Australian
Competition &
Consumer
Commission

Benchmarking Opex and Capex in Energy Networks

Working Paper no.6, May 2012

ACCC/AER WORKING PAPER SERIES

ISBN 978-1-921964-51-0

Citation details: ACCC/AER Working Paper 6 /May 2012

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Foreword

The working paper *Benchmarking Opex and Capex in Energy Networks* reviews five alternative benchmarking methods – namely partial performance indicators, index-number-based total factor productivity, econometric method, stochastic frontier analysis, and data envelopment analysis – with a particular focus on their use in the benchmarking and regulation of energy networks. The review covers published studies from the academic literature and also consulting reports written for regulatory purposes, as well as regulatory applications of benchmarking methods from 15 OECD countries, including Australia, New Zealand, the United States, Canada, Japan and various European countries (Austria, Denmark, Finland, Germany, Ireland, the Netherlands, Norway, Spain, Sweden, and the United Kingdom).

The paper covers the key methods, relevant literature and regulatory practices, as well as the major technical and implementation issues in benchmarking energy networks. This provides a resource that will be of substantial benefit to regulatory analysts in years to come. I found the various tables providing comprehensive and up-to-date summaries of the wide range of empirical studies to be particularly valuable.

The document carefully lists the advantages and disadvantages of each benchmarking method, in the context of regulation of energy networks. I was particularly pleased to see the emphasis that was placed on obtaining good-quality data, since this is a key prerequisite for any defendable benchmarking exercise. The majority of the data, acquired during regulatory processes and practices, would be fundamental to future benchmarking research.

Overall, I believe that this paper makes an important contribution to the current discussion of the use of benchmarking for price regulation in energy networks in Australia, and I hope that it will be widely read by stakeholders in Australia and where ever benchmarking is being used in regulatory processes.

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About the working paper

In November 2011, the Regulatory Development Branch of the Australian Competition and Consumer Commission (ACCC) commenced a joint project with the Australian Energy Regulator (AER), *Benchmarking Opex and Capex in Energy Networks*. The project has a number of outputs, one of which is to be the sixth working paper in the ACCC/AER series.

Because of the nature of the project being research-oriented, highly technical and broad-ranging, this working paper draws upon contributions from a diversity of staff with relevant knowledge and expertise. This paper also benefited from the insightful thoughts provided by the external reviewer – Professor Tim Coelli, a distinguished researcher in the efficiency and productivity field and one of the most highly cited academic economists in Australia.

Of course final responsibility for the working paper rests with the ACCC/AER staff working on this project. Dr Su Wu has led the overall project. The paper has evolved from many rounds of drafting and revision by Dr Rob Albon, Dr Darryl Biggar, Dr Hayden Mathysen and Megan Willcox, as well as a team of AER staff including Jess Manahan, Cameron Martin, and Israel del Mundo. The finalisation of the working paper also draws heavily on the reviewing contributions from Paul Dunn, Kylie Finnin, Dr Jason King and Dr Anne Plympton.

The supporting research of regulatory practices in Australia and internationally draws upon three separate pieces of work by WIK-Consult, Malcolm Tadgell from Utility Regulation Services, and an internal research team led by Megan Willcox, with assistance from Kylie Finnin, Jess Manahan, and Cameron Smith. Two outputs – *Regulatory Practices in Other Countries* prepared internally and *Cost Benchmarking in Energy Regulation in European Countries* prepared by WIK-Consult – are published as reference documents.

Genevieve Pound has provided valuable editorial assistance.

For comments on this working paper, please contact the ACCC on this e-mail address:

workingpapers@accc.gov.au

It is hoped that this working paper will encourage further discussion about benchmarking issues relevant to the ACCC/AER regulatory work.

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Synopsis

This paper reviews different benchmarking techniques that may be applied to a cost assessment of energy networks, particularly electricity and gas distribution businesses, under the regulatory determinations.

The purpose of cost benchmarking is to improve cost efficiency in the operation of energy networks and to assist in achieving the legislative goals set for the economic regulators. In this paper, benchmarking is broadly defined as the comparison of a utility's performance with some pre-defined reference performance (see for example, Jamasb and Pollitt, 2001, p. 108), such as its past performance (e.g., trend analysis) or best-practice or average performance of similar entities in the country or in the world.

Five benchmarking methods are reviewed:

- Partial Performance Indicator (PPI) method;
- Index-number-based Total Factor Productivity (TFP) analysis;
- Econometric method (EM);
- Stochastic Frontier Analysis (SFA); and
- Data Envelopment Analysis (DEA).

Each of the methods is covered in a method-based chapter containing: a discussion of the respective benchmarking method; a review of the literature in relation to that method; a survey of international regulatory practices that have employed that method; and a section setting out key issues regarding use of the method.

After this review has been undertaken, common analytical and empirical issues in cost benchmarking of energy networks are identified. Issues associated with implementation of cost benchmarking for regulatory purposes are examined in a final chapter.

Chapter 1 Introduction and executive summary

1.1 Context

The search for better ways of regulating energy utilities has increasingly included 'cost benchmarking', where the reasonableness of costs proposed is assessed against those of other utilities or even against costs estimated in economic-engineering models. Benchmarking has been applied in a large and increasing number of countries across the Organisation for Economic Cooperation and Development (OECD) in relation to both operating expenditure (opex) and capital expenditure (capex); particularly for distribution service operators in both the electricity and gas sub-sectors.

In Australia, there has long been interest in this approach, stretching back at the state level to the late 1990s. Currently the Australian Energy Regulator (AER) must have reference to the costs of an 'efficient operator' in a revenue or price determination. Further, interest in benchmarking has been heightened recently by two major inquiries; one by the Productivity Commission (PC) on benchmarking;[1] and the other, by the Australian Energy Market Commission (AEMC), in relation to proposed rule changes.[2]

The AEMC's investigation commenced in October 2011 and includes consideration of requests from the AER and the Energy Users' Rule Change Committee. The AER's proposals relate to 'changes to the capital and operating expenditure frameworks' and 'changes to the expenditure incentive arrangements'. Many submissions have raised the benchmarking issue. The PC's inquiry (commenced January 2012) is particularly apposite (Swan, 2012, paragraph 3):

> The purpose of the inquiry is to inform the Australian Government about whether there are any practical or empirical constraints on the use of benchmarking of network businesses and then provide advice on how benchmarking could deliver efficient outcomes, consistent with the National Electricity Objective (NEO).

The reason for this heightened interest in benchmarking is clear. Efficient energy production and pricing are vital to the efficient functioning of a developed economy operating in an internationally competitive environment. Ultimately, the prices paid by end users for energy primarily depend on the underlying costs of production. Both electricity and gas are produced using sophisticated supply chains, and elements of these supply chains exhibit, to greater and lesser extents, natural monopoly characteristics such as economies of scale, economies of scope and economies of density. In turn, these features militate against competition – natural monopoly means that duplication of production facilities will fracture these economies, resulting in higher-than-necessary production costs. On the other hand, production by a single entity gives rise to market power which could be exploited to the detriment of end users and to economic efficiency.

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[1] For background information, see the Productivity Commission's website at: http://www.pc.gov.au/projects/inquiry/electricity [accessed on 22 December 2011] and Productivity Commission (2012).

[2] For proposals and submissions, see the AEMC's website at: http://www.aemc.gov.au/Electricity/Rule-changes/Open/Economic-Regulation-of-Network-Service-Providers-.html [accessed on 22 December 2011].

Across the OECD countries, it is common for governments to operate regulatory regimes aimed at producing more efficient outcomes than the unrestrained market. In Australia, as in most OECD countries, efficiency is interpreted broadly to include the 'trilogy' of economic efficiencies – cost efficiency (encompassing production efficiency, technical efficiency and X-efficiency, meaning producing output at the least cost); allocative efficiency (relating prices to underlying costs to minimise deadweight loss); and dynamic efficiency (encouraging innovation of new technologies and production methods) (see ACCC/AER, 2010). These efficiency criteria underlie both the National Electricity Law (NEL) and the National Gas Law (NGL). They date back to the Hilmer reforms of the early nineties (Independent Committee of Inquiry into National Competition Policy, 1993), and pervade all of Australia's infrastructure regulation.

Excessive production costs can arise in a variety of ways, and the concept of 'cost inefficiency' has a number of interpretations. For example, a producer's input choice can be distorted by a tax on a particular input produced in a competitive upstream market, forcing it to use less of that input and more of other inputs to produce a given level of output, resulting in wasteful input use and higher-than-necessary economic costs. Other interventions, such as input subsidies and restrictions on input use, can have similar effects on production costs. There are other reasons why producers might be using an inefficient mix of inputs and/or too many inputs to produce outputs. For example, Hicks (1935) referred to the 'easy life' as an objective of management, where monopoly power can be enjoyed through the avoidance of difficult decisions about cost minimisation (e.g., maintaining over-staffing); and Leibenstein (1987) introduced the term 'X-inefficiency' to describe situations where management adopts a stance of producing with too many inputs.

Some regulatory approaches may also discourage cost minimisation. In particular, the traditional approach to infrastructure regulation in the United States is described either as 'rate-of-return regulation' or 'cost-of-service regulation', and could involve one or both of the distortion of input choice (the 'Averch-Johnson effect'; Averch and Johnson, 1962) and 'cost padding' (Albon and Kirby, 1983) in lieu of monopoly profits. Cost inefficiency can also be associated with the 'building-block model' approach practised in Australia, where there is limited or unsuccessful scrutiny of capex and opex levels proposed by regulated entities. As a consequence, excessive costs may be built into the prices of electricity and gas to end users.

1.2 Aim and purpose

Five benchmarking methods are examined by providing an extensive review of:

- academic literature; and
- regulatory applications of benchmarking techniques across selected countries.

This includes a review of academic papers, research reports and consultancy reports with a focus on the different methods used to assess costs and/or efficiency and productivity performance of networks operating in the electricity and gas sub-sectors.

This paper considers the theoretical basis for the use of each method for benchmarking. Data and model requirements are considered, as well as the strengths and weaknesses of each statistical method. Key issues arising in the literature are identified and summarised.

The review of regulatory practice consists of 15 OECD countries: Australia, Austria, Canada (Ontario), Denmark, Finland, Germany, Ireland, Japan, the Netherlands, New Zealand, Norway, Spain, Sweden, the United Kingdom and the United States (California).[3] The review covers most of the leading countries, including the largest of these and many smaller countries. It reviews techniques used, modelling undertaken, data availability, results and processes of implementation. For Australia, benchmarking applications by both the AER and the state and territory regulators (in performing their roles in energy network regulation preceding the transfer of regulatory responsibilities to the AER) are reviewed. For Canada and the United States, the scope of the review is limited to relevant practices by the Ontario Energy Board and the California Public Utilities Commission, as an example of regulatory applications in these two countries.

Based on the review, the paper attempts to draw out guidance for economic regulators in their pursuit of better regulation of transmission and distribution networks in electricity and gas. This guidance relates to the particular techniques and approaches that are most promising; the data and model specification issues that arise in applying these techniques including issues such as adjustments for factors beyond the regulated entity's control; and the processes that could be followed in applying cost benchmarking.

1.3 Summary of findings

Findings consist of:

- an assessment of the benchmarking methods;
- lessons from regulatory practices; and
- concluding observations.

1.3.1 Assessment of the benchmarking methods

This paper systematically reviews five benchmarking methods, namely Partial Performance Indicator (PPI) method, Index-number-based Total Factor Productivity (TFP) analysis, Econometric method (EM), Stochastic Frontier Analysis (SFA); and Data Envelopment Analysis (DEA).

In summary:

- There is a large range of data requirements reflecting differences in the comprehensiveness and accuracy of methods arrayed along the spectrum of simplicity to complexity. PPI has limited data requirements while TFP is information-intensive as it requires both price and quantity information on

[3] A large part of the work has been conducted internally and documented in a supporting reference document titled 'Regulatory Practices in Other Countries' (ACCC/AER, 2012). The work has also been enhanced by a consultancy report on 'Cost Benchmarking in Energy Regulation in European Countries – Final Report' prepared by WIK-Consult (WIK-Consult, 2011). The report provides information on several non-English-speaking European economies.

inputs and outputs. Between the two ends of the spectrum, the other three methods (EM, SFA and DEA) are more effective the larger the number of observations in the sample.

- PPI analysis calculates a single explanatory variable and therefore requires less data than other approaches. Results obtained by PPI may suggest that significant cost differences exist between businesses. However, PPI can only provide a partial indication of performance and is not able to separately account for multiple inputs. This approach may have a role in conjunction with other methods.

- Index-number-based TFP accommodates multiple inputs and outputs. While this differentiates it favourably from the PPI method in terms of capturing the overall picture, there are a number of challenges. First, it requires a large amount of high-quality data. Second, there may be conceptual issues in determining the capital input. Third, it is difficult to directly incorporate quality-of-services into the analysis. Fourth, it is a non-parametric technique. This means that statistical testing cannot be performed. With respect to regulatory use, TFP is more commonly used in the regulatory practices to inform industry-wide productivity change. Other methods are more often used to inform comparative performance.

- SFA is the most complete approach that is relatively strong on both theoretical and statistical grounds. By modelling all relevant inputs and outputs and explicitly including a stochastic element for statistical testing, it can provide additional insights into the significance of key cost drivers and the role of technology over time. A shortcoming of the conventional econometric method, compared with SFA, is that it does not separate the inefficiency measure of the businesses from 'noise' in the data. This makes interpretation of the estimated residual difficult. Nevertheless, with careful examination of data and selection of model specifications and estimation methods, this method has the potential to provide important insights.

- DEA is a relatively simple technique, which has been widely applied in academic literature and regulatory practice. However, as a deterministic method, DEA results are sensitive to the presence of outlying observations.

The following technical and application issues in relation to cost benchmarking arise from the review of the literature:

- The selection of the input-output specification and functional form should be informed by a combination of sound economic theory, good engineering knowledge and rigorous 'cost driver' analysis.

- In principle it is preferable to compare the total expenditure across businesses. However, this requires an assessment of the consumption of the volume of capital services in a period (or an allocation of the total capital expenditure to that period). There are conceptual issues in carrying out that assessment or allocation. As a consequence, many regulators put aside capital expenditure and compare operating expenditure across businesses. This may create incentives for businesses to substitute between capital expenditure and operating expenditure.

- Effective benchmarking requires the modelling of relevant factors affecting the expenditure of the energy networks. These businesses provide a range of services using different types of inputs and may operate in different environmental conditions. Inevitably, benchmarking requires some aggregation of those services, inputs, or environmental conditions into a few variables, resulting in some degree of approximation in the estimation.

- Given the need to use a large dataset for benchmarking, panel-data analysis and international benchmarking can be potentially helpful.

- Where the choice of benchmarking methods and model specifications cannot be settled on theoretical grounds, it may be useful to apply more than one technique or model specification to test consistency. However, academic studies have found that different benchmarking techniques do not exhibit a very high degree of mutual consistency. In some cases, the inability to produce similar results with alternative model specifications and methods require further investigation so that benchmarking outcomes can be supported by more rigorous analysis.

- It is critical to control for exogenous influences beyond the control of the regulated business ('environmental noise'). That is, it is important to consider the role of exogenous environmental factors that are out of management control but may influence the comparative cost performance. Depending on the benchmarking method(s) selected, either one-step or two-step analysis can be conducted to remove the impact of those exogenous influences (Yu, 1998).

1.3.2 Lessons from regulatory practices

The following general observations emerge from a review of regulatory practices across 15 OECD jurisdictions where important applications of benchmarking have been adopted:

- Cost benchmarking methods have been employed by numerous international energy regulators to analyse the efficiency of the electricity distribution sub-sector for the purposes of regulatory determinations. To a lesser extent, cost benchmarking has been employed in relation to the gas distribution sub-sector and only a few energy regulators appear to have employed cost benchmarking to analyse the energy transmission sub-sectors.

