher the probability that the environmental factor exerts an influence on the efficiency scores.

Year	**Customer density**		**HV network proportion**	
	Intercept	Slope	Intercept	Slope
2011	0.8221(0.0000)	0.0007(0.0491)	0.8418(0.0000)	0.0458(0.4910)
2012	0.8280(0.0000)	0.0006(0.0905)	0.8528(0.0000)	0.0141(0.8450)
2013	0.8168(0.0000)	0.0007(0.0563)	0.8322(0.0000)	0.0682(0.329)
2014	0.8297(0.0000)	0.0004(0.2800)	0.8365(0.0000)	0.04455(0.512)
2015	0.8218(0.0000)	0.0009(0.0141)	0.8396(0.0000)	0.1001(0.1590)
2014	0.7745(0.0000)	0.0008(0.0193)	0.7844(0.0000)	0.1083(0.0988)
2015	0.7675(0.0000)	0.0013(0.0003)	0.7858(0.00000)	0.1686(0.0154)
2016	0.7623(0.0000)	0.0015(0.0000)	0.7961(0.0000)	0.1311 (0.0509)
2017	0.7879(0.0000)	0.0010(0.0040)	0.8080(0.0000)	0.1058(0.1210)

Table 7.11: Tobit regression 2011-2017

As can be seen, results from the two sets of data seem to converge to say that the customer density is probably a factor related to the efficiency score. Nevertheless, the fact that the customer density is related to the efficiency score does not mean that it is the cause. A confounding factor could exist. The climate can influence both the customer density and the costs related to the grid of an operator. For instance, a cold climate would result in a lower customer density and higher cost. This is especially true in a country like Sweden with some areas facing extreme temperatures or climatic conditions. Therefore, some other environmental variables need to be tested and possibly integrated to take into account these effects and provide a fairer benchmarking to the operators.

Concerning the proportion of high-voltage energy delivered, the results are more balanced. On the one hand, no link can be found when applying the Tobit regression on the efficiency scores obtained from the data for 2011-2015. On the other hand, a link seems somewhat probable when looking at the p-value for 2014-2017. Once again, it seems that the valuation method of the capital costs would be relevant to explain these differences. However, more research would be needed to understand these results.

7.3 Limitations of the research

In view of these results, it is however important to bear in mind that the results displayed in this chapter does not offer us a perfect picture of the real activities of the operators. The productivity change could appear utterly different with the use of other variables. For instance, the inclusion of non-discretionary variables related to geographical conditions would certainly have been useful for our two models.

Besides, as already explained, the operators are constantly trying to maximize their revenue cap. Thus, incentives given to operators to have higher capital costs and controllable operating costs can bias the two models. For instance, the reward of the operators with a more recent grid will penalize them in our model since it will lead to higher capital costs.

A change in the reporting of the cost is also likely to affect our model. As an example, at the end of each regulatory period, the return on capital is reassessed. This results in different capital costs for a same operator with the same operation conditions.

Finally, even if comprising most of the Swedish operators, there is still a possibility to obtain different results with all the operators present in the distribution sector. We can also question if the operators presenting excellent performance are not merely the luckiest firm of our samples. The causality of a bright management of these operators and their excellent performances is not demonstrated.

8 Conclusion

In this research, we have attempted to perform an evaluation of the productivity development of the Swedish electricity distribution sector. This thesis echoes the lack of productivity development research in Sweden within the last years. Besides, it was also the opportunity to evaluate both the demoted Network Performance Assessment Model and the Revenue Cap Model established since 2012. At first, a review of the literature has been achieved. The main families of regulatory regimes for network regulations and the previous Swedish regimes were introduced. Then, the benchmarking methods extensively employed throughout this research were presented.

The productivity has been assessed by means of the Malmquist index following the decomposition proposed by Färe et al. (1994) and Ray and Desli (1997) for both the period 2002-2006 and 2011-2017. Besides, these two distinct analysis have been completed by second stage analysis aiming to determine if the ownership structure or environmental factors could contribute to the productivity development. Note that due to a difference in reporting the capital costs, the period 2011-2017 was divided into two distinct periods: 2011-2015 with capital costs based on an annuity depreciation method; 2014-2017 with capital costs based on a linear depreciation method.

After the completion of the analysis for 2002-2006, it may be concluded that:

1. The industry was more heterogeneous than now with many peer and underperforming operators.
2. Many of the operators already had an optimal size. This is the sign that the industry was already mature.
3. The low-powered NPAM regime did not provide proper incentives to the productivity development of Swedish operators.
4. Privately owned distribution utilities seemed to perform better than municipally owned and cooperative operators.