- All five methods have been used in at least three of the jurisdictions examined:
    - PPI or unit-cost benchmarking methods have been used in Ireland, the United Kingdom, the Netherlands, New Zealand, in Ontario, Canada and by the AER and other Australian energy regulators.
    - Index-number-based TFP methods have been used in New Zealand, Germany, Austria, in Ontario, Canada and in some states (e.g., California) in the United States, and by the Northern Territory Utilities Commission in Australia.

    - Econometric methods have been used in Austria, the United Kingdom, Ireland, as well as in Ontario, Canada, and California, the United States.

    - SFA has been used in Germany, Finland, and Sweden.

    - DEA has been applied in Finland, Norway, the Netherlands, Germany, Austria, and by the Independent Pricing and Regulatory Tribunal of New South Wales (IPART) in Australia.

- Some regulators have analysed energy networks using a number of benchmarking techniques. For example, the German regulator used DEA and SFA to determine the comparative performance of gas and electricity distribution networks. It also relied on an index-number-based TFP method to determine the productivity change common to all networks. Some regulated utilities in the United States have submitted index-number-based TFP studies to support their preferred value of the productivity-offsetting factor under a CPI–X price/revenue path. The econometric method may also be employed in this context to support the primary analysis.

- Benchmarking has only recently been adopted in many European countries. This coincides with the recent introduction of incentive-based regulation in these countries. From those reviewed by WIK-Consult (2011): Norway was the first to introduce incentive regulation and efficiency benchmarking in 1997; Austria commenced in 2006; Finland in 2008; and Germany in 2009. Sweden will move from a reference network model to *ex ante* revenue caps in 2012.

- In North America, voluntary participation in benchmarking studies by regulated energy utilities is popular. This provides businesses with an insight into how they can improve their own performance relative to their peers. Some have used these studies to support requests to the regulator for tariff reviews (First Quartile Consulting, 2010).

The review of international regulatory practices shows that stakeholders and regulators appear to be more confident with the use of cost benchmarking in circumstances where:

- there was extensive consultation with industry and the views of industry were incorporated into the benchmarking regime where reasonable argument was provided. For example, the Ofgem's application of benchmarking to electricity distribution included an extensive consultation process over a number of years.

- benchmarking was used as a routine part of the regulatory process to inform the regulatory decisions. That is where benchmarking was used to adjust the business's forecast costs up and down, rather than including the numerical outputs from benchmarking directly into the determination of efficient costs or X factors. Examples of this approach undertaken by the regulators include the gas and electricity distribution sub-sectors in the United States, the United Kingdom and Ireland.

- there are a large number of comparable businesses in the sample. Regulators have generally placed less weight on the results from benchmarking studies where there is a small sample size. For example, Ireland has only two gas networks and the United Kingdom has eight networks owned by four companies. Because of the limited sample size available, benchmarking analyses of gas distribution networks in the United Kingdom (and Ireland, if applicable) have been used in combination with bottom-up assessments of specific activities to inform the regulators' determinations of efficient costs. In contrast, of the European countries reviewed by WIK-Consult (2011), Germany and Austria have heavily relied on benchmarking results in their respective regulatory decisions for gas distribution.[4]

- multiple benchmarking techniques are used and considered. To account for the different results that may arise using different methods, Finland and Germany combined the results from the SFA and DEA methods, Austria combined results of DEA and Modified Ordinary Least Squares (MOLS) and the Ontarian regulator combined the results of econometric and unit-cost models. Finally, the Ofgem in the United Kingdom compared the ranking of electricity distribution networks derived from OLS and DEA methods to test the sensitivity of the results.

1.3.3 Concluding observations

A key message from the review is that cost benchmarking is most effectively pursued as an integral part of the broad regulatory process. Use of cost benchmarking would move from being mainly an informative tool to being a deterministic tool through the built-up of expertise (including learning by doing) and the gathering of necessary resources.

Reflecting current practice and existing expertise, benchmarking should initially be used as an informative tool rather than a determinative one. For example, it can be used as a starting point for a conversation with regulated utilities about the level of operating and/or capital expenditures being incurred and proposed. A more sophisticated application could emerge over time.

Effective cost benchmarking requires a clear understanding of the structure of the costs of the regulated utilities. This, in turn, requires an understanding of the key outputs provided by the benchmarked utilities, the inputs used (and/or the prices of those inputs), and the key environmental factors. It is also useful to understand the nature of any economies of scale or scope in the industry. Engineering studies can help provide a picture of the likely cost drivers, including how the cost drivers interact. This involves complementing in-house resources through access to expert consultants with specialised engineering knowledge and experience in the application of cost-benchmarking methods.

The effectiveness of the use of more sophisticated techniques will be greater, the greater the availability of relevant data. Achieving this will likely require the investigation of international datasets if the number of regulated utilities in a sub-sector is small. A key step is to identify compatible international data that are

[4] The Austrian regulator has relied primarily on benchmarking results to determine the X factors, supplemented by engineering studies to inform model specifications for benchmarking 20 gas distribution businesses in the country. For more details, see WIK-Consult (2011).

available and to understand the issues that arise when using international data to benchmark domestic utilities. Accessing and understanding the limitations of data from other countries or jurisdictions is likely to involve cooperation with regulators in the relevant jurisdictions.

For cost-benchmarking applications, it is important to ensure that there are no artificial incentives that create cost inefficiency through one or more of cost padding (such as expense preferencing and empire building); pursuit of the 'quiet life' (such as acquiescing to labour demands) and substitution of capital expenditure for operating expenditure.

1.4 Structure of the paper

The remainder of this paper is structured as follows. Chapters 2 to 6 each reviews a benchmarking method – namely PPI, TFP, EM, SFA and DEA – each chapter covering a method description, literature review, regulatory applications, and issues arising from the review. Chapter 7 considers common issues in benchmarking of energy networks and Chapter 8 examines implementation issues in achieving effective regulation using benchmarking.

Chapter 2 Evaluation of partial-performance-indicator method

2.1 Introduction

Partial-performance-indicator (PPI) method involves the use of trend or ratio analysis on part (but not all) of a business's inputs or outputs to allow judgements or comparisons to be made on some aspects of the productivity or efficiency performance of comparable businesses or an industry average.

PPI has been used as a means of benchmarking the performance of gas and electricity utilities by various international energy sector regulators, including in the United Kingdom (UK), New Zealand, the Netherlands and Ontario, Canada. PPI has also been used by Australian regulators including the AER and state jurisdictional regulators.

While PPI has been commonly used by regulators in Australia and internationally, its use in energy regulation has not been explored in the academic literature to any great extent. The academic literature on benchmarking in the energy sector relates mostly to the more complex techniques such as SFA, DEA, index-number-based TFP and econometric methods. However, there is some literature relating to PPI measures, which is outlined in this chapter.

The remainder of this chapter is structured as follows: A description of PPI is provided in section 2.2. Section 2.3 provides a summary of the academic literature relating to PPI method and section 2.4 provides a summary of the use of PPI by energy regulators. Section 2.5 discusses some of the issues associated with the application of PPI and conclusions are drawn in section 2.6.

2.2 Description of the PPI method

PPI method is carried out by calculating different measures of the financial, operating and quality-of-services performance of comparable businesses. In terms of efficiency and productivity performance, commonly adopted measures include:

- single input factor productivity measures in terms of labour, capital stock, material and/or fuel respectively; and
- unit-cost measures, such as average total costs (total costs divided by a single measure of output).

2.2.1 Method

At a basic level, PPI can be expressed in the following terms:

$$PPI = \ input \ \ measure \ / \ output \ \ measure \qquad (2.1)$$

The key assumptions of the PPI measure is that a linear relationship exists between the input and output measured and that any change in the input can be explained by a change in the output (or vice versa).

In electricity distribution, the input measure may represent a single input, such as the cost of clearing vegetation, or a more aggregated measure, such as opex or capex. The output measure is usually represented by a measure such as network length, power delivered, customer numbers or customer density.

2.2.2 Data requirement

PPI measurements can be carried out using any measure of input and output, from aggregated measures of opex or capex, down to individual business activities to model. The data requirements depend on what the regulator is seeking to benchmark (e.g. opex, capex, a component of opex, etc) and the level of information disaggregation required. For example, benchmarking that is carried out on expenditure relating to clearing vegetation will require a greater level of disaggregated information than if benchmarking is carried out on total opex. The key requirement is that, for any given input or output, the data collected must be measured on a consistent basis across businesses. If data are not collected on a consistent basis, then any comparison or benchmarking carried out using the data is likely to be flawed.

2.2.3 Advantages and disadvantages

The indicators produced through PPI are generally easy to compute and simple to interpret. They are also widely used by the industry, regulators and practitioners. They can be used to compare certain aspects of efficiency and productivity performance. Comparisons could be made either across different businesses at a single point in time (i.e., cross-sectional analysis based on a sample of peers in the group) or across time for the same business or industry (i.e., time-series analysis) or both (i.e., panel-data analysis). The analysis can help identify trends, determine baselines and establish target performance.

While PPIs provide some insights, they can give misleading information regarding the overall economic performance of energy utilities producing multiple outputs and multiple inputs. For example, when considered in isolation, a labour productivity measure would tend to overstate the growth of overall productivity in a utility experiencing a substantial degree of capital deepening (i.e., capital substituting for labour in the production). Similarly, inadequately accounting for the multiple outputs produced by a utility would also make performance comparison over time or across utilities less useful for the regulator.

PPIs assume a linear relationship between the input and output measures and also assume that any change in the input measure can be described by a change in the output measure. However, in most circumstances the change in an input usage will be dependent on a number of inputs, outputs and other factors that may not be described in the model. In particular, PPIs used in isolation cannot easily take into account differences in the market or operating environment that impact upon a business but are beyond the control of management. For example, a utility may have a relatively high or low unit cost simply because it faces input prices or serves customers that are different from those for utilities operating in other regions. Because of this, they may present problems in providing a meaningful comparison of businesses in different operating environments.

The use of a matrix of partial performance measures to compare performance of utilities, grouped by scale of operation (such as a composite scale variable), customer type or density, network density, capital density, or a combination of these, often leads to the identification of different best and worst performers in the different dimensions. A weighted-average performance indicator to combine a set of core performance measures also raises some potential problems because the choice of weights may be arbitrary and the overall indicator may fail to account for differences in the operating environment. These problems suggest a need for a method to derive comprehensive performance measures that can capture all the information on the inputs used and outputs produced (and thus take into account potential trade-off among outputs and inputs) and that can adjust for differences in non-controllable factors that may affect utility performance.

2.3 Literature review of PPI method

In spite of the common use of PPI method by energy regulators, literature relating to the regulatory use of PPI method is fairly limited. The limited amount of academic attention paid to PPI applications to energy regulation may be a result of the relatively simple nature of the method and potentially a preference amongst academics and researchers to utilise a more advanced benchmarking technique that is capable of giving a unified measure of productivity or efficiency, rather than a method based on partial performance.

London Economics (1999) was somewhat negative in its assessment of PPI as a means of efficiency analysis, noting that 'while partial performance indicators can provide useful insights into particular areas of inefficiency, they cannot provide an overall picture of performance. Indeed, used by themselves, partial performance indicators can provide a distorted picture of performance.' (p. 7). The paper considered that, for electricity distribution with multiple inputs and multiple outputs, it was difficult to interpret the set of individual partial performance indicators required to capture the different dimensions of the performance of the activities (London Economics, 1999, p. 7).

Carrington, Coelli and Groom (2002, pp. 196-197) considered that 'partial productivity measures are often used to measure efficiency because they are simple to calculate and are readily understood'. However, they further noted that 'partial productivity measures need to be implemented with care. The measures do not provide a complete view of performance because they do not consider the various relationships or trade-offs between inputs and outputs of gas distribution. Furthermore, they can vary for reasons other than inefficiency; for example, a distributor may have a different mix of customers or population density.'

Costello (2010, p. 44) pointed out that accounting indicators allow the user to identify potential problem areas, provide preliminary information for in-depth inquiry and allow a comparison of a utility's performance over time or with other utilities. However, he also recognised many shortcomings of the method. For example, it does not allow for the separation of management effects from other factors of performance; and narrow-based measures may not account for interdependencies between utility functions, and do not provide a definite benchmark.

Noting the common use of PPIs by Australian regulators to examine many different aspects of the efficiency of regulated distribution utilities, Cambridge Economics Policy Associates (CEPA) (2003, pp. 25-26) warned that partial productivity measures can be highly misleading as they are often significantly impacted by capital substitution effects (where capital is substituted for labour, therefore improving labour productivity). According to CEPA (2003), the main problem with these measures is that it is not clear what can be done with them. For example, there is no meaningful way of summing up the different efficiency savings given by PPIs to give a measure of overall efficiency savings that could be achieved. CEPA (2003) also noted that the partial approach neglects the fact that companies may choose to substitute one type of expenditure for another, hence giving them best performance on some measures but not on others, leaving best performance on all measures simultaneously unachievable.

CEPA (2003) indicated a preference for TFP indices to PPI because the TFP method gives a more balanced view of efficiency and productivity performance. However, the paper did evaluate both the advantages and disadvantages of PPI. The advantages of PPI include that it is easy to compute and understand and can be used to cross check results from more advanced benchmarking techniques such as Data Envelopment Analysis (DEA) and Corrected Ordinary Least Squares (COLS) for plausibility and transparency. The disadvantages of PPI include: no allowance for evaluation of uncertainty associated with calculating benchmarks; difficulties in accounting for differences in operating environments between businesses; potentially misleading results by focussing on a subset of factors of production; and failure to give an overall measure of potential for cost improvement that is supported by a strong theoretical rationale.

2.4 Regulatory practices using PPI method

2.4.1 Regulatory practices review

PPI benchmarking method has been used as part of revenue or price determinations for electricity and gas distribution networks by energy regulators in Australia and some other countries, such as Ireland, the United Kingdom, the Netherlands, New Zealand and Canada.[5]

Ireland[6]

Ireland's energy regulator, the Commission for Energy Regulation (the CER), utilised PPI methods to inform revenue decision for its single electricity distribution business, ESB Network (ESBN), for the period 2011 to 2015. PPI analysis was carried out on certain categories of opex (*bottom-up* analysis) and the results were considered in conjunction with the results of total opex benchmarking (*top-down analysis*) based on econometric methods (refer section 4.4).

The CER engaged the services of an engineering and technical consultant, Sinclair Knight Merz, to carry out the PPI benchmarking. Sinclair Knight Merz considered it possible to benchmark certain costs directly where costs are mainly fixed costs or where a simple driver can be identified.

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[5] As it is not possible to cover all countries, there may be other examples of energy regulators applying PPI benchmarking method that have not been captured in this paper and the supporting research. Haney and Pollitt (2009) also undertook an international survey of benchmarking applications by energy regulators.

[6] Refer to chapter three of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

PPI benchmarking was carried out in relation to:

- tree-cutting costs per network kilometre and tree coverage per kilometre;
- fault costs per network kilometre; and
- IT/Telecoms costs and System Control support costs per annum.

The benchmarks used for Ireland's ESBN were 14 electricity distribution businesses in the UK.

Sinclair Knight Merz noted that bottom-up PPI benchmarking indicates that some repairs and maintenance costs in Ireland are inherently lower than in the United Kingdom. The ESBN's overhead line networks are simple and there is less urban cable network. Sinclair Knight Merz considered that the real country differences in terms of networks, practices and costs were beginning to be understood. Sinclair Knight Merz, however, advised that its benchmarking results should be used with caution. It was noted that identifying inefficiency of ESBN through international benchmarking was becoming more difficult due to the narrowing efficiency gap and the absence of detailed knowledge of cost allocations and network characteristics.

Based on the advice, the CER questioned whether benchmarking against distribution businesses in the UK was applicable to Ireland which has four times more lines than the UK companies of the same customer base. Nevertheless, the CER, taking into account both the bottom-up and top-down benchmarking, adopted most of Sinclair Knight Merz's recommendations and reduced ESBN's controllable opex costs.

ESBN has also taken advantage of the benchmarking information, which led to the review of maintenance practices and PAS 55 asset management accreditation under the auspices of the accreditation authority for the UK (Sinclair Knight Merz, 2010, p. 29).[7]

United Kingdom[8]

The UK energy regulator, Ofgem, determined the revenue allowance for its eight gas distribution networks (under four ownership groups) for the regulatory period 2008-09 to 2012-13. The Ofgem's consultant LECG utilised PPI benchmarking methods for benchmarking indirect opex. PPI benchmarking was undertaken at the ownership level and included actual and forecast costs data between 2005-06 and 2012-13. Data from earlier periods could not be incorporated into the analysis due to significant industry restructuring in 2005-06 which affected the data consistency across time.

PPI benchmarking was carried out separately in relation to:

- total support costs, finance and audit costs, legal costs, information systems costs and insurance costs (each as a percentage of adjusted revenue);

[7] PAS 55 is the British Standards Institution's (BSI) Publicly Available Specification (PAS) for the optimised management of physical assets – it provides clear definitions and a 28-point requirements specification for establishing and verifying a joined-up, optimised and whole-life management system for all types of physical assets. More information can be obtained at http://pas55.net.

[8] Refer to chapter two of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

- property management costs – by taking: the rental cost for each square foot of property and comparing it with market data; total facilities costs per square foot of floor space across gas networks; and total floor space per kilometre of pipeline across the gas networks;

- regulation costs, corporate and communications costs and procurement and logistics costs (each as a percentage of total operational cost); and

- human resources costs as the percentage of total revenue and as a percentage of total operating costs.

LECG set the benchmark at the median and upper quartile of each PPI. The Ofgem chose to set the benchmark at the second best distribution business for most of the PPIs, otherwise at the upper quartile. The Ofgem then gave an upward adjustment to the results based on the total opex benchmarks, which were derived using econometric methods (refer to section 4.4).

New Zealand[9]

For the 2008-2012 gas distribution authorisations for Vector and Powerco, the New Zealand Commerce Commission (NZCC) employed the consultancy services Parsons Brinckerhoff (PB) Associates to assess forecast operating and capital costs.

PB Associates assessed opex and capex using both the PPI benchmarking method and a bottom-up engineering-based approach. PB Associates developed the following PPIs:

- total opex aggregated across the regulatory period against number of customers, volume distributed and network length; and

- total capex aggregated across the regulatory period against number of customers, volume distributed and network length.

PB Associates, however, relied primarily on the engineering based assessment in forming the recommendations to the NZCC.

In the period preceding the gas authorisations, gas distribution businesses were not subject to regulation in New Zealand and there were no information reporting requirements. Consequently, PB Associates's analysis was constrained by a lack of consistent data both across gas distribution businesses and for the same distribution business across time.

Ontario, Canada[10]

Since 2000, the Ontario Energy Board (OEB) has applied an incentive regulation framework for electricity distribution based on a price cap of the form: $PCI = P - X \pm Z$, where the growth in the price-cap index (PCI) is determined by the inflation rate (P), a productivity-offsetting factor (X), and an additional factor to account for unforeseen events (Z).

[9] Refer to chapter four of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).
[10] Refer to chapter six of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

The X factor includes an industry-wide productivity component estimated by TFP (refer to section 3.4), an inflation differential component and a 'stretch factor'. For the third Generation Incentive Regulation Plan commencing in 2008, the Ontario Energy Board (OEB) estimated the 'stretch factor' for each of the 83 distribution businesses through the combination of two benchmarking methods, a unit-cost or PPI assessment (described in this section) and an econometric model (refer to section 4.4).

The unit-cost indicator was constructed by dividing an input variable by an output quantity index. The input variable was average total opex relative to the sample average, and normalised by an input price index. The output quantity index was a weighted average of three variables, namely circuit kilometres, retail deliveries and number of customers, weighted by cost elasticity shares that were derived from econometric estimates.

The 83 distribution businesses were classified into 12 peer groups based on region, network size, degree of undergrounding, rates of population growth and system age. A three-year average of the unit-cost indicator was calculated for each distribution business and compared with the peer group average. Each distribution business in the sample was ranked based on the percentage difference between its unit-cost indicator and the group average. The distribution businesses were then noted as being ranked in the top quartile, the middle two quartiles or the bottom quartile.

The unit-cost rankings were combined with the econometric benchmarking results to develop three final groups. Each final group was assigned a value for the stretch factor, a lower value for the relatively more efficient groups. The final groupings are re-assessed each year as new data become available; this enables distribution businesses to change groups and, therefore, the assigned stretch factor during the regulatory period.

The Netherlands[11]

The Dutch energy regulator, DTe, also used a unit-cost index to assist in the calculation of the general efficiency-change component of the X factor (i.e., the difference between the industry-wide productivity and the economy-wide productivity) in the determination of the CPI–X revenue cap for its 20 electricity distribution businesses[12].

The input variable was 'standardised economic costs' including operating costs, standardised depreciation and the cost of capital allowance on standardised asset values. The output variable was a composite measure, calculated as the tariff charged to each customer group associated with each tariff element (excluding initial and on-going connection charges), weighted by the respective share of total revenue. Annual productivity change was then calculated by measuring the annual rate of change in the input to output ratio. Only the distribution businesses that were classified as efficient from the DEA benchmarking analysis (refer to section 6.4) were included in the estimate of annual productivity change. The general efficiency-change component

[11] Refer to chapter five of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

[12] This information was obtained from the DTe website for the regulatory period 2004 to 2006. The same method may have been applied in other regulatory periods; however, this cannot be confirmed as other available documents are in Dutch.

was estimated at the beginning of the regulatory period and then adjusted at the end of the period when the actual data became available.

Australian Energy Regulator

Opex

In the 2009 NSW/ACT electricity distribution determination, the AER's consultant, Wilson Cook, initially developed a composite size variable (CSV) (based on the Ofgem work) that consisted of a geometric weighting of outputs including customer numbers, network length and maximum demand. Using data on the 13 electricity distribution businesses within the AER's jurisdiction for 2007-08, Wilson Cook reported a graphical analysis of a variety of comparative opex indicators:

- Opex versus size (represented by the CSV);
- Opex per size versus customer density;
- Opex per size versus size;
- Opex per customer versus customer density;
- Opex per megawatt (MW) versus customer density; and
- Opex per kilometre versus customer density.

However, following criticism of the CSV approach, Wilson Cook adopted a multivariate regression model (refer to section 4.4). The AER (2009b, p. 176) noted that the results of the regression model were 'not materially different to those of the original analysis' and that the top-down analysis provided 'a useful test of the reasonableness' of the bottom-up assessment.

In the 2010 Victorian electricity distribution determination, the AER and its consultant, Nuttall Consulting, utilised opex ratios using RAB, line length, customer numbers, electricity distributed (megawatt hour – MWh) and maximum demand as denominators. The AER also plotted these ratios against customer density (number of customers per kilometre of line length as a proxy). An industry 'average' was calculated and inefficient businesses were identified.

In the 2010 Queensland and South Australian electricity distribution determinations, opex ratios against the same set of variables as the Victorian determination (RAB, line length, customer numbers, electricity distributed and demand) were developed. The AER's consultant, PB Australia, used the PPI analysis to test the reasonableness of the bottom-up assessment. The AER also undertook regression analysis based on the method used for the NSW/ACT determinations.

The AER and its consultant, Nuttall Consulting, used similar opex ratios in its benchmarking analysis for the 2011 Tasmanian electricity distribution draft determination.

The AER has included trend analysis of distribution businesses' opex in all of its distribution determinations. The trend analysis was performed by comparing differences in actual opex with proposed opex over time.

Capex

In the 2009 NSW/ACT distribution determination, the AER's consultant, Wilson Cook, did not use benchmarking to assess the NSW and ACT electricity distribution network businesses' system capex. Wilson Cook (2008, p. v) stated that benchmarking capex using denominators such as customer numbers or line length was 'generally inappropriate'. However, Wilson Cook included benchmarking of non-system capex with size and customer numbers as the denominator.

In the 2010 Victorian distribution determination, the AER and its consultant, Nuttall Consulting, utilised capex ratios using RAB, line length, customer numbers, electricity distributed and maximum demand as denominators. The AER also plotted these ratios against customer density and load profile.[13] An industry 'average' was calculated and inefficient businesses were identified.

The AER and its consultant, Nuttall Consulting, used similar capex ratios in its benchmarking analysis for the 2011 Tasmanian draft determination.

In the 2010 Queensland and South Australian distribution determinations, the AER used the following ratios to inform its analysis of the forecast capex:

- Capex/RAB; and
- Non-system capex ratios using customers, line length, demand and energy as denominators.

The AER provided these ratios to its consultant, PB Australia, for the latter's review of the businesses' proposals.

The AER has included trend analysis of capex in all of its electricity distribution determinations. The trend analysis was performed by comparing differences in actual capex with proposed capex over time.

Australian state and territory regulators

Prior to the transfer of energy regulation to the AER in 2008, each state or territory was responsible for setting the regulatory controls on energy utilities.

Electricity distribution

Each state or territory regulator in Australia has used some form of PPI analysis to benchmark capex and/or opex for electricity distribution businesses. New South Wales, Victoria, Queensland, South Australia, Tasmania and Western Australia used ratio and/or trend analysis to benchmark opex and capex. The Australian Capital Territory and the Northern Territory used PPI methods to benchmark opex but not

[13] Load profile is the ratio of demand and energy (MW/GWh); load density is the ratio of demand and line length (MW per kilometre).

capex. Further information on the number of electricity distribution utilities regulated by each jurisdiction and the particular ratios used by each regulator for benchmarking opex and capex is provided in table 2.1.

Gas distribution

All Australian state regulators of gas distribution businesses, excluding Western Australia, have used a form of PPI to benchmark opex and capex. New South Wales used trend analysis in capex and opex, as well as a multifactor productivity measure (sourced externally) to determine efficiency savings for operations and maintenance expenditure. Victoria, the ACT, Queensland and South Australia each used ratio and/or trend analysis to benchmark capex and opex. Further information on the number of gas distribution utilities regulated by each jurisdiction and the particular ratios used by each regulator for benchmarking opex and capex is provided in table 2.2.

2.4.2 Summary of regulatory practices

The review of regulatory practices in Australia and other countries shows that the PPI benchmarking method has been used by a number of energy regulators for the electricity and/or gas distribution sub-sectors. Notably, PPI benchmarking methods appear to have been relied on when there are a small number of comparable regulated utilities, for example one Irish electricity distribution business, two New Zealand gas distribution businesses, four ownership groups for the eight UK gas distribution businesses and the 20 Dutch electricity distribution businesses. In Australia, where PPI has been the main form of benchmarking method, the AER has regulatory responsibilities over 13 electricity distribution businesses and 11 gas distribution businesses, although these were previously regulated across six different jurisdictional regulators.

This suggests that more advanced benchmarking methods may be more applicable to jurisdictions where a larger sample of comparable regulated utilities is available and regulators have access to quality data which are consistent across businesses and/or over time.

Also notable is that PPI benchmarking methods appear to often be complemented with other benchmarking methods; for example the Ontario Energy Board in Canada and the Irish CER considered the results of both PPI and econometric benchmarking methods. The NZCC, the AER and other Australian jurisdictional regulators have also relied on engineering-based benchmarking methods and in some cases considered econometric analysis. This observation may suggest that PPI benchmarking provides useful preliminary indicators of performance that can be combined with other more technical benchmarking methods.

Table 2.1: PPI-based Benchmarking Undertaken by Australian Jurisdictional Regulators in relation to Electricity Distribution

Regulator / State	Electricity distribution businesses	Opex	Capex	Regulatory application
Independent Pricing and Regulatory Tribunal (New South Wales) – IPART	• EnergyAustralia • Integral Energy • Country Energy	• Opex between 1999-2000 and 2008-09 • Opex as a percentage of the RAB for 2003-04 compared with 2008-09 • Opex per customer for 2003-04 compared with 2008-09 • Opex per MWh of energy for 2003-04 compared with 2008-09 • Opex per circuit kilometre for 2003-04 compared with 2008-09	• Changes in total capex between 1998-99 and 2003-04 • Trends in total capex between 1999-2000 and 2008-09 • Capex as a percentage of the regulatory asset base for 1999-2000 compared with 2003-04 • Capex per customer for 1999-2000 compared with 2003-04 • Capex per MWh energy distributed for 1999-2000 compared with 2003-04 • Capex per circuit kilometre for 1999-2000 compared with 2003-04	The benchmarking results were used, among other things, to test the reasonableness of the opex and capex allowance for 2004-05 to 2008-09.
Independent Competition and Regulatory Commission (Australian Capital Territory) – ICRC	• ActewAGL	Comparison of ActewAGL for 2002-03 with the five Victorian distribution businesses in relation to: • Opex per GWh • Opex per customer • Ratio of planned/unplanned maintenance	Capex benchmarking was not carried out.	The benchmark ratios were used by the ICRC and its consultants to test the conclusions about ActewAGL's total opex allowance for 2004-05 to 2008-09, rather than as a device for arriving at these conclusions.

Regulator / State	Electricity distribution businesses	Opex	Capex	Regulatory application
Essential Services Commission (Victoria) – ESCV	• Powercor • SPAusNet • United Energy • CitiPower • Jemena	'Partial factor productivity' was calculated as the difference between the change in operating and maintenance expenditure and the change in operating and maintenance expenditure attributable to changes in growth factors such as customer numbers, energy consumption and peak demand.	Trend analysis over the period 2001 to 2010, using actual, estimated and forecast capex data, was performed. Comparisons with NSW and New Zealand businesses were also made in relation to capex: • Average annual net capex • Capex per customer • Capex per line kilometre • Capex per MVa ranges. Comparisons were also made in relation to network characteristics, such as system length, maximum demand, customer numbers, regulatory asset base, indicative sales growth, customers per kilometre of line and load density.	For opex, the ESCV carried out benchmarking to determine a 'rate of change' and 'growth factor'.
Queensland Competition Authority (Queensland) – QCA	• Energex • Ergon Energy	A comparison of Energex with AGL, United Energy and EnergyAustralia was performed, using three opex ratios: • Opex per circuit kilometre • Opex per customer • Opex per GWh	The Queensland distribution businesses were compared with their Victorian counterparts in relation to: • Capex per new customer • Capex per MW increase in maximum demand • Capex per MWh saved.	The QCA used this benchmarking as one element of the overall assessment of the efficiency of the Queensland businesses and the reasonableness of their capex and opex proposals.

Regulator / State	Electricity distribution businesses	Opex	Capex	Regulatory application
Essential Services Commission of South Australia (South Australia) – ESCOSA	• ETSA Utilities	Opex benchmarking of ETSA Utilities against ten other distribution businesses in relation to: • Opex as a percentage of asset value • Opex per kilometre of line • Opex per customer • Opex per kilovolt ampere (kVa) maximum demand.	• Capex as a percentage of asset value • Capex per kilometre of line • Capex per customer • Capex per kVa maximum demand.	These measures were not used to set opex or capex, but rather to identify areas where more detailed analysis may be required.
Office of the Tasmanian Economic Regulator (Tasmania) – OTTER	• Aurora Energy	The OTTER included in its price determination trend analysis of Aurora Energy's opex over the period 2002-03 to 2011-12.	The OTTER included in its price determination trend analysis of Aurora Energy's capex over the period 2002-03 to 2011-12.	The OTTER considered the use of industry benchmarking in relation to opex and capex, and instructed its consultants to consider high-level comparisons. However, the OTTER's consultant did not consider that weight should be placed on the industry benchmarking and they were not considered in the revenue decision.
Economic Regulation Authority (Western Australia) – ERA	• Western Power	The efficiency of Western Power's 2007-08 actual opex relative to other Australian distribution businesses was assessed by using benchmarks of the following metrics prepared by Wilson Cook based on publicly available information: • Opex per line kilometre • Opex per customer and • Opex per kilowatt hour (kWh).	No capex benchmarking was carried out.	The results were only used by the ERA to assess the base year of 2007-08 and do not appear to have been used in approving changes to opex in the access arrangement for the 2009-10 to 2012-13 period.