Secondly, the analysis for the period 2011-2017 added many interesting conclusions:

1. The efficiency scores has shown that the technologies employed by the firms are

quite homogeneous.

2. The productivity has raised in 2011-2012 due to an increase in the electricity delivered and possibly due to a ratchet effect before the establishment of the Revenue Cap Model.

3. The productivity fell slightly in 2012-2015 but is due to a decrease of the electricity consumption

4. The productivity grew mildly in 2014-2017 if we do not take into account change in reporting.

5. The general efficiency requirement of 1% imposed by the EI would need to be reassessed since it does not reflect the global productivity growth of the operators.

6. The recent inclusion of an individual efficiency requirement by the Swedish regulator seems to be effective with a catch-up to best-practice by the least competitive operators.

7. The operators located on the best-practice frontier present a lower productivity development than the industry. A mechanism to maintain incentives to improve such as super-efficiency would be relevant to solve this issue.

8. The private companies are likely to perform better than cooperative and municipal operators given that their network appears to be more modern and reliable.

9. A link can be found between the performance of an operator and the density of its customers.

Nevertheless, these results need to be contrasted by some major limitations. The choice of the variables is also debatable and other benchmarking models would have certainly given significant divergences in their results. For instance, the real performance of the operators could be utterly different if non-discretionary variables accounting for the geographical, topological and climatic conditions were included in the two models. Besides, the linear depreciation of the assets is a bias to the capital costs and an operator with an old grid will perform better than a similar operator with a newer grid. Oppositely, an operator will be penalized if its grid is recent. The quality of our data can also be discussed. Indeed, it seems that costs have probably been reported differently throughout the years. Finally, note that some operators were not included in our samples. Therefore, the results obtained in this research may not correspond perfectly to the real situation of the distribution sector.

In light of those limitations, additional research need to be conducted with other samples, models and productivity tools in order to define with certainty the productivity development of the Swedish distribution operators. A particular emphasis is placed on model which would incorporate geographical variables. Productivity development studies of electricity distribution sectors in other Scandinavian countries would also be relevant in order to understand the differences between the distribution sectors. Case studies to explain the noticeable performances of the most and least competitive operators underlined by this study could be achieved as well.

References

Agrell, P. and Grifell-Tatjé, E. (2016). A dynamic model for firm response to non-credible incentive regulation regimes. *Energy Policy*, 90(3):287–299.

Agrell, P. and Niknazar, P. (2014). Structural and behavioral robustness in applied best-practice regulation. *Socio-Economic Planning Sciences*, 48(3):89–103.

Agrell, P. J. (2015). Incentive regulation of networks: Concepts, definitions and models. *Reflets et perspectives de la vie économique*, 54(1-2):103–132.

Agrell, P. J. and Bogetoft, P. (2017). Regulatory benchmarking: Models, analyses and applications. *Data Envelopment Analysis Journal*, 3(1-2):49–91.

Agrell, P. J., Bogetoft, P., and Tind, J. (2005). Data envelopment analysis and dynamic yardstick competition in scandinavian electricity distribution. *Journal of Productivity Analysis*, 23(2):173–201.

Agrell, P. J. and Brea-Solís, H. (2017). Capturing heterogeneity in electricity distribution operations: A critical review of latent class modelling. *Energy Policy*, 104:361–372.

Agrell, P. J. and Teusch, J. Making the belgian distribution system fit for the energy transition: The case for yardstick competition. *Reflets et Perspectives*, 2(1-2).

Aigner, D., Schmidt, P., and Lovell, K. (1973). Formation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1):21–37.

Amado, C., Santos, S., and Sequeirac, J. (2013). Using data envelopment analysis to support the design of process improvement interventions in electricity distribution. *European Journal of Operational Research*, 228(1):226–235.

Armstrong, M. and Sappington, D. (2007). *Recent Developments in the Theory of Regulation*, volume 3, chapter 27, pages 1557–1700. Elsevier.

Banker, R. (1993). Maximum likelihood, consistency and data envelopment analysis: A statistical foundation. *Management Science*, 39(10):1265–1273.

Banker, R. and Chang, H. (2006). The super-efficiency procedure for outlier identification, not for ranking efficient units. *European Journal of Operational Research*, 175(2):1311–1320.

Banker, R., Charnes, A., and Cooper, W. (1984). Some models for estimating technical and scale inefficiency in data envelopment analysis. *Management Science*, 30(9):1078–1092.

Banker, R., Charnes, A., Cooper, W., Swarts, W., and Thomas, D. (1989). An introduction to data envelopment analysis with some of its models and their uses. research in governmental. *Research in Governmental and Nonprofit Accounting*, 5(1):125–163.