Regulator / State	Electricity distribution businesses	Opex	Capex	Regulatory application
Northern Territory Utilities Commission – NTUC	• Power and Water	A 'multilateral unit opex' method was applied to benchmarking utilities. This involved the inclusion of a number of input and output factors.[14] Simple measures such as 'opex per customer' or 'opex per kilometre' were considered to be biased in favour of either rural or urban businesses.	Benchmarking does not appear to have been used for capex.	

[14] The specific inputs and outputs used in the 'multilateral unit opex' by the NTUC were: outputs – GWh supplied, system line capacity measured by its total MVA kilometres, and number of connections; inputs – Opex, length of overhead network, length of underground network, and the rated MVA capacity of the installed zone substation and distribution transformers.

Table 2.2: PPI-based Benchmarking Undertaken by Australian Jurisdictional Regulators in relation to Gas distribution

Regulator / State	Gas distributors	Opex	Capex	Regulatory application
Independent Pricing and Regulatory Tribunal (New South Wales)	• Jemena • ActewAGL • Wagga Wagga • Central Ranges System	Trend analysis of opex over the period 2000 to 2010.	No explicit reference to capex benchmarking, though a comparison was made between AGLGN's unit cost per dollar of gas main for different types of customers against information from other states.	The information from benchmarking appears to have been used along with other factors to test the reasonableness of the revenue proposal.
Independent Competition and Regulatory Commission (Australian Capital Territory)	• ActewAGL	Opex ratios used to determine efficient base-year opex: • Opex per kilometre of main; • Opex per terajoule (TJ); • Customers per kilometre of main; • Opex per customer; • Marketing costs as a share of operating costs; • Network marketing cost per new customer; • Network marketing cost per gigajoule (GJ) Benchmarking was also carried out to assess the reasonableness of ActewAGL's cost allocation between gas distribution and other services, but the report is not available publicly.	Growth – market expansion related capex: capex per customer for mains, services and meters/regulators for residential and industrial and commercial customers Growth – capacity development capex: unit costs per meter for secondary and primary steel mains and cost per customer Stay in business capex (mainly related to meter renewal and upgrade): meter renewal unit costs and meter purchase costs.	Benchmarking ratios were used to test the reasonableness of ActewAGL's efficient opex and capex.
Essential Services Commission (Victoria)	• SP AusNet • Multinet • Envestra	Trend analysis of each gas distributor's opex over the period 2003 to 2012.	A capex PFP factor was developed, which reflected labour and capital productivity improvements. Also considered changes in capex unit costs.	Trend analysis used to determine the rate of change in opex. Capex PFP measure was used to determine a capex escalator.

Regulator / State	**Gas distributors**	**Opex**	**Capex**	**Regulatory application**
Queensland Competition Authority (Queensland)	• APT Allgas • Envestra	Trend analysis of previous opex against forecast opex. Comparison of Allgas and Envestra Queensland's unaccounted-for gas rates with those of interstate gas distributors and the other Queensland gas distributor, Allgas, in order to determine an appropriate rate for the two Queensland gas distributors.	Trend analysis of previous capex against forecast capex. Comparison of the cost of new connections in Queensland with that of gas distributors in other States.	Used to test the reasonableness of aspects of opex and capex.
Essential Services Commission of South Australia (South Australia)	• Envestra	Trend analysis of opex	Capex ratios were used to compare results across jurisdictions. The comparative ratios (based on unit costs) included: • Meter costs; • Service costs; and • Mains renewal costs.	ESCOSA relied on its consultant's advice in making its Final Decision, and therefore also implicitly relied on the benchmarking analysis carried out by its consultant. However benchmarking played a relatively minor role in its overall capex decision-making.
Economic Regulation Authority (Western Australia)	• WA Gas Networks	Trend analysis of: • Operating expenditure per kilometre of main; • Operating expenditure per GJ delivered; and • Operating expenditure per customer connection. This analysis only tracked the change in opex over time and was not used for external comparison with other businesses.	No external benchmarking was used. Trend analysis in the change in key capex performance indicators was considered.	No external benchmarking was used, though trend analysis was considered.

2.5 Issues arising from the review

2.5.1 Limitations of PPI

PPI offers a relatively straightforward method of benchmarking compared with other benchmarking techniques. However, PPI is of limited use. It considers only one aspect of a business at a time, namely the business's inputs and outputs. It does not account for differences in other aspects of a business. As described earlier, PPI assumes a linear relationship between inputs and outputs, and that all changes in the value of an input can be associated with a corresponding change in the output (or vice versa).

The current literature identifies shortcomings associated with the PPI approach. These include that PPI only provides a partial indication of performance and cannot be used to provide an overall 'benchmark' performance. CEPA argued that partial productivity measures can be misleading because they disregard substitution possibilities between inputs. For example, when capital is substituted for labour in the production process, labour productivity increases (CEPA, 2003, pp. 25-26). CEPA noted that the partial approach to productivity measurement neglects the fact that businesses may choose to substitute one type of expenditure for another, hence giving them best performance on some measures but not on others, leaving an overall performance difficult to measure. CEPA (2003) found that compared to PPI, the TFP approach provides a more complete measure of productivity.

Australian state regulators and the AER have previously found that PPI measurements were sensitive to the selection of outputs, and that the subsequent results were likely to be biased in favour of either rural or urban networks (See for example, AER, 2010, pp. 78-79). That is, using the PPI method, results differ if opex is used as a proportion of customer numbers, or if opex is used as a proportion of network length. Consequently, in Australia, while PPI methods have been used to inform the review process, they have not been used not as a direct input in the determination.

2.5.2 Legislative and regulatory requirements

The National Electricity Rules (NER) govern the operation of the National Electricity Market and the associated electricity transmission and distribution network service providers (DNSPs).[15] Clauses 6.5.6(e) (regarding opex) and 6.5.7(e) (regarding capex) of the NER set out the ten factors that the AER must consider when deciding whether to accept a revenue proposal from an electricity distribution business. Clause 6.5.6(e)(4) specifies that, in assessing a revenue proposal from a DNSP, the AER must have regard to benchmark operating expenditure that would be incurred by an efficient DNSP in the given operating circumstances over the regulatory control period,[16] while clause 6.5.7(e)(4) specifies that the AER must have regard to benchmark capital expenditure.

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[15] The current consolidated version of the NER is version 49, which can be found at: http://www.aemc.gov.au/Electricity/National-Electricity-Rules/Current-Rules.html [accessed on 1 March 2012].

[16] Clause 6.5.6(c)(2) of the NER specifies that the AER must accept the forecast of required operating expenditure of a DNSP if it is satisfied that the total of the forecast operating expenditure for the regulatory control period reasonably reflects the costs that a prudent operator in the circumstances of

These provisions have been used to support the use of PPI methods as a part of previous AER reviews.

2.5.3 Industry characteristics

As noted above, the AER must have regard to DNSP-specific business conditions in the determinations of benchmark operating and capital expenditure. However, a significant issue in the use of PPI relates to the way in which different operating environments are treated to allow meaningful comparisons to be made between different sets of results.

For example, the Irish regulator, in its international benchmarking of opex activities for electricity distribution found that tree trimming costs per kilometre were lower in Ireland than in the UK. The UK has higher tree coverage and is subject to stricter safety regulations. This increases the amount of tree trimming in the UK compared to Ireland. Costs of fault repairs were also found to be lower in Ireland. This appears to reflect the fact that the network in Ireland has less underground wires than in the UK. Underground wires are generally more expensive to repair than overhead wires.

The AER also noted in the Victorian electricity distribution draft determination in 2010 that, differences in network characteristics may impact on the usefulness of benchmarking.

2.5.4 Data availability and quality

PPI-based benchmarking methods were used in the AER's Victorian electricity distribution draft determination in June 2010. The AER identified a number of limitations with the available data that limited the reliability of the performance comparisons between distribution businesses in different jurisdictions using PPI (AER, 2010, pp. 78-79). Specifically, the AER noted the following affect PPI analysis:

- the lumpiness of capex programs;
- different licensing requirements between NEM jurisdictions;
- differences in whether distribution businesses buy or lease assets;
- differences in balance date (i.e., the last day of the company's financial year);
- variations in the characteristics of distribution businesses and the age, size and maturity of their networks and the markets they serve;
- capitalisation, cost allocation and other accounting policies, as well as regulated service classifications, are assumed to be the same across all DNSPs, and across regulatory control periods in the sample; and
- the nature of the sample of rural, urban and CBD distribution businesses.

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the relevant DNSP would require to achieve the operating expenditure objectives. Clause 6.5.7(c)(2) specifies a similar criteria for accepting capex.

A big challenge to using PPI, and to benchmarking generally, is the comparability of the data in the AER's information collection templates (RINs).

Prior to 1 January 2008, state-based regulators oversaw the economic regulation of DNSPs. In developing RINs for the first round of distribution determinations under the AER's jurisdiction, the AER considered potential issues with transitioning from state based jurisdictional regimes to the national regime. The capex and opex items in the RINs therefore do not perfectly align between businesses. This has posed challenges, for example, in the Aurora distribution determinations:

- Nuttall Consulting found that sub-transmission lines formed an insignificant part of Aurora Energy's (Aurora) capex. In Tasmania, the majority of sub-transmission assets are owned by a different business, Transend. In contrast, DNSPs own and operate sub-transmission assets in other jurisdictions.

- To improve comparability between Aurora and other DNSPs, Nuttall Consulting suggested producing ratio analysis charts of all NEM DNSPs using capex data minus sub-transmission expenditure. However, this was not possible because data were only available for Aurora and the Victorian DNSPs. That is, only these Aurora and the Victorian DNSPs separated sub-transmission expenditure in their RINs.

- Nuttall Consulting (2011, pp. 157-160) used ratio analysis charts that compared Aurora with all other NEM DNSPs. The effect of including sub-transmission expenditure in the capex ratio analysis is unclear.

Definitions of line items in the capex and opex information between the different collection templates used by jurisdictional regulators, and subsequently incorporated into the AER's RINs, are not identical and thus may not be directly comparable. The differences result in problems when comparing expenditure between DNSPs. PPI techniques require consistent 'like-for-like' definitions across all businesses in each subsector. Consistent definitions across jurisdictions also enlarge the sample size available for analysis. A noteworthy example is the United States, which has long-standing rules about the public disclosure of detailed financial and operational data on regulated utilities. The data provided to the Federal Energy Regulatory Commission (FERC) must comply with the 'uniform system of accounts' developed by the regulator using FERC Form 1 – Electricity Utility Annual Report. The annual reports from 1994 to 2011 are available from the FERC website.[17]

In the Aurora distribution determination, Nuttall Consulting performed benchmarking analysis. Emergency response opex was used in the analysis as this category of opex was most easily comparable between businesses (Nuttall Consulting, 2011, p. 27).

2.5.5 The use of benchmarking results

Stakeholders and DNSPs often argue that the PPI-based benchmarking used by the AER is at a very high level, and cannot be used to determine forecast capex or opex. Indeed, it is difficult to determine an efficient level of capex or opex using this

[17] See the FERC website at; http://www.ferc.gov/docs-filling/forms/form-1/data.asp#skipnav [accessed on 1 March 2012].

approach. For example, is the trend line from a PPI graph (effectively the average of the scatterplot) indicative of efficient expenditure? Or is further work required to ascertain the efficient expenditure level?

In response to the 2010 Victorian distribution draft determination, the Energy Users Association of Australia (EUAA, 2010, p. 20) argued that the benchmarking techniques used by the AER did not meet minimum standards required by the NER. The EUAA has urged the AER to develop more extensive benchmarking techniques.

In contrast, EnergyAustralia argued that the differences in benchmarking outcomes were because of the unique characteristics of each business. EnergyAustralia (2010, p. 16) argued that because of this, no meaningful conclusions could be drawn from this level of analysis in relation to the comparative performance of DNSPs.

The debate between stakeholders over the relevance of PPI-based benchmarking reflects the inherent problems with PPI analysis. These problems suggest a need for more advanced methods to derive performance measures that can better capture multiple-input and multiple-output production process (and thus take into account the potential trade-off between outputs and inputs) and that can adjust for differences in non-controllable factors affecting utility performance. For example, the Consumer Action Law Centre (2010, p. 5) recommended developing a TFP approach to limit the distortions of PPI.

2.6 Conclusions

PPI has been used as an assessment tool in energy regulation in both Australia and a number of other countries such as Ireland. It has provided regulators with information on how the performance (e.g., certain expenditure incurred a particular activity) of a utility compares with others in the industry. The AER has used this as part of its past assessments to determine where greater scrutiny is required of particular types of expenditure.

While useful in the regulatory process, PPI has a number of limitations, particularly relating to data quality and accounting for differing network characteristics and operating environments. It is also difficult to obtain good price deflators (e.g., for labour and/or opex) when comparing utilities over time and across geographical locations. Due to these limitations, PPI-based benchmarking results are best viewed as providing a useful means of comparison and an indication of where certain expenditure may be above efficient levels, but should not be viewed in isolation as a definitive assessment on the efficiency of an energy network business.

Chapter 3 Evaluation of the index-number-based TFP analysis

3.1 Introduction

Total Factor Productivity (TFP) – a ratio of a measure of total output to a measure of total input use – measures the overall productivity change, which cannot be captured in a partial performance indicator examining the relationship between one output and a single factor of production. The TFP method is best used to measure productivity performance of a business or a group of businesses over time.

There are a number of alternative methods for measuring TFP growth. These include non-parametric approaches such as index numbers and Data Envelopment Analysis (DEA), and parametric approaches such as Stochastic Frontier Analysis (SFA) and econometric cost-function models. Index-number-based TFP is commonly used for measuring productivity growth when there are a limited number of observations available. This chapter examines the index-number-based TFP method.

TFP analysis can be used as an informative tool under the current building-block approach to cross-check the reasonableness of a business's forecast demand and costs and thus that of the implied productivity growth potential. For example, under certain conditions historical productivity growth experienced by comparable utilities in a sub-sector provides a reasonable benchmark for past and prospect productivity performance for the utility under consideration. Therefore, a comparison of past industry-average productivity change with potential growth implied from utility-specific forecast data can assist the AER's assessment of expenditure proposals from individual utilities.

TFP analysis can also be used as a deterministic tool to set revenue or price path, replacing the building-block approach to assessing expenditure proposals. The Australian Energy Market Commission (AEMC) has recently completed a review into the possible uses of a TFP-based method for the determination of prices and revenues in the national energy markets covering electricity and gas transmission and distribution sub-sectors.[18] The AEMC found that, with more consistent and robust data, the direct application of an index-number-based TFP method in revenue determinations could contribute to improvements in electricity and gas network regulation. In its final decision report, released on 30 June 2011, it was proposing to the Standing Council on Energy and Resources (SCER, formerly the Ministerial Council on Energy) initial rules which would facilitate data collection and the assessment of whether the necessary conditions for introducing TFP as an alternative to the current building-block approach were met.

The remainder of this chapter is structured as follows: A description of the index-number-based TFP method is provided in section 3.2. Section 3.3 provides a summary of academic applications of index-number-based TFP and section 3.4 provides a summary of regulatory applications of the method. Section 3.5 discusses

[18] For detailed information, see the AEMC website at: http://www.aemc.gov.au/Market-Reviews/Completed/Review-Into-the-Use-of-Total-Factor-Productivity-for-the-Determination-of-Prices-and-Revenues.html [accessed on 3 January 2012].

some of the potential issues associated with the use of index-number-based TFP in energy regulation and conclusions are drawn in section 3.6

3.2 Description of the TFP method

Total factor productivity (TFP) growth is defined as output growth net of input growth. There are alternative approaches to the calculation of TFP growth, one of which is the index-number approach described below.

3.2.1 Method

The index-number approach applies the chosen index number formula to construct input and output quantity indices. The TFP growth is then defined as the difference between the rate of output quantity growth and input quantity growth. This approach is known as 'growth accounting'; i.e., productivity growth is the residual, or technical change as defined by Solow (1957), from output growth after accounting for input growth.

A general form of TFP index (in logarithmic form),[19] as defined in Coelli, Rao, O'Donnell and Battese (2005), is given in the following math equation:

$$Ln(TFP_{st}) = Ln(Output\ \ Index_{st} \,/\, Input\ \ Index_{st}) \qquad (3.1)$$

where the output and input indices are computed using suitable index-number formulae and subscripts *s* and *t* represent two observations (e.g., time periods or businesses).

The index numbers measure weighted-average change in outputs relative to weighted-average change in inputs, using revenue and cost shares as the output and input weights respectively. There are a number of index-number formulae available for measuring TFP, showing different ways of aggregating inputs and outputs. The Fisher ideal index (see Fisher, 1922) and the Tornqvist index (see Tornqvist, 1936) are most frequently used for TFP analysis, owing much to the work of Diewert (1976; 1981; 1992) and Caves, Christensen and Diewert (1982a) that provides the economic and theoretical justifications for TFP indexes. Box 3.1 provides a mathematical presentation of Tornqvist index as an example of TFP indexes.

Diewert (1976) showed that a Tornqvist index is a discrete-time approximation for its continuous-time equivalent Divisia index, implying that the underlying production function follows a homogenous translog function developed by Christensen, Jorgenson and Lau (1973). That is, under the assumption of cost minimisation, a quantity index taking the form of Tornqvist index is consistent with the homogenous translog function. Diewert (1992) recommended the use of the Fisher ideal index for TFP work because of its superior axiomatic properties while the Tornqvist index could also be used as it closely approximates Fisher's ideal index.

[19] The logarithmic form is commonly used due to its computational conveniences and mathematical properties (i.e., first differentiation is an approximation of growth rate).

Box 3.1 Tornqvist TFP index

A Tornqvist input quantity index is calculated as a weighted geometric average of the relative changes in each of a set of *M* inputs, weighted by the average cost shares of two observations. Mathematically, it can be expressed (in its logarithmic form) as:

$$\ln(X_{st}^{T}) = \sum_{j=1}^{M}\left(\frac{\omega_{js} + \omega_{jt}}{2}\right)(\ln x_{jt} - \ln x_{js})$$

where X_{st}^{T} is the Tornqvist input quantity index between two observations *s* and *t* (e.g., from period *s* to period *t*), ω_{js} and x_{js} is the cost share and quantity respectively, of the j^{th} input in observation *s*.

Analogously, a Tornqvist output quantity index for a set of *N* outputs can be expressed (in log-change form) as:

$$\ln(Y_{st}^{T}) = \sum_{i=1}^{N}\left(\frac{\omega_{is} + \omega_{it}}{2}\right)(\ln y_{it} - \ln y_{is})$$

where Y_{st}^{T} is the Tornqvist output quantity index between two observations *s* and *t* (e.g., from period *s* to period *t*), ω_{is} and y_{is} are the revenue share and quantity respectively, of i^{th} output in observation *s*.

A Tornqvist TFP index is measured as a weighted geometric average of the relative changes in each of the outputs relative to a weighted geometric average of the relative changes in each of the inputs. It is calculated (in log-change form) as the difference between the foregoing output quantity index and input quantity index:

$$\begin{aligned}\ln(TFP_{st}^{T}) &= \ln(Y_{st}^{T}) - \ln(X_{st}^{T}) \\ &= \sum_{i=1}^{N}\left(\frac{\omega_{is} + \omega_{it}}{2}\right)(\ln y_{it} - \ln y_{is}) - \sum_{j=1}^{M}\left(\frac{\omega_{js} + \omega_{jt}}{2}\right)(\ln x_{jt} - \ln x_{js})\end{aligned}$$

The Tornqvist index (as discussed above) fails to satisfy the transitivity test so that a direct comparison between two observations produces the same result as an indirect comparison via a third observation – a requirement for cross-sectional analysis.

Following Caves, Christensen and Diewert (1982b), a generalisation of the Tornqvist index to multilateral comparisons involving more than two businesses can be expressed (in its logarithmic form) as:

$$\begin{aligned}\ln(TFP_{st}^{T*}) &= \ln(Y_{st}^{T*}) - \ln(X_{st}^{T*}) \\ &= \left[\sum_{i=1}^{N}\left(\frac{\omega_{it} + \overline{\omega_i}}{2}\right)(\ln y_{it} - \overline{\ln y_i}) - \sum_{i=1}^{N}\left(\frac{\omega_{is} + \overline{\omega_i}}{2}\right)(\ln y_{is} - \overline{\ln y_i})\right] \\ &\quad - \left[\sum_{j=1}^{M}\left(\frac{\omega_{jt} + \overline{\omega_j}}{2}\right)(\ln x_{jt} - \overline{\ln x_j}) - \sum_{j=1}^{M}\left(\frac{\omega_{js} + \overline{\omega_j}}{2}\right)(\ln x_{js} - \overline{\ln x_j})\right]\end{aligned}$$

where Y_{st}^{T*} is the multilateral Tornqvist productivity index, and the bar means the average over the sample businesses, time periods or a combination of both. The method compares two businesses (*t* and *s*) by comparing their differences relative to the average business in the sample.

Diewert and Nakamura (2003) used the axiomatic approach to reviewing alternative index number formulations for measuring TFP. The tests applied to evaluating quantity indexes included the constant quantities test,[20] constant basket test,[21] proportional increase in output test,[22] and time reversal test.[23] Among the four most popular index formulations evaluated, only the Fisher ideal index satisfies all four tests. The Laspeyres and Paasche indexes fail the time reversal test,[24] while the Tornqvist index fails the constant basket test. The Fisher index is 'ideal' in that it decomposes the value index exactly into price and quantity components. However, even the Fisher index fails to satisfy another commonly used test, namely the circularity (transitivity) test, to ensure that a direct comparison between two observations produces the same result as an indirect comparison via a third observation.[25] This notwithstanding, transitivity is not considered essential for time-series analysis, but is required for cross-sectional comparison (Coelli, Rao and Battese 1998, pp. 91-92).

Conventional TFP indices only measure TFP growth and not TFP levels. Although they can be used to measure productivity change either over time or across businesses, it is most commonly used for the former. Transitive multilateral TFP indices, developed by Caves, Christensen and Diewert (1982b) using the EKS method,[26] provide a means of comparing both TFP levels and growth rates using panel data. As shown in Box 3.1, the essence of these multilateral indices is that comparison between any pair of two businesses is made relative to the sample-average business to ensure consistency in the relative productivity levels measured.

Empirical applications of multilateral TFP include Bureau of Industry Economics (1996) that compared productivity levels and growth rates for electricity supply businesses in Australia and the United States (US) spanning the period of corporatisation of the Australian businesses. The study found that the gap between Australian and US TFP levels narrowed markedly during the corporatisation period. A series of studies led by Denis Lawrence (see, for example, Lawrence (2003a) and Lawrence and Diewert (2006)) utilised multilateral TFP to examine comparative productivity performance for electricity distributors in New Zealand.

3.2.2 Data requirements

The index-number-based TFP method requires price and quantity information on input and output for two or more businesses or time periods.

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[20] This states that if quantities are the same in two periods, then the output index should be equal to one irrespective of the prices of the goods in both periods.
[21] This states that if prices are constant over two periods, then the level of output in the current period t compared to the base period s is equal to the value of output in period t divided by the value of output in period s.
[22] This states that if all outputs in period t are multiplied by a common factor, λ, then the output index in period t compared to period s should increase by λ.
[23] This states that if the prices and quantities in period s and t are interchanged, then the resulting output index should be the reciprocal of the original index.
[24] The Laspeyres index uses the base-period weights whereas the Paasche index uses the current-period weights to define an index.
[25] This states that for any three periods, s, t and b, a direct comparison between periods s and t yields the same index as an indirect comparison through period b.
[26] EKS stands for Elteto-Koves (1964) and Szulc (1964) whose work led to the derivation of transitive index numbers for multilateral price comparison.

The essential pieces of information include price and quantity of each input variable and each output variable to model. While quantity information on output (e.g., number of customers or kilowatt hours of electricity sold) is generally available, information on the physical quantity of inputs (e.g., labour, capital, and other inputs) may not be readily available. For example, for labour input, the measure of number of full-time-equivalent (FTE) staff or total hours worked may not be reported to the regulator or published in the public domain. Indirect measures that deflate value of the relevant costs (e.g., labour costs) by suitable price indexes (e.g., labour price index) may be used to obtain implicit quantity measures. The price indexes used may not be perfect because they are generally compiled for the industry by a statistical agency (for details, see Coelli, Estache, Perelman and Trujillo, 2003, p. 29).

Of the inputs modelled, capital input is most problematic to measure, which may explain the common practice of benchmarking opex as opposed to the 'total cost' approach. The calculation of capital input in terms of physical quantity (and cost) is important for TFP analysis, particularly in a capital-intensive network industry. The proper measure of capital input is the flow of capital services during a period. A proxy is the measure of capital stock in place, which is assumed to be in proportion to the periodic flow of capital services, regardless of the age of assets. For electricity distribution, physical quantities of two main distribution assets are commonly modelled – network line length (in route/circuit kilometres) and installed transformer capacity (in megavolt amperes – MVa).[27] This specification implies the one-hoss shay model of physical deterioration that assumes constant provision of services at full productive efficiency until the end of the service life of an asset.[28] Other depreciation profiles may also be assumed in the empirical studies; for example, a declining-balance approach to depreciation called perpetual inventory method (PIM) has generally been adopted in the consultancy work conducted by Pacific Economics Group (PEG) for constructing the constant-dollar replacement cost of utility assets using detailed capital data over time.

For TFP analysis, price or revenue/cost share information is also required as weights to aggregate relevant inputs and outputs. Where revenue/cost shares for outputs modelled are not directly observable, either empirical evidence is required (e.g., estimating econometric cost functions) or a subjective judgement needs to be made on the appropriate weights to attribute to the outputs specified. As noted above, the input price indexes may be sourced from statistical agencies. A service-price approach to capital cost measurement is generally used to measure the price of periodical capital services, which incorporates three components reflecting depreciation rate (the return of capital), opportunity cost (the return on capital) and capital gains. Alternatively, the cost of using capital inputs may be measured indirectly at *ex post* return (i.e., the residual between revenue and operating costs realised) if restrictive assumptions about the technology and market characteristics are held to be true.[29]

[27] Network line length models transmission of energy to customer, and installed transformer capacity captures transformation of high voltage energy to low-voltage energy.

[28] A number of researchers in the area consider that the one-hoss shay depreciation pattern reasonably reflects the depreciation process in electricity distribution. See for example, Makholm and Quinn (2003, p. 5) and Lawrence and Diewert (2006, p. 217). For a definition of the term, see OECD (2012).

[29] These include competitive input and output markets and constant returns-to-scale production technology. See relevant discussions in Hulten (1986).

Additional information on key operating environmental characteristics may also be required for the TFP analysis. The relevant data can be used for testing whether the businesses should be grouped on the basis of comparable operating environments or for second-stage regression analysis to adjust business performance for external factors that are beyond management control.[30] For electricity distribution businesses, key operating environment conditions that may affect productivity performance include (but are not limited to):

- energy density as measured by GWh per circuit kilometre;
- customer density, measured as customers per square km of service area or customers per route kilometre;
- network density, measured as route kilometre per square kilometre of service area;
- peak demand: note that this may also be included as an output in the model specification;
- customer mix, measured as the ratio of domestic customers to commercial and industrial customers; and
- the ratio of underground to overhead network.

The datasets used can be cross-sectional data that compare productivity differences across businesses at a point in time, time-series data that examine productivity change of the business (industry, sector or economy) over time, or panel data for both time-series and cross-sectional productivity analysis. For possible regulatory applications, the availability of a quality and reliable TFP dataset that covers comparable businesses over a sufficiently long time period is desirable.

3.2.3 Advantages and disadvantages

The index-number-based TFP can be used to measure productivity change either over time or across businesses. It is most commonly used for time-series analysis to measure temporal TFP change and/or gauge trend TFP growth.

The index-number-based TFP has a number of merits. First, the commonly adopted Tornqvist or Fisher TFP indexes have economic-theoretic properties relating to the underlying production technology that they present. Second, all inputs can be accounted for conceptually. Third, it requires fewer observations than alternative approaches to measuring productivity change (e.g., Malmquist TFP index under DEA or SFA). Fourth, the approach is relatively simple and transparent, and the results are readily reproducible.

However, the index-number-based TFP approach is associated with certain limitations. The approach can be information-intensive as it requires not only

[30] For example, an input-requirements function can be estimated econometrically to adjust total input usage for a range of operating environment factors. This will then permit the calculation of the input usage that would be required by each distributor if they all faced the same values of the specified operating environment variables.

quantity information, but also price (or revenue/cost share) information to compute the TFP index. As a non-parametric technique, it cannot produce confidence intervals and other statistical tests. Further, unlike TFP measured under DEA or SFA, index-number-based TFP does not allow for a decomposition of productivity changes into the sources. Implicitly assumed under growth accounting are full technical efficiency,[31] constant returns to scale (CRS), a behavioural objective such as cost minimisation, and neutral technical progress. If these assumptions are inconsistent with the data, then the index number method will provide a biased estimate of technical change that can be attributable to a combination of factors, such as changes in technical efficiency, allocative efficiency or scale efficiency.

3.3 Literature review of the TFP method

3.3.1 Literature review

The index-number-based TFP method has been used in several studies on all or part of the energy sector in Australia, covering a broad range of research objectives. An early study conducted by Lawrence, Swan and Zeitsch (1991) used multilateral TFP to examine the productivity of Australian state-based vertically integrated electricity authorities. The study found great variations in productivity changes across states, but the differences declined over time. Later studies were carried out to examine the impact of microeconomic reform on the energy sector. In assessing the productivity performance of the electricity supply sub-sector in New South Wales (NSW), Pierce, Price and Rose (1995) reviewed a number of empirical studies, including two studies (London Economics and Energy Supply Association of Australia (ESAA); 1993, 1994) of New South Wales metropolitan distributors supplying distribution and retailing services, commissioned by the Independent Pricing and Regulatory Tribunal of New South Wales (IPART). The review found that productivity improvements were realised by each distributor over the sample period 1981-82 to 1993-94.

Jamasb and Pollitt (2001) discussed the use of index-number-based TFP as a benchmarking technique for regulatory purposes. They noted that the method could use the Tornqvist index as a measure of historical productivity growth at the firm, industry, or economy-level and in setting the productivity-offsetting factor X in price-cap regulation. In their view, this method is relatively easy to implement, but may inadvertently favour less efficient firms, as they may be in a better position than more efficient firms to outperform the uniform productivity target and earn large profits.[32]

The IPART commissioned a report on the efficiency of NSW electricity distribution businesses (i.e., London Economics, 1999) that benchmarked the NSW utilities against 219 utilities operating in Australia, New Zealand, the US and the UK, using DEA. Various other benchmarking techniques were used for sensitivity analysis of

[31] The work of Balk (1998) relaxed the assumption of full technical efficiency in deriving various index numbers.

[32] By their nature, less efficient businesses are theoretically more capable of making productivity gains than more efficient businesses, as they are more capable of implementing changes to their businesses that will improve efficiency and lead to greater productivity (assuming that all businesses face the same environment).

the DEA results, including Tornqvist TFP.[33] The Tornqvist TFP index was calculated for the NSW distributors using a single output – total energy delivered (GWh), three inputs – total operating and maintenance (O&M) expenditure (in 1997-98 $AUS), route kilometres and nameplate transformer capacity, and cost share information from other similar Australian electricity distributors as the input weights. The outcome of the review indicated inefficiency among the NSW electricity distribution businesses.

Cambridge Economics Policy Associates (CEPA 2003) prepared a report for the Ofgem to develop the use of benchmarking in the 2005 electricity distribution price control review (DPCR4). The report reviewed the Ofgem's past practices;[34] alternative benchmarking methods; the appropriateness of cost drivers; and distribution network service data in 2001-02 for an application of the COLS method used in DPCR3. CEPA (2003) considered a combination of DEA and COLS as the most appropriate approach to determining the efficiency frontier for the distributors, given the data currently available. CEPA (2003) considered that the index-number-based TFP method was useful for assessing frontier shift, but, found that, due to the disparity shown in the estimated productivity performance, there were application issues for setting the firm-specific X factors.