Banker, R. and Morey, R. (1986). Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research*, 34(4):513–521.

Barnett, V. and Lewis, T. (1994). *Outliers in statistical data*, volume 3. Wiley Sons Edition.

Battese, G. and Coelli, T. (1992). Frontier production functions, technical efficiency and panel data: Wi *Journal of Productivity Analysis*, 3(1-2):153–169.

Bishnoi, N. and Gaur, P. (2018). Decomposition of malmquist productivity index using technical and financial paremeters: A case of indian electricity distribution utilities. *Productivity*, 59(3):293–310.

Bjørndal, E. (2018). Regulation and benchmarking of network companies.

Bjørndal, E., Bjørndal, M., and Fange, K.-A. (2010). Benchmarking in regulation of electricity networks in norway : An overview.

Bogetoft, P. (2012). *Performance Benchmarking: Measuring and Managing Performance*. Springer Science Business Media, New York.

Bogetoft, P. and Otto, L. (2011). *Benchmarking with DEA, SFA, and R*. Springer Science Business Media, New-York.

Caves, D., Christensen, L., and Diewert, E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica: Journal of the Econometric Society*, 50(6):1393–1414.

Charnes, A., Cooper, W., and Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6):429–444.

Chaudhuri, D. (2016). Impact of economic liberalization on technical efficiency of firms: Evidence from india's electronics industry. *Theoretical Economics Letters*, 6(3):549–560.

Cheng, X., Bjørndal, E., Gudbrand, L., and Bjørndal, M. (2014). *Productivity Development for Norwegian Electricity Distribution Companies 2004-2013 (Doctoral dissertation)*. Discussion paper, Norwegian School of Economics, Department of Business and Management Science.

Coelli, T., Estache, A., Perelman, S., and Trujillo, L. (2003). A primer on efficiency measurement for utilities and transport regulators. Technical report, Washington DC, USA.

Coelli, T., Rao, D. P., O'Donnell, C., and Battese, G. (2005). *An introduction to efficiency and productivity analysis*. Springer, New-York.

Cook, W. and Seiford, L. (2009). Data envelopment analysis (DEA): Thirty years on. *European Journal of Operations Research*, 192(1):1–17.

Cooper, W., Seiford, L., and Tone, K. (2007). *Data Envelopment Analysis*. Kluwer Academic Publishers, New York.

Cooper, W. W., Seiford, L. M., and Zhu, J. (2004). *Handbook on Data Envelopment Analysis*. Springer.

Council of European Energy Regulators, C. (2019). Report on regulatory frameworks for european energy networks. Technical report, Brussels.

Daraio, C. and Simar, L. (2007). *Advanced Robust and Nonparametric Methods in Efficiency Analysis*. Springer, Boston.

Edvardsen, D. F. and Førsund, F. (2003). International benchmarking of electricity distribution utilities. *Resource and Energy Economics*, 25(4):353–371.

Eisenhardt, K. (1989). Agency theory: An assessment and review. *The Academy of Management Review*, 14(1):57–74.

Ek, G. and Fredriksson, Y. (2010). Förhandsregleringens krav på effectiviseringar. Technical report, Eskilstuna, Sweden.

Farrell, M. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120(3):253–290.

Färe, R., Grosskopf, S., Lingren, B., and Roos, P. (1992). Productivity changes in swedish pharamacies 1980-1989: A non-parametric malmquist approach. *The Journal of Productivity Analysis*, 3(2):85–101.

Färe, R., Grosskopf, S., Norris, M., and Zhang, Z. (1994). Productivity growth, technical progress and efficiency change in industrialized countries. *The American Economic Review*, 84(1):66–83.

Färe, R., Grosskopf, S., and Roos, P. (1998). *Malmquist productivity indexes: A survey of theory and practice*, pages 127–190. Springer, Boston.

Førsund, F. (2002). On the circularity of the Malmquist productivity index. *Working Paper Series from RePEc.*

Førsund, F. and Kittelsen, S. (1998). Productivity development: Norwegian electricity distribution utilities. *Resource and Energy Economics*, 20(3):207–224.

Hackett, S. (2010). *Environmental and natural resources economics: Theory, policy and the sustainable society.* ME Sharpe, London.

Hattori, T., Pollitt, M., and Jamasb, T. (2005). Electricity distribution in the uk and japan: A comparative efficiency analysis 1985-1998. *The Energy Journal*, 26(2):23–47.

Hjalmarsson, L. and Veiderpass, A. (1992). Productivity in swedish electricity retail distribution. *Scandinavian Journal of Economics*, 94:193–205.