CEPA (2003) also raised an issue with examining opex efficiency alone. The TFP results showed that businesses that displayed limited improvements in opex performance, despite being some way from the frontier, had generally shown good improvements in TFP under the totex approach. Nevertheless, measuring the capital expenditure element of totex is not straightforward.[35]

Lawrence (2005a), in a commissioned report, examined the performance of Western Power's distribution operations over the period 1999 to 2003 compared to 12 other Australian electricity distribution businesses. A comprehensive range of performance indicators was used for comparative performance analysis. The TFP analysis specified three outputs – energy throughput in gigawatt-hours, system capacity in MVa-kilometres and number of customers, and five inputs – O&M expenditure, overhead lines, underground lines, transformers, and other capital. According to the report, this three-output specification has the advantage of incorporating key features of the main density variables (customers per kilometre and sales per customer) driving distributors' costs. The report considered that the comprehensive analysis enabled effective benchmarking of the many facets of electricity distributor performance.

Lawrence and Diewert (2006) conducted a TFP study that was used by the New Zealand Commerce Commission (NZCC) as the basis for setting X factors under the CPI–X regulation for electricity networks in New Zealand. Price-path thresholds were in place which set a maximum change in real output prices that each distribution network business would be allowed without triggering further investigation. The X factors in the thresholds were made up of three components: a *B* factor reflecting

[33] Additional analyses included: sensitivity analysis using SFA, sensitivity checks (such as those based on exchange rates) and a second-stage Tobit regression to adjust the DEA efficiency scores to account for environmental differences.

[34] The Ofgem previously used Corrected Ordinary Least Squares (COLS) regression to benchmark distribution businesses on normalised controllable operating costs.

[35] This issue is discussed further in chapter 8 of this paper.

industry-wide TFP growth, a C_1 factor reflecting comparative-productivity performance and a C_2 factor reflecting comparative profitability.

Using multilateral TFP and econometric cost function methods, TFP levels and growth rates for 29 electricity distributors were examined over an eight-year period from 1996 to 2003. With three outputs – energy throughput in gigawatt–hours, system capacity in MVa-kilometres, and number of customers; and five inputs – O&M expenditure, overhead lines, underground lines, transformers, and other capital a Fisher TFP index was calculated. As revenue for each output specified was unobservable, the study used the relative shares of cost elasticities derived from an econometric cost function estimated for the sampled New Zealand distributors.

In this study, Lawrence and Diewert (2006, p. 215) provided reasons for not including a quality variable (e.g., frequency and duration of interruptions). They considered that the index-number-based TFP does not incorporate 'bad outputs' (i.e., a decrease in the measure represents an increase in service-quality output) easily. They also discussed other major measurement problems encountered in electricity network productivity studies, particularly the specification of outputs and capital inputs. This work (commissioned by the Commerce Commission) has been published in various forms: see for example, Lawrence, Diewert and Kain (2007), and Lawrence (2003a).

Makholm and Quinn (2003) provided a detailed description of the index-number-based TFP method and its potential use in the price-cap regulation for electricity distribution; applying the method to the determination of the productivity of electricity distribution networks in the United States. A Tornqvist TFP index was constructed with principal outputs, measured according to customer groups (by either number of customers, system capacity or sales volume) – residential, commercial, industrial or public entities, and three categories of inputs – labour, capital, and material and others. Relevant regulatory data on 87 companies operating in 37 states over 23 years from 1972 to 1994 were used to measure TFP at the industry level and for each of the four regions (i.e., northeast, midwest, south and west). The authors suggested using the estimated industry-wide TFP growth as a productivity-offsetting factor (X factor) in the price-cap formula. The authors considered the TFP method a useful tool for computing the X factor under the price-cap regulatory formulas.

In a study commissioned by the AEMC, Brattle Group (2008) reviewed the use of TFP in energy network regulation outside Australia. International experience using TFP includes electricity distribution in New Zealand; gas distribution in Ontario, Canada; energy networks in the UK; electricity distribution in the Netherlands; and selected jurisdictions in North America. The report first examined how each regulator had gone about the process of undertaking a TFP study; and second, how TFP results were used in determining the maximum allowed growth rate of regulated prices. The report also discussed design issues associated with TFP measurement and practice, one of which is the time period for measuring TFP growth. Brattle Group (2008, p. 4) considered that using the longest time period possible to compute average TFP growth over the longer term could mitigate the impact of cyclical variations, temporary and one-off events.

Another study by Economic Insights (2009a) was also commissioned by the AEMC to conduct a sensitivity analysis of TFP results to variations in the estimation method, including alternative output and input specifications, lengths of the time period, and methods used for indexing, weighting inputs and outputs, and calculating the TFP growth rates. The study found that (Economic Insights, 2009a, pp. i-v, 22-23):

- sensitivity of input-output specifications depends on whether the alternative outputs (and inputs) grow at similar or different rates;
- the difference in results from the use of the Fisher and Tornqvist indexes may not be material; and
- the difference in using the average methods as opposed to the use of regression-based methods for calculating growth rates can be substantial. This is demonstrated by the application to estimating TFP growth for the Victorian gas distribution sub-sector between 1998 and 2007. The geometric-average growth rate was found to be substantially different from the trend growth rate when the starting and ending years were outlying observations relative to the trend of the intervening years.

3.3.2 Summary of the studies

The literature review shows that a number of empirical studies have applied the index-number-based TFP method to the examination of the energy sector in Australia and other countries. Table 3.1 below summarises the studies specific to electricity distribution networks in terms of methods (including index-number-based TFP), index formula (Tornqvist versus Fisher index), data, input-out specification and other important elements of the TFP analysis.

In summary, the literature suggests that the Fisher index and the Tornqvist index are commonly used for TFP analysis, and that time-series or panel data are generally used to measure industry-level productivity growth. The choice of input-output specifications is often constrained by data availability and quality. For example, single or multiple output measures may be used due to the availability of the relevant revenue/cost share information. The capital input raises some measurement issues. There is also some debate on the appropriate output quantity measures. It does not appear to be a common practice to use second-stage regression analysis to test the significance of a range of operating environmental factors in explaining the differences in productivity change.

In general, there is a consensus that the index-number-based TFP method is a useful tool for calculating the productivity-offsetting factor under the CPI–X price-cap regulatory formulas. However, depending on the regulatory framework, the method may not necessarily be used as the primary assessment tool. Instead, it can be used for sensitivity analysis to check the robustness of results with respect to method.

Table 3.1: Summary of the Literature Applying TFP to Benchmarking Energy Networks*

Author/s	Country / Territory	Sector / years	Methods	Inputs	Outputs	Other factors/specification issues/findings
London Economics (1999)	NSW (Australia), New Zealand, the UK and the US	6 electricity distribution businesses in NSW (1995-96 to 1997-98)	DEA – VRS (primary); SFA; TFP (Tornqvist)	▪ Total O&M expenditure (1997-98 $AUS) ▪ Route kilometres[36] ▪ Nameplate transformer capacity	▪ Total energy delivered (GWh)	Tornqvist TFP index was computed for NSW distributors as part of the sensitivity analysis.
Makholm and Quinn (2003)	US	Electricity distribution (1972 to 1994)	TFP (Tornqvist)	▪ Labour ▪ Capital (one-hoss shay) ▪ Material and other operating costs	▪ Outputs by customer type (residential, commercial, industrial and public entities)	The paper suggested using the estimated industry-wide TFP growth as the productivity-offsetting factor in the price-cap formula.
CEPA (2003)	UK	Electricity distribution (1997-98 to 2001-02)	COLS, SFA, DEA, TFP (Tornqvist), Partial factor productivity (PFP)	▪ Total expenditure	▪ Total energy delivered (GWh) ▪ Total number of customers ▪ Network length	Wide disparities in the firm-level performance showed that it was premature to use these directly to set X factors. However, TFP can be a useful tool for assessing frontier shift.
Lawrence (2005a)	Australia	Electricity distribution (1999 to 2003)	TFP, PPI	▪ Total O&M expenditure (constant price) ▪ Overhead lines ▪ Underground line ▪ Transformer capacity ▪ Other capital	▪ Total energy delivered (GWh) ▪ Total number of customers ▪ System capacity (MVa)	The report considered that comprehensive performance analysis enabled effective benchmarking of electricity distribution businesses.
Lawrence and Diewert (2006)	New Zealand	29 electricity distribution businesses (1996 to 2003)	TFP	▪ Total O&M expenditure ▪ Overhead lines ▪ Underground line ▪ Transformer capacity ▪ Other capital	▪ Total energy delivered (GWh) ▪ Total number of customers ▪ System capacity (MVa)	An econometric cost function was estimated to inform the cost share of outputs specified.

* The ‘Inputs’ and ‘Outputs’ columns of the table only present the input-output specifications for the index-number-based TFP analysis.

[36] The route kilometres measure is the linear distance between poles regardless of how many circuits are supported. The circuit kilometres measure is the length between poles by number of circuits, which is at least the same as route kilometres. Countries/jurisdictions may report one or both of the measures. For example, route kilometre measure is available for the US distributors while the UK and NZ distributors report only circuit kilometres (London Economics, 1999, p. 38).

3.4 Regulatory practices using the TFP method

3.4.1 Regulatory practices review

Index-number-based TFP benchmarking methods have been used by energy regulators in the determination of price and revenue requirements for electricity and gas distribution businesses in countries, such as Australia, New Zealand, the Netherlands, Germany, and Austria, and in some Canadian provinces (e.g., Ontario). In addition, state-based regulators in the US, such as the California Public Utilities Commission (CPUC), have received applications from energy utilities that include supporting productivity studies on the basis of index-number-based TFP and econometric cost function methods.[37]

Germany and Austria[38]

According to WIK-Consult (2011), the regulation of electricity and gas distribution sub-sectors in Germany and Austria has involved the use of index-number-based TFP analysis to estimate the frontier shift component of the X factor. The X factor also incorporates a business-specific efficiency improvement component (or stretch factor) which has been determined using alternative benchmarking methods such as DEA and Modified Ordinary Least Squares (refer to sections 6.4 and 4.4 respectively).

The energy regulator in Austria, E-control, decided on a frontier shift at 1.95 per cent per annum for both electricity and gas distribution based on its review of international studies, international practices, own preliminary calculation and consultation with stakeholders (WIK-Consult, 2011, p. 7). The Federal Network Agency (BNetzA) in Germany applied the Tornqvist TFP index to the computation of the frontier shift component, the value of which was heavily disputed. Several industry-commissioned studies suggested lower values, based on different data sources and base periods. The High Court decision finally ruled out the inclusion of industry-economy productivity differential in the revenue-cap formula (WIK-Consult, 2011, pp. 29-31).

However, for these two countries, no detailed information on the derivation of the frontier shift component is available from the relevant regulatory decision papers. The determination of this component is often a result of a bargaining process between stakeholders rather than a regulatory decision based on sound and transparent economic analysis (WIK-Consult, 2011, p. 60).

California, United States[39]

In many US states, performance-based regulation (PBR) has been adopted for the regulation of electricity and gas distribution businesses. TFP studies, sometimes combined with the econometric cost model approach, have been submitted by the regulated utility as supporting evidence and thus have become an important input to the regulatory process of setting of the X factor. The TFP studies typically examine

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[37] As it is not possible to cover all countries, there may be other examples of energy regulators applying TFP benchmarking methods that have not been captured in this paper and the supporting research. Haney and Pollitt (2009) undertook a survey of current benchmarking methods applied by energy regulators worldwide.
[38] Refer to sections 3.1 and 3.4 of WIK-Consult (2011).
[39] Refer to chapter seven of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

industry and company-specific TFP performance using the index-number approach (Division of Ratepayer Advocates (DRA), 2007, p. 1).

For example, in California, price caps in the form of industry-specific inflation index and productivity index differential (including a stretch factor) were approved by the CPUC for the gas and electricity distribution services of San Diego Gas and Electric Company (SDG&E) in 1999 for the years 1999 to 2002 and subsequently extended to 2003 (Lowry and Getachew 2009c, p. 67). As part of this process SDG&E commissioned PEG to conduct an index-number-based TFP analysis for both its electricity distribution and gas distribution services (PEG, 2008, p. 97). Similar supporting TFP studies have since been presented to the CPUC by SDG&E in subsequent General Rate Case (GRC) applications in 2003, 2008 and 2011.[40] SDG&E has also commissioned efficiency benchmarking studies using the econometric cost function method to support its argument for a zero value of the stretch factor in the GRC application in 2008.[41] The final regulatory decisions were based on a settlement process between SDG&E and DRA (and other stakeholders).

For SDG&E's 2008 GRC, the supporting PEG study used Tornqvist TFP index to estimate productivity trends for the sampled US utilities as a group, large Californian utilities as a group, and SDG&E itself. Gas distribution and electricity distribution were estimated separately. The weights used to construct weighted-average output growth were derived from the econometric cost model approach.

Details of the electricity distribution analysis are:

- Sample: a total of 77 major investor-owned electricity distributors in the US over the period 1994 to 2004;
- Services covered: electricity distributor services covering distribution, customer accounts, sales and general administration;
- Outputs: electricity sales (in kilowatt hours; 50 per cent) and customers (50 per cent);[42] and
- Inputs: cost weighted sum of labour, capital, fuel and non-labour O&M inputs.

Details of the gas distribution analysis are:

- Sample: 34 large gas distributors, from 1994 to 2004. Some gas distributors also provided gas transmission and/or storage services;
- Services covered: gas distributor services covering costs comprising O&M expenses and costs of plant ownership applicable to distributing gas. Expenses for customer service and information and uncollectible bills were excluded

[40] A General Rate Case (GRC) occurs when the utility requests that the regulator considers future tariffs proposal. GRCs generally occur every three to four years.
[41] The description is not based on the original PEG study, primarily drafted by Mark Lowry, due to no access to the report. Instead, the summary is based on two papers – Lowry and Getachew (2009c) that summarised the PEG indexing and benchmarking work and Division of Ratepayer Advocates (DRA) (2007) that replicated and critiqued that PEG study.
[42] The output weights were taken from the cost elasticity results in the accompanying econometric cost modelling of electricity distribution undertaken in the original PEG study.

because those expenses rose sharply over the sample period due to circumstances beyond management control;

- Outputs: throughput (27 per cent) and customers (73 per cent);[43] and
- Inputs: cost weighted sum of labour, capital, fuel and non-labour O&M inputs.

Ontario, Canada[44]

Electricity distribution

In Canada, PEG studies have been used in informing the Ontario Energy Board (OEB)'s determination of the price path for electricity distribution businesses. Since 2000, the OEB has introduced an incentive regulation framework based on a price cap of the form: $PCI = P - X \pm Z$ where the growth in the price cap index (*PCI*) is determined by the inflation rate (*P*), a productivity-offsetting factor (*X*) and an additional factor to account for unforseen events (*Z*).

The *X* factor includes an industry-wide productivity component estimated by the index-number-based TFP method, an inflation differential component and a 'stretch factor' estimated by the unit-cost and econometric methods (refer to sections 2.4 and 4.4 respectively).

The estimate of industry-wide productivity was based on a long-run TFP trend analysis conducted by PEG using US data for the period 1988 to 2006 as a proxy for the Ontario electricity distribution sub-sector. The US data were used as the Ontario data were not sufficiently long to estimate a long-run productivity growth. The study is similar to the TFP analysis performed for the study of SDG&E (PEG, 2008, p. 34), including the following:

- Tornqvist index;
- TFP trend is the simple average of annual TFP growth rates;
- Three inputs (capital, labour, and materials and services) and two outputs (number of retail customers and total electricity deliveries – kWh); and
- Econometric model was used to determine cost elasticity shares to weigh outputs (PEG, 2008, pp. 128-132).