Hollingsworth, B. (2003). Non-parametric and parametric applications measuring efficiency in health care. *Health Care Management Science*, 6(4):203–218.

International Energy Agency, I. (2019). Energy policies of countries: Sweden. Technical report.

Jamasb, T. and Pollitt, M. (2001). Benchmarking and regulation: international electricity experience. *Utilities Policy*, 9(3):107–130.

Jamasb, T. and Pollitt, M. (2007). Reference models and incentive regulation of electricity distribution networks: An evaluation of sweden's network performance assessment model. *Energy Policy*, 36:1788–1801.

Joskow, P. L. (2008). Incentive regulation and its application to electricity networks. *Review of Network Economics*, 7:1–14.

Kahn, A. (1970,1971). *The Economics of Regulation: Principle and Institutions*, volume 1-2. Whiley, New-York.

Korhonen, P. and Syrjänen, M. (2003). Evaluation of cost efficiency in finnish electricity distribution. *Annals of Operational Research*, 121(1-4):105–122.

Kruskal, W. and Wallis, A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association*, 47(260):583–621.

Laffont, J.-J. and Tirole, J. (1993). *A Theory of Incentives in Procurement and Regulation*. MIT Press, Boston.

Lantz, B. (2003). Nätnyttomodellens regleringsprincip. Technical report, Sweden.

Larsson, M. B.-O. (2005). *A new framework of regulating the Electricity Network Companies*. Phd. thesis, KTH School of Electrical Engineering, Sweden.

Littlechild, S. (1983). Regulation of british telecommunications profitability: report to the secretary of state. Technical report, Department of Industry.

Littlechild, S. and Beesley, M. (1989). The regulation of privatized monopolies in the united kingdom. *The RAND journal of economics*, 20(3):454–472.

Lovell, K. (1993). *Production Frontiers and Productive Efficiency*. Oxford University Press, New-York.

Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de Estadistica y de Investigacion Operativa*, 4:209–242.

Maniadakis, N. and Thanassoulis, E. (2004). A cost Malmquist productivity index. *European Journal of Operational Research*, 154(2):396–409.

Miguéis, V., Camanho, Bjørndal, E., and Bjørndal, M. (2012). Productivity change and innovation in Norwegian electricity distribution companies. *Journal of the Operational Research Society*, 63(7):982–990.

Nishimizu, M. and Page, J. M. (1982). Total factor productivity growth, technological progress and technical efficiency change: Dimensions of productivity change in yugoslavia, 1965-1978. *The Economic Journal*, 92(368):920–936.

Nordic Energy Regulators, N. (2011). Economic regulation of electricity grids in Nordic countries. Technical report, Copenhagen.

Parteka, A. and Wolszczak-Derlacz, J. (2013). Dynamics of productivity in higher education: Cross-european evidence based on bootstrapped malmquist indices. *Journal of Productivity Analysis*, 40(1):67–82.

Pastor, T. J. and Lovell, C. K. (2006). Circularity of the Malmquist productivity index. *Economic Theory*, 33:591–599.

Persson, L. and Tornqvist, J. (2006). Elnätbolagens anpassning till nätnittomodellen. Master's thesis, School of Business, Economics and Law, Gothenburg University, Sweden.

Rahimiana, M. and Soltanifar, M. (2013). An application of the malmquist productivity index in university performance analysis. *Management Science Letters*, 3(1):337–344.

Ray, S. (1991). Resource-Use Efficiency in Public Schools: A Study of Connecticut Data. *Management Science*, 37(12):1620–1628.

Ray, S. and Desli, E. (1997). Productivity growth, technical progress, and efficiency change in industrialized countries: Comment. *The American Economic Review*, 87(5):1033–1039.

Ruggiero, J. (1996). On the measurement of technical efficiency in the public sector. *European Journal of Operations Research*, 90(3):553–565.

Ruggiero, J. (1998). Non-discretionary inputs in data envelopment analysis. *European Journal of Operations Research*, 111(3):461–469.

Ruggiero, J. (2004). Performance evaluation when non-discretionary factors correlate with technical efficiency. *European Journal of Operations Research*, 159(1):250–257.

Schweinsberg, A., Stronzik, M., and Wissner, M. (2011). Cost benchmarking in energy regulation in european countries. Technical report, Wik-Consult.

Shleifer, A. (1985). A theory of yardstick competition. *The RAND Journal of Economics*, 16(3):319–227.

Swedish Energy Inspectorate, S. (2018). Network price regulation.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica*, 26(1):24–36.