Gas distribution

TFP analysis has also been undertaken by PEG and the Brattle Group for Canada's gas distribution industry. The PEG study, commissioned by the OEB, used an econometric approach to estimate TFP. The Brattle Group study, commissioned by Enbridge (one of the two major distributors in Ontario), used an index-number-based approach to estimate TFP. In both studies, the X factor was calculated as the sum of a 'productivity differential' component and an 'input price differential' component. The productivity differential was the difference between the productivity trends of the

[43] The output weights were taken from the cost elasticity results in the accompanying econometric cost modelling of gas distribution undertaken in the original PEG study.

[44] Refer to chapter six of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

gas distribution industry and the economy as a whole. The input price differential was calculated as difference between the input price trends in the economy as a whole and the gas sub-sector in particular.

As with electricity distribution, estimation of the historic TFP growth was undertaken using data from 36 US gas distributors as a proxy for the Canadian gas distribution sub-sector. In the index-number-based TFP application, the Brattle Group study specified four inputs (labour, material and supply, capital, and gas use) and volume of gas distributed, disaggregated by customer type, as output measures.

However, the results from these TFP studies were not used directly by the OEB in its final determination. Rather, the OEB determined revenues by the application of a 'distribution revenue requirement per customer' formula.

New Zealand[45]

As discussed above in section 3.3, the index-number-based TFP method has been used in New Zealand for setting the X factor(s) under the CPI–X price path for electricity distribution and gas pipeline businesses.[46] For this purpose, the New Zealand Commerce Commission commissioned a number of productivity studies, led by Lawrence (some reviewed in section 3.3 above), to measure industry-wide productivity growth.

Electricity distribution

In a series of studies performed by Lawrence (see for example, Lawrence 2003a and Economic Insights 2009b), the index-number-based TFP method was employed for determining industry-wide productivity for the regulatory periods 2004 to 2009 and 2010 to 2015 respectively. For the period 2004 to 2009 under the previous threshold regulatory regime, the X factor included the estimates of industry-wide productivity relative to economy-wide productivity and an input price differential, comparative productivity and comparative profitability. For the period 2010 to 2015, the X factor consisted of only the estimate of industry-wide productivity relative to economy-wide productivity and the input price differential.

The data used for measuring industry-wide TFP covered 28 electricity distributors since 1996. The Fisher index was used to measure productivity of the electricity distribution sub-sector using three outputs – energy throughput in gigawatt–hours, system capacity in MVa–kilometres and number of customers, and five inputs – O&M expenditure, overhead lines, underground lines, transformers, and other capital. The output weights were based on the cost elasticity results derived from an econometric cost function study by Lawrence (2003a).

In addition, under the previous threshold regulatory regime which applied from 2001 to 2009, multilateral TFP analysis was also undertaken to determine the comparative productivity component. The results were used to group electricity distributors and assign stretch factors. The amendments to the Commerce Act in 2008 prohibit the

[45] Refer to chapter four of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

[46] Electricity distribution and gas pipeline (transmission and distribution) businesses are subject to default price–quality path regulation, where the price path is of a CPI–X form. The electricity and gas default price-quality paths are assessed separately.

inclusion of comparative performance in the setting of the new default price-quality paths.

Gas distribution

Lawrence, through Economic Insights, was also engaged by the Commerce Commission to assess whether, for New Zealand, long–run productivity growth rates, as well as input price growth, were significantly different between gas pipeline businesses (i.e., distribution and transmission pipelines) and the economy as a whole. With data only available for the three gas pipeline businesses between 2006 and 2010, a preliminary TFP analysis was undertaken based on two inputs, opex and pipeline length, and two outputs, energy throughput and customer numbers. Different input and output weightings were considered and compared. The analysis was 'exploratory' in the sense that additional data would have been required to estimate a long-run average industry productivity growth rate. Economic Insights (2011) also examined the literature for TFP results for overseas gas distribution businesses and for other New Zealand industries. The results assisted the Commerce Commission in setting a zero X factor in the default price-quality path applying to all New Zealand gas pipeline businesses.

Australia

In Australia where the forward-looking, multi-year building-block-model (BBM) framework has been commonly adopted, ratio and trend analysis have been the most commonly used benchmarking approaches although TFP, PFP, multifactor productivity and regression analysis have had limited application. It is noted that:

- In assessing Power and Water Corporation's electricity distribution services, the Northern Territory Utilities Commission (NTUC) used TFP to determine the X factor in the CPI–X price path formula for the 2009-10 to 2013-14 regulatory period with the base-year costs determined using a building-block-model approach (NTUC, 2009); and

- Jemena Gas Networks in NSW, Envestra Queensland and Envestra South Australia all presented the AER with TFP analysis as part of their recent gas access arrangement reviews. The analysis also included Partial Factor Productivity (PFP) analysis.

GHD Meyrick was engaged by the NTUC to advise on the TFP application. To that effect, GHD Meyrick reviewed relevant academic and regulatory evidence, providing productivity growth trends in electricity distribution industries in New Zealand, the US and Victoria. GHD Meyrick also performed a TFP analysis of Power and Water Power Networks (PWPN) covering the years 2000 to 2008 (GHD Meyrick, 2008). The chained Fisher index was used to measure TFP for electricity distribution modelled by three outputs (throughput – gigawatt-hour, system line capacity – MVa kilometres, and number of connections) and four inputs (opex – constant price, overhead network, underground network, and transformers). The output weights used were based on Lawrence (2003a), which produced 'an output cost share for throughput of 22 per cent, for system line capacity of 32 per cent and for connections of 46 per cent' (GHD Meyrick, 2008, p. 13). The results were used by the NTUC (2009, p. 43) to decide the long-run industry TFP growth.

In a submission to the Ministerial Council on Energy's Expert Panel on Energy Access Pricing, the Essential Services Commission in Victoria (ESCV) set out the data requirements that it considered necessary or desirable to undertake TFP analysis for electricity distribution. These are re-summarised below in table 3.2.

Table 3.2: ESCV view on TFP Data Requirements for Electricity Distribution

Category	Necessary	Desirable
Output	▪ total number of customers ▪ total volume delivered ▪ peak demand	delivery volume was broken down into each customer segment
Output cost shares	revenue for total number of customers, total volume and peak demand to weight them in determining the output index	revenue to be broken down into each customer segment
Input	input price indexes	more specific input quantity measures, for example data on labour quantity (number of employees) or the cost of labour ($ per employee)
Cost	total O&M expenditure, the optimized depreciated replacement cost of the plant for the earliest year available, and the dollar value of additions to the plant	salaries and wages associated with O&M expenditure and superannuation contributions and other elements charged to O&M expenditure

Source: *ESCV (2006*, pp. 20-21).

3.4.2 Summary of regulatory practices

The foregoing review shows that the index-number-based TFP method has been used in a number of countries and/or jurisdictions for the regulation of the electricity and/or gas distribution sub-sectors. Tables 3.3 and 3.4 below summarise the regulatory applications in terms of regulatory jurisdiction, methods (including index-number-based TFP), index formula (Tornqvist versus Fisher index), data, input-output specification and other important elements of the TFP analysis, for electricity distribution and gas distribution respectively.

Table 3.3: Summary for the Applications of Index-number-based TFP to the Regulation of Electricity Distribution*

Country	Regulator	Data / time period	Method	Inputs	Outputs	Regulatory application
New Zealand	NZCC	▪ Business disclosure data covering 13 years 1996 to 2008 for 28 electricity distribution businesses (EDBs); ▪ Data on Victorian and investor-owned US electricity distribution businesses or international productivity analysis	▪ Fisher TFP index, supplemented with regression analysis to measure trend TFP growth ▪ Multilateral TFP index used previously to derive comparative performance	▪ Operating expenditure ▪ Overhead network ▪ Underground network ▪ Transformers ▪ Other assets.	▪ Throughput ▪ System capacity ▪ Connections	TFP analysis was used to determine the industry-wide productivity change component of the X factor, which contains two terms – industry-economy differential in TFP growth and industry-economy differential in input price change.
Canada	OEB	Data on 69 US electricity distribution companies from 1988 to 2006 using FERC Form 1	▪ Tornqvist TFP index ▪ Trend TFP growth is the simple average of annual TFP growth rate	▪ Capital ▪ Labour ▪ Materials and services	▪ Number of retail customers ▪ Total electricity deliveries (kWh) weighted by cost elasticity share, estimated econometrically	TFP analysis was used to determine the productivity factor (i.e., industry-economy productivity differential) which, together with the inflation differential and the stretch factor, makes up the X factor.
US	CPUC	Data on 77 major investor-owned electricity distributors in the US over the period 1994 to 2004	▪ Tornqvist TFP index	▪ Labour ▪ Capital, ▪ Fuel and non-labour O&M input	▪ Electricity sales (in kilowatt hours; 50 per cent) ▪ Customers (50 per cent) Econometric cost function method to estimate the weights	Industry and company-specific productivity performance was examined. It was used by the regulated companies as supporting evidence for its GRC application.

Country	Regulator	Data / time period	Method	Inputs	Outputs	Regulatory application
Australia	NTUC	▪ TFP analysis for Power and Water covering 2000 to 2008 ▪ Review of empirical evidence of productivity growth of electricity distribution in Victoria, New Zealand and US	Fisher TFP index to measure industry TFP growth trend	▪ Opex – constant price ▪ Overhead network ▪ Underground network ▪ Transformers	▪ Throughput – gigawatt-hour (22 per cent) ▪ System line capacity – MVa-kilometres (32 per cent) ▪ Number of connections (46 per cent) weights as per Lawrence (2003a)	TFP was used to calculate the industry productivity growth trend, which is used to determine the X_1 factor (i.e., industry-economy differential).
Germany	BNetzA		Tornqvist TFP index as the frontier shift terms (but law prohibiting its inclusion)			
Austria	E-Control	▪ 1996 to 2001 ▪ Around 20 distribution businesses for each of the gas and electricity sub-sectors (not separated into sub-sectors)	TFP analysis			TFP was used to set the frontier shift component at an annual rate of 1.95 per cent (for the first regulatory period), in addition to the efficiency catch up component (using DEA and MOLS).

* The ‘Inputs’ and ‘Outputs’ columns of the table only present the input-output specifications for the TFP analysis.

Table 3.4: Summary for the Applications of Index-number-based TFP to the Regulation of Gas Distribution*

Country	Regulator	Data	Method	Inputs*	Outputs*	Regulatory application
New Zealand	NZCC	▪ Data from gas distribution businesses (GDBs) 2006 to 2010 ▪ Economy-wide productivity growth for the period 1997 to 2009	TFP Index and multilateral TFP index to derive an economy-wide productivity growth	▪ Opex ▪ Pipeline length	▪ Energy throughput ▪ Customer number	The TFP results for the three GDBs were compared with the economy wide TFP. The X factor was set at zero for the GDBs as there was insufficient evidence to indicate otherwise.
Canada	OEB	Data on 36 US gas distributors – as a proxy for Canadian gas distributors	TFP index approach	▪ Labour ▪ Material and supply ▪ Capital ▪ Gas use	▪ Volumes distributed, divided into three groups for customer types	The TFP analysis was performed by Brattle Group for the business. The OEB did not apply this method directly in its regulatory decision. Instead it determined revenues by the application of a Distribution Revenue Requirement per Customer.
United States	CPUC	Data on 41 gas distributors for 1994 to 2004, from a number of sources	Tornqvist TFP index	▪ Capital services ▪ Labour services ▪ Non-labour O&M inputs	▪ Number of retail customers (73 per cent) ▪ Volume of retail deliveries (27 per cent)	The TFP analysis was included with SDG&E's GRC application. Based on the study, SDG&E proposed a progressive productivity factor. The final decision was based on a settlement process which set annual revenue requirements rather than setting individual components of the annual adjustment rate such as escalation factor, productivity-offsetting factor and customer growth rate.
Austria	E-Control	▪ 1996 to 2001 ▪ Around 40 distribution businesses for gas and electricity (not separated into sub-sectors)	TFP analysis			TFP was used to set the frontier shift component at an annual rate of 1.95 per cent (for the first regulatory period), in addition to the efficiency catch up component (using DEA and MOLS).

* The 'Inputs' and 'Outputs' columns of the table only present the input-output specifications for the TFP analysis.

The analyses have been based on data covering 20 to 80 comparable distribution businesses over a period of five to 13 years. In terms of model specification and estimation, the findings of the regulatory practices review are consistent with the literature. This may be attributable to the debate evolving from two streams of work, led by Dr Denis Lawrence (and his association with Meyrick and Associates previously and Economic Insights presently) and Dr Larry Kaufmann and Dr Mark Lowry (with their PEG work) respectively, which have heavily influenced both the academic and regulatory work. The main differences between the PEG and Lawrence specifications for electricity distribution are set out in table 3.5 below.

It also appears that the index-number-based TFP method is generally used to measure the industry-wide TFP growth trend, which is a component of the productivity offsetting factor in the CPI–X price-path formula. It is less commonly used to assess individual distribution businesses' performances relative to each other and less commonly used under the forward-looking multi-year BBM framework in countries like Australia or the UK. Therefore, the method may be most useful, as a cross-check under the BBM approach rather than a primary assessment tool.

Table 3.5: PEG and Lawrence Model Specifications for Electricity Distribution

Issue	PEG (February 2008)	Lawrence and Diewert (2006)
Index	Tornqvist index	Fisher index
Output	Number of customers Throughput	Number of customers Throughput Network system capacity
Output weighting	Output cost shares based on econometric cost function estimation; constant weights for whole period	Output cost shares based on econometric cost function estimation; constant weights for whole period
Input	O&M expenditure Capital input quantity proxied by single deflated, depreciated asset value series	O&M expenditure Capital input quantity proxied by physical quantities for four asset categories (overhead network, underground network, transformers, other).
Input weighting	Exogenous capital cost measure (costs did not equal revenue)	Exogenous capital cost measure (costs did not equal revenue)

3.5 Issues arising from the review

While index-number-based TFP has had limited application in Australia, it is more commonly used in New Zealand, Canada, the US and some European countries. This is possibly due to the statutorily-required use of the BBM approach to energy determinations in Australia,[47] which does not explicitly incorporate the productivity-offsetting factor.[48] Also as previously noted by the ACCC (2003, p. 48),

[47] This is set out under Chapter 6 of the NER.

[48] Note that the X factor under the Post-tax Revenue Model (PTRM) is merely a smoothing factor.

index-number-based TFP and other benchmarking approaches are difficult to undertake because of the limited productivity data available and the potential for variations in productivity growth between individual businesses. More recently, in the review of the TFP approach to regulation, the AEMC found that one of the reasons for limited use of benchmarking techniques in the AER's regulatory determinations was because of a lack of consistent data needed to apply benchmarking techniques (AEMC, 2011, p. ii). Indeed, the AEMC recommended the establishment of a more robust and consistent dataset facilitating the use of TFP indexes (AEMC, 2011, p. ii). Australian researchers in the field of productivity and efficiency analysis have long and constantly argued for this (see, for example, Coelli, Estache, Perelman and Trujillo, 2003; Lawrence, 2003b; and Economic Insights, 2009c). In the US, the Federal Energy Regulatory Commission (FERC) has assembled a comprehensive historical database that is suitable for productivity analysis.

Nevertheless, the National Electricity Law (NEL) and National Gas Law (NGL) permit rules to allow the use of index-number-based TFP, either as a deterministic or informative tool, in addition to the existing building-block approach (AEMC, 2009, p. ix). It is therefore important to understand the issues that may arise when using an index-number-based TFP method for regulatory purposes.

3.5.1 Data requirements

The index-number-based TFP method requires price and quantity information on inputs and outputs for comparable businesses over a sufficiently long time period so that the long-run industry productivity growth trend can be accurately estimated for informing the appropriate productivity-saving target.

Under the AEMC review, a set of pre-conditions for the possible application of TFP to the Australian energy networks is identified (AEMC, 2009, p. 47). The first condition is the availability of robust and credible data. In addition, the TFP measurement must: accurately reflect the industry's productivity growth; be immutable to the behaviour of the regulated businesses and regulator; represent comparable businesses; and reflect stable business performance. Finally, historical TFP performance must be a good indication for future productivity growth; that is, it must be a good predictor.