Tovar, B., Ramos-Real, F., and Almeida, E. (2011). Firm size and productivity: Evidence from the electricity distribution industry in brazil. *Energy Policy*, 39(2):826–833.

Wallnerström, C. and Bertling, L. (2008). Investigation of the robustness of the swedish network performance assessment model. *IEE Transaction on Power System*, 23(2):773–780.

Wallnerström, C. and Bertling, L. (2010). Learning from experiences of the prior swedish electrical distribution system regulation. *IEEE PES Innovative Smart Grid Technologies Conference Europe.*

Wallnerström, C., Grahn, E., and Johansson, T. (2016). The regulation of electricity network tariffs in sweden from 2016. Technical report, Swedish Energy Market Inspectorate, Stockholm.

Wangensteen, I. (2012). *Power System Economics: the Nordic Electricity Market*. Tapir Academic Press.

Wangensteen, I. and Dahl, E. (1989). An investigation of distribution costs by means of regression analysis. *IEE Transactions on Power Delivery*, 5(1):521–526.

Zou, P., Hang, B., and Poh, K. (2008). A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research*, 189(1):1–18.

Çelen, A. (2013). Efficiency and productivity of the turkish electricity distribution companies: An application of two-stage analysis. *Energy Policy*, 63:300–310.

Appendix

A1 Adjustments of the Revenue cap - Swedish regulatory scheme

Three adjustments of the revenue cap were conducted by the Swedish regulator. All the explanations provided below have been taken from the paper of Wallnerström and al.(2016).

A1.0.1 Quality

The quality adjustments is calculated from the information yearly provided by every operator concerning their outages planned or unplanned faced in the past year. Because customers have different outage costs (no electricity for a company will have a greater impact than for a household for instance), every customer belongs to one of the five categories facing different outage costs determined in advance by the EI. The annual quality adjustments are computed for each operator as follows:

$$Q = \sum_{k=1}^{5} \sum_{j=1}^{2} \big((SAIDI_{b,j,k} - SAIDI_{o,j,k})Ke_{j,k} + (SAIFI_{b,j,k} - SAIFI_{o,j,k})Kp_{j,k}\big)P_{av}$$

where SAIDI is the system average interruption duration index and SAIFI the system average interruption frequency index, k represents the customer group concerned and j the nature of the interruption (planned or unplanned), b is the norm level (that is to say, the SAIDI and SAIFI levels tolerated by the EI) and o is the outcome during the period of regulation, Ke is the cost parameter given in SEK/kWh, Kp is the cost parameter given in SEK/kW and P_{av} is the average yearly power usage defined as a fraction between the total energy consumption for a customer and the number of hours within a year.

A1.0.2 Energy losses

The energy losses are considered as non-controllable costs. However, on the long run, lines can be changed. For this reason, the following incentive mechanism has been imagined.

$$L = \frac{(N_{\text{norm}} - N_{\text{turn-out}})pE_{\text{turn-out}}}{2}$$

where N_{norm} and $N_{turn-out}$ are respectively the historical average share of electricity network losses in the previous regulatory period and the share of network losses for the operator during the year in percentage.The parameter p is the corresponding price per megawatt hour for network losses calculated as an average price during the regulatory period and $E_{turn-out}$ represents the amount of distributed energy during the regulatory period.

A1.0.3 System utilization

The cost for feeding grid paid to the superior operator is comprised in the non-controllable cost and therefore the consumer has to pay for it. Nevertheless, this tariff often depends on the highest load. Since the network is designed to consider the peak loads, the capacity of the system will rarely be fully utilized and a better utilization leads to lower tariffs. To account for this, the following equation depicts the incentive measure set up the EI:

$$U = \left\{ \begin{array}{c} |\text{Lf}_{turn-out} * B_{\text{diff}} * E_{\text{turn-out}} \quad if \quad B_{\text{diff}} < 0 \\ 0 \quad \text{if} \quad \text{B}_{\text{diff}} \leq 0 \end{array} \right\}$$

where s the sum of all daily load factors Lf_i divided by the number of days during the regulatory period. $B_{\text{diff}} = B_{\text{norm}} - B_{\text{turn-out}}$ is the saving for the cost that DSOs pay to the feeding grid (kSEK/MWh). This can be computed as the difference between the cost paid to the superior grid during the previous period and during the current regulatory period divided by the amount of distributed energy during the period (SEK/MWh). $E_turnout$ is the distributed energy during the regulatory period (MWh).

The term $Lf_{\text{turn-out}}$ can be found as follows:

$$Lf_{\text{turn-out}} = \frac{\sum_{i=1}^{D} Lf_i}{D}$$

where Lf_i is the average load divided by the maximum load in day i and D is the amount of day for the regulatory period.

A1.1 Consequences on the revenue cap

Based on the incentives presented previously, the total adjustment of the revenue cap (RC) can be computed as shown below:

$$\text{Total adjustments} = \left\{ \begin{array}{c} \text{-0.05[RC]} \quad \text{if} \quad \text{(Q+L+U)} \leq -0.05\text{[RC]} \\ +0.05\text{[RC]} \quad \text{if} \quad \text{(Q+L+U)} \geq +0.05\text{[RC]} \\ \text{Q+L+U} \quad \text{otherwise} \end{array} \right\}$$

A2 Outliers

We can distinguish two different definitions according to Agrell and Niknazar (2014):

"According to a typical intrinsic definition, cf. Barnett and Lewis (1994), an outlier is an observation which appears to be inconsistent with the rest of the data set [...] According to an influence perspective, a unit acquires the quality of outlier for a given method and reference set through the (undue) impact that its inclusion exerts on the quality of the estimation."

In view of those two different definitions, two different methods has been used.

A2.1 Outliers via data cloud method

For outliers such as presented in the first definition, we will use what is commonly called the data cloud method (Bogetoft and Otto, 2011). This method first consists of computing the determinant of the matrix representing the dataset. Since this determinant is directly proportional to the volume of the data cloud, removing outliers would greatly reduce the data cloud and therefore the determinant. Therefore, a determinant being far lower than the initial determinant after the removal of an observation underlines that it is part of the outliers.

In light of what has been said, let us consider the following ratio:

$$R^i = \frac{D^i}{D} \tag{.1}$$

Where D^i is the determinant without the observation(s) i and D is the initial determinant.

The method proposed relies on an iterative process that aims to deduce which observation are minimizing the ratio R^i when deleted. Since the process requires an exponential number of combination as the number of observations deleted increases, the reasonable number of three observations removal is chosen as the best trade-off between the time consumed and the accuracy of the answer.

Results for the dataset 2002-2006 can be observed in Table A2.1.

Additional firm deleted	Firms deleted (DSO number)	R^i
2002-2006		
Vattenfall Eldistribution AB	583	0.0822
E.ON Elnaet Sverige AB	583,593	0.0094
Fortum Distribution	583,593,176	0.0013
2011-2015		
Jukkasjärvi Sockens	83	0.0081
E.ON Energidistribution	93, 957	0.0009
Ellevio AB	93,957,3008	0.0000
2014-2017		
Jukkasjärvi Sockens	93	0.0015
E.ON Elnät Sverige	93,957	0.0002
Vattenfall Eldistribution	93,957,572	0.0000

Table A2.1: Outliers according to the data cloud method

A2.2 Outliers via super-efficiency

Another way of determining the outliers proposed by Banker and Chang (2006) is to make use of the super-efficiency. The main idea is to compute the super-efficiency of each firm. If the super-efficiency is higher than a predetermined threshold, the observation will be seen as greatly influencing the best-practice frontier. The method suggested to compute the threshold according to the data is to use the following formula:

$$T = q(0.25) + 2 * [q(0.75) - q(0.25)] \tag{.2}$$

Based on this method, outliers for our different dataset are displayed in Table A2.2

2002-2006	Super-efficiency
Larvs Elektriska	1.48
LJW Naet HB	2.50
NVSH Energi AB	1.53
2011-2015	
Carlfors Bruk	99.66
Sturefors Eldistribution	10.10
Vaggeryds kommun	1.56
2014-2017	
Carlfors Bruk El. Björklund	32.40
Jukkarsjärvi Belysnings.	3.32
Vaggeryds kommun Elverket	1.72

Table A2.2: Outliers according to the super-efficiency method

A2.3 Discussion

In view of the table presented, it can first be concluded that the two methods lead to sensible different results when classifying observations as outliers, confirming our intuition that several kinds of outliers exist. Another conclusion regarding the data cloud methods is that it tends to systematically detect biggest operators as outliers. Based on this, only outliers detected thanks to the super-efficiency method are removed.

A3 Variables significance

A3.1 Inputs and outputs

It is important to verify that our models fits correctly to the data. On the one hand, a simplified model would offer less accurate performance. On the other hand, it would increase the discriminatory power of the model and allows a clearer ranking of the firms. In order to determine the relevance of a variable, we can compare the efficiency scores which would be obtained with and without the variable. The intuition is that if efficiency scores deduced from the two models are divergent above a certain threshold, the initial model offers a better representation of the performance of the firms.