According to the AEMC, it is likely that a TFP application could be appropriate for use in the electricity and gas distribution sub-sectors; however, an improvement in regulatory reporting requirements is needed first (AEMC, 2009, p. 79). This implies that, for the electricity distribution sub-sector, although the industry characteristics are suitable for 'forming a stable, comparable industry-wide benchmark' (Brattle Group, 2008, p. 8), it may take a few more years to get the required data to accurately measure the long-run industry productivity growth.

As pointed out by Economic Insights (2009c, p. 18), without a high degree of data consistency and comparability, TFP analysis may not be suitable for being a deterministic tool for setting revenues/prices. Its assessment of the available data showed that the key requirement for a consistent set of TFP data – detailed and consistent definitions of key input, output and environmental condition variables to be reported – was not met.

Data availability and quality is a key precondition for the regulatory use of TFP analysis. In general, the more disaggregated the specifications in relation to heterogeneous inputs and outputs, the more accurate the measure of aggregate output growth and input growth, and thus TFP growth. However, the choice of input and output specifications is often constrained by the availability of quality data. Data availability and quality may also limit what data adjustment or normalisation can be performed to ensure like-with-like comparisons across businesses.

3.5.2 Model specifications

The following issues in relation to model-specification and measurement of variables regularly arise in the literature:

- Output specification and measurement:
    - The output specifications for the many dimensions of an energy network service typically cover the demand-side of services. That is, the output specifications generally include measures of electricity delivered and customers connected. However, they do not always address the supply-side of network provision. That is, they may not include coverage and the capacity of the network and the quality and reliability of supply (e.g., frequency and duration of outages).
    - Demand-side models tend to favour urban distributors with dense networks. Supply-side models tend to favour rural distributors with sparse networks and long line lengths. Some studies, for example those by Lawrence (e.g., Lawrence and Diewert, 2006) suggest that it is important to account for both supply and demand sides of services in the TFP analysis, and to consider the impact of different operating conditions. However CEPA (2003, p. 88) argues that it is risky to include network length as an output variable (or account for network density) as this may introduce perverse incentives for the businesses because it may encourage network expansion only to improve measures of relative efficiency performance.
    - Consistent data measuring any of the three aspects of quality of services – reliability of supply (e.g., System average interruption duration index (SAIDI), System average interruption frequency index (SAIFI), Customer average interruption duration index (CAIDI), Momentary average interruption frequency index (MAIFI)), technical quality of services (e.g., number of complaints, distribution network loss or cost of loss), and quality of customer services (e.g., call centre performance) – are generally not available.
    - Additional reasons for the failure to incorporate quality of services in the index-number-based TFP analysis are: first, the method does not easily incorporate 'bad outputs' (i.e., a decrease in the measure represents an increase in service-quality output); and second, it is difficult to value

quality improvement to consumers in order to weigh the quality output appropriately.[49]

- Input specification and measurement: labour, materials and services, and capital are inputs that are generally modelled in productivity studies. Capital input is more difficult to measure consistently. This is discussed in section 3.2.

- Output weighting: prices for the multi-dimension outputs are generally not directly observable. Where revenue/cost share information for outputs is not available, empirical evidence may be used, such as econometric studies that estimate the relevant cost functions. In the alternative, a subjective judgement may need to be made to determine the weights to attribute different outputs.

- Input weighting: capital input price may be measured directly. For example, data may be used in relation to the annual user cost of capital, taking account of depreciation, opportunity costs and capital gains. Alternatively, capital input price may be measured indirectly through the realised residual between total revenue and operating and maintenance costs. The direct or indirect measure of capital input price may generate differences in the calculated rates of TFP. The AEMC considered that capital user costs should be set exogenously for consistency with regulatory asset base (RAB) and the *ex ante* financial capital maintenance (FCM) (AEMC, 2011, p. 24).

In relation to alternative model specifications, it is important to consider the assumptions underpinning the model and their implications for the TFP measurement. If there is no strong theoretical foundation favouring a particular model specification, sensitivity analysis can be conducted to ensure robustness of the results.

Finally, while differences in operating conditions are likely to affect achievable unit costs and productivity levels, their impact on business-specific productivity growth remains an empirical question (AEMC, 2010, p. 77). The literature suggests that, in energy distribution studies, energy density and customer density are generally found to be the two significant operating environment variables affecting unit costs and productivity levels. See for example, AEMC (2008, s. 3.1.1, p. 2) and Lawrence, Diewert and Kain (2007, p. 10). With limited and inconclusive evidence on their productivity growth impact, it is important to empirically examine the impact of key operating conditions in a study of energy networks. It may be necessary to group businesses based on comparable operating environments in order to generate robust TFP results that are appropriate for regulatory use.

3.5.3 Applications

Index-number-based TFP can be used to measure historical long-run industry productivity growth. The estimate can then be used as the best proxy for future productivity growth to determine the productivity-offsetting factor in the CPI–X price-path formula. This approach has had limited application in Australia under the BBM framework.

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[49] Recent studies on French electricity distribution by Coelli, Crespo, Paszukiewicz, Perelman, Plagnet and Romano (2008) and Coelli, Gautier, Perelman and Saplacan-Pop (2010) have estimated shadow prices for quality of services using Data Envelopment Analysis and Stochastic Frontier Analysis.

While index-number-based TFP can be an important tool for estimating past productivity growth patterns, regulatory purposes require an assessment of future growth. Clearly, there is a need to consider whether past trends will reasonably be expected to reflect future growth. That is, the regulatory question is forward-looking, to examine the extent to which the regulated companies could be reasonably expected to reduce future costs, in real terms. Therefore, it is important to consider whether future productivity growth prospects are likely to depart from the historical long-run industry performance.

3.6 Conclusions

The review into the literature and regulatory practices shows that the *benchmark* industry-wide productivity growth rate derived from the index-number-based TFP method can be used either to inform or determine the productivity-offsetting factor – an implicit or explicit component to consider for setting revenues or prices for energy network service providers. The effective use of index-number-based TFP method in energy regulation requires fundamentally 'reliable, credible historical data reported regularly and consistently' (Utility Regulators Forum, 2005, p. 6) and an accurate measure of the underlying long-run productivity growth.

Chapter 4 Evaluation of the econometric approach to benchmarking

4.1 Introduction

A central task of any utility regulator is the determination of a level of revenue which is sufficient for a business, operating under a given incentive framework and operating environment, to cover the costs of delivering a given set of outputs. In order to carry out this task, the regulator must form a view about the cost structure underlying the industry. This assessment may be captured by the use of a 'cost function', which shows the output-cost relationship for a cost-minimising business. That is, by modelling the technology in place, the output quantities, the input prices, and the operating conditions in which the business operates, a minimum-cost function yields the periodic costs incurred by an efficient business to deliver those services in that environment.

Therefore, the econometric modelling of the cost function requires information on: the cost incurred, the range of services that the businesses produce (in quantity), the prices for inputs, and the operating environmental conditions. It also requires the selection of the functional form to use. Conventionally, least-squares-type estimation or other appropriate estimation methods are used to econometrically estimate the parameters of the cost function for comparable businesses in an industry. For benchmarking purposes, the estimated results are then used to derive the expenditures required by individual businesses if they are minimising costs (the 'benchmark cost'), which are to be compared with their observed costs. Any difference in the observed cost from the benchmark cost is attributable exclusively or largely to management-controllable inefficiency. One of the shortcomings of the conventional econometric approach to benchmarking is that it does not allow for a separate random error term from the inefficiency term in the modelling. This is addressed by the more advanced Stochastic Frontier Analysis (SFA), as further explored in Chapter 5.

A number of academic studies and utility regulators have pursued this approach for modelling the energy networks, particularly for those operating in electricity and gas distribution.

The remainder of this chapter is structured in five parts. The next section describes this econometric approach to benchmarking in more detail. Section 4.3 briefly reviews the literature on the econometric approach to benchmarking energy networks. Section 4.4 reviews the practices of energy regulators which have applied the econometric method. Section 4.5 identifies the potential issues associated with the use of the econometric approach to benchmarking, and section 4.6 concludes.

4.2 Description of the econometric approach to benchmarking

4.2.1 Method

The econometric approach to benchmarking estimates a common benchmark cost function for a set of businesses.

Given a vector of outputs $y = (y_1, y_2, \dots, y_N)$, a vector of input prices $w = (w_1, w_2, \dots, w_M)$, and a vector of environmental variables $z = (z_1, z_2, \dots, z_K)$, a benchmark cost function reflects the annualised costs of an efficient business at a given point in time as a function of y, w, and z:

$$\hat{C}(y, w, z) \tag{4.1}$$

This approach suggests that the difference between the actual cost incurred by a business and the corresponding cost given by the benchmark cost function is management-controllable inefficiency. By assuming a multiplicative inefficiency term, the cost inefficiency of the business is:

$$e = \frac{C}{\hat{C}(y, w, z)} \tag{4.2}$$

where C denotes the actual cost and $e \geq 1$ represents the level of inefficiency.

That is, the cost inefficiency of a business is defined as the ratio of the business's actual cost to the estimated benchmark cost. Mathematically, the above equation is equivalent to:

$$\ln C = \ln \hat{C}(y, w, z) + u \tag{4.3}$$

where $u = \ln(e) \geq 0$ is a non-negative term associated with inefficiency.

When data for a sufficiently large sample of comparable businesses in an industry are available, equation 4.3 can be estimated econometrically.

The following five steps are required for the 'benchmark cost function' approach:

(1) The selection of variables which reflect:

- outputs produced by the businesses;
- input prices paid by those businesses; and
- environmental conditions that affect the production costs.

Collectively, these variables capture all factors that systematically affect the costs of the businesses and that are beyond management control.

(2) The selection of the type of cost function (the 'functional form');

(3) The selection of an estimation method that sets out a way to estimate the specified cost function that best fits the available data;

(4) The compilation of data in relation to costs, outputs, prices, and environmental variables for a set of comparable businesses; and

(5) The estimation process and the interpretation of the residual (the difference between the estimated and actual costs) for each business as a measure of the inefficiency of that business.

The first step in this process, the selection of variables, is discussed in the next sub-section.

The second step is the selection of appropriate function form for the cost function. That is, choosing a class of cost functions $f(y, w, z|\alpha)$ parameterised by a finite number of parameters α, into which the true industry cost function is assumed to fall:

$$\hat{C}(y, w, z) = f(y, w, z|\alpha^*) \text{ for some choice } \alpha^* \text{ of the parameters.} \tag{4.4}$$

A variety of function forms have been used in the empirical studies, ranging from the simple Cobb-Douglas function to the more complex 'flexible' functional forms such as the translog function.[50] The Cobb-Douglas function assumes a (first-order) log-linear functional form; that is, the logarithm of the benchmark cost is assumed to be linear in the logarithm of the output quantity and input price variables specified. For example, with two output variables and two input prices, a log-linear cost function is:

$$\ln \hat{C}(y_1, y_2, w_1, w_2) = a + b_1 \ln y_1 + b_2 \ln y_2 + c_1 \ln w_1 + c_2 \ln w_2 \tag{4.5}$$

The functional-form specifications impose restrictions on the possible shape of the benchmark cost function. The Cobb-Douglas function specified above requires constant elasticity of the cost with respect to each output. This implies that if a ten per cent increase in the output of a service results in a five per cent increase in cost when the output is small, then the same percentage increase in cost will incur with a ten per cent increase in the output when the output is large. This rules out, for example, product-specific fixed costs.

Instead, a more flexible functional form is the translog function that allows for linear, quadratic and interaction terms in the logarithms of the output quantity and input price variables. For the two-output and two-input example, a translog cost function is:

$$\begin{aligned}
&\ln \hat{C}(y_1, y_2, w_1, w_2) = a + b_1 \ln y_1 + b_2 \ln y_2 + c_1 \ln w_1 + c_2 \ln w_2 \\
&+ b_{11}(\ln y_1)^2 + b_{12} \ln y_1 \ln y_2 + b_{22}(\ln y_2)^2 + c_{11}(\ln w_1)^2 + c_{12} \ln w_1 \ln w_2 + c_{22}(\ln w_2)^2 \\
&+ d_{11} \ln y_1 \ln w_1 + d_{12} \ln y_1 \ln w_2 + d_{21} \ln y_2 \ln w_1 + d_{22} \ln y_2 \ln w_2
\end{aligned} \tag{4.6}$$

This form of the cost function is more flexible compared to the simple Cobb-Douglas form because it allows a greater range of possible estimated outcomes. While the results of less flexible functional forms may reflect the underlying technology of the subject industry, this is only the case if the underlying technology does fall within the subset of possible outcomes provided by these functional forms. In other words, between a more flexible functional form and a less flexible functional form representing a subset of technologies (e.g., translog versus Cobb-Douglas), results obtained using a more flexible functional form are more likely to better approximate reality.

The third step in the process of econometric benchmarking is to choose an estimation method to estimate the specified cost function.

One approach following Winsten (1957) is to use Corrected Ordinary Least Squares (COLS). Under this approach, the model is first estimated using the ordinary least

[50] The Cobb-Douglas production functional form was developed and empirically tested by Charles Cobb and Paul Douglas in the early 1900s. For further information about its development, see Douglas (1976).

squares (OLS) regression. This is followed by a second step where the intercept parameter a is shifted down by the smallest estimated residual (i.e., the most negative residual). This correction is to ensure that the estimated frontier bounds the data points from below. Given certain stringent conditions, COLS provides consistent and unbiased estimates of the parameters of the selected cost function. Under the COLS approach, the business with the smallest estimated residual is assumed to be efficient and thus operate on the estimated cost frontier. Other businesses are relatively inefficient, the extent of which is the difference between their residuals and that of the identified efficient business.

A variation on COLS is the modified ordinary least squares approach (MOLS), as proposed by Afriat (1972) and Richmond (1974). Similar to COLS, the cost function is initially estimated using OLS. The estimated intercept is then shifted down by the mean of an assumed one-sided distribution of cost inefficiencies. The distributions assumed include an exponential or half normal distribution. A more recent application is proposed by Lowry, Getachew and Hovde (2005), which measured the cost inefficiency 'relative to the average rather than the frontier' (p. 81) using a maximum-likelihood estimation (MLE)-equivalent generalised least squares (GLS) method suitable for an unknown structure of the error distribution.

While these econometric techniques are relatively straightforward, they share a serious deficiency in their applications to cost benchmarking. Namely, all or most of variation in costs that is not associated with the variation in the explanatory variables modelled is attributed to inefficiency. These applications do not allow for the effect of measurement errors or random shocks that may affect the actual costs. This deficiency, discussed further below in section 4.5, has lead to the development of the Stochastic Frontier Analysis method. The latter method is specifically reviewed in Chapter 5.

Once the estimation technique has been selected, the fourth step is to compile the data required for the estimation. This is discussed in the next sub-section.

The fifth and final step in the process is the interpretation of the residual – the difference between the observed costs and the benchmarked costs predicted by the model. That is, it is the cost difference that the specified model has failed to explain.

Irrespective of the estimation method adopted, the differences in the values of the estimated residual between observations are fully attributable to their differences in cost efficiencies. This relies on very stringent assumptions such as the absence of statistical noise or other components of the random error term. The method also hinges on correct model specifications that capture all the relevant cost drivers in the appropriate functional forms (Farsi and Filippini, 2004).

This approach has been criticised as one cannot automatically conclude that the entire residual or residual difference is due to relative cost inefficiency. Therefore, in regulatory applications of conventional econometric approach to benchmarking, the regulator is confronted with the challenge to ensure that the model specifications are correct and the cost data are of high quality and relatively free of non-systematic impacts. Regulators may need to make a judgement call on what is deemed efficient. For example, for its 2009 electricity distribution price control review (DPCR5), the Ofgem moved from COLS to MOLS by setting base-year efficient cost based on the upper third and upper quartile for network operating costs and indirect costs respectively (Ofgem 2009, p. 40).

4.2.2 Data requirements and selection of explanatory variables

As noted earlier, the econometric estimation of a benchmark cost function requires information in relation to the cost, the volume of outputs