The Kolmogorov-Smirnov (KS) test proposed by Banker (1993) can be seen as a convenient test with free assumption on the distribution in order to test the significance of the variables. The test statistic can be defined as:

$$T_{KS} = max\{|G_1(E^k) - G_2(E^k)|\} \tag{.3}$$

Where G_1 and G_2 are the empirical cumulative distributions of the model with and without the variable such as T_{KS} is the largest vertical distance between the cumulative distribution. A large value for T_{KS} indicates that the distribution differ and therefore, that the variable is significant.

The results of the test on our set below.

Variable	Statistical value	P-value
2002-2006		
CAPEX	0.567	0.0000
OPEX	0.998	0.0000
Connections	0.062	0.0427
Power sub-transformers	0.017	0.7885
Peak load	0.0121	0.8858
Energy delivered LV	0.383	0.0000
Energy delivered HV	0.094	0.0006
2011-2015		
CAPEX	0.583	0.0000
Controllable OPEX	0.280	0.0000
Connections	0.096	0.0038
Network stations	0.371	0.0000
Peak load	0.005	0.9852
Energy delivered LV	0.238	0.0000
Energy delivered HV	0.149	0.0000
2014-2017		
CAPEX	0.673	0.0000
Controllable OPEX	0.280	0.0000
Connections	0.096	0.0038
Network stations	0.371	0.0000
Peak load	0.005	0.9852
Energy delivered LV	0.238	0.0000
Energy delivered HV	0.149	0.0000

Table A3.1: Kolmogorov-Smirnov test

The application of the Kolmogorov-Smirnov test shows interesting results. A first conclusion is that the number of power sub transformers does not seem to be a relevant variable for Model 1 and can be removed. Being highly insignificant, the variable referring to the peak load is also removed from Model 2.

A3.2 Non-discretionary variables

As you may have noticed, the non-discretionary variables of Model 1 have not been tested through the Kolmogorov-Smirnov test. Instead, Tobit regressions such as explained in Section 6.3.1 seem to be more adequate. To conduct these regressions, efficiency scores without the non-discretionary variables have been computed for each year. Then, the Tobit regression has been performed to see if there is any link between them and the non-discretionary variables.

Year	**Cable proportion**		**LV proportion**		**Network size**	
	Intercept	Coefficient	Intercept	Coefficient	Intercept	Coefficient
2002	0.459 (0.0000)	0.260 (0.0000)	0.485 (0.0000)	0.222 (0.1830)	0.636 (0.0000)	-0.0000 (0.679)
2003	0.453 (0.0000)	0.301 (0.0000)	0.316 (0.0030)	0.515 (0.0012)	0.661 (0.0000)	-0.0000 (0.463)
2004	0.463 (0.0000)	0.251 (0.0002)	0.471 (0.0000)	0.248 (0.1340)	0.636 (0.0000)	-0.0000 (0.937)
2005	0.479 (0.0000)	0.197 (0.0057)	0.531 (0.0000)	0.131 (0.445)	0.618 (0.0000)	-0.0000 (0.934)
2006	0.382 (0.0000)	0.347 (0.0000)	0.282 (0.0884)	0.521 (0.0012)	0.630 (0.0000)	-0.0000 (0.704)

Table A3.2: Tobit regression for 2002-2006

Obviously, a relation between the cable proportion and the efficiency score is detected. This legitimates its presence in the model.

A boxplot chart depicting the efficiency scores obtained with and without the non-discretionary variable is depicted below.

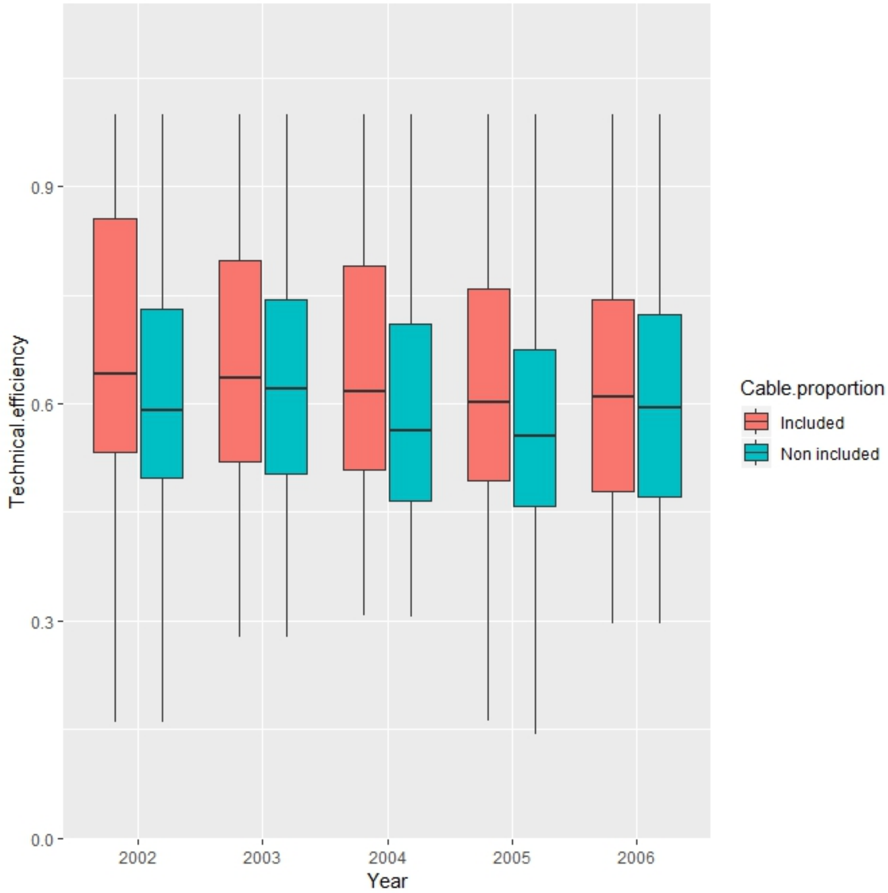

Figure A3.1: Efficiency scores with and without non-discretionary variables 2002-2006

A4 Effect on average productivity change when removing biggest operators

Year	MPI
2002-2006	-0.0090
2002-2003	-0.0032
2003-2004	-0.0028
2004-2005	-0.0092
2005-2006	0.0038
2011-2015	0.0001
2011-2012	0.0007
2012-2013	-0.0002
2013-2014	0.0000
2014-2015	-0.0005
2014-2017	-0.0003
2014-2015	-0.0011
2015-2016	0.0016
2016-2017	-0.0005

Table A4.1: Difference in the Malmquist with and without the biggest operators 2011-2017

A5 Histograms of the Malmquist index and its components 2002-2006

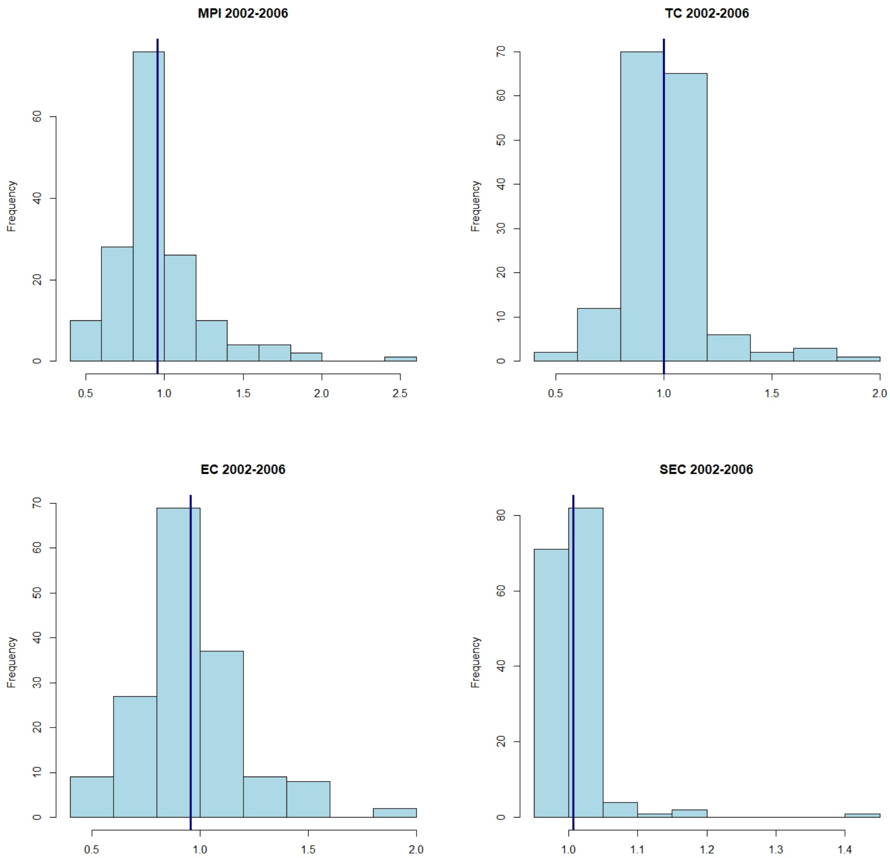

Figure A5.1: Histograms of the Malmquist index and components 2002-2006

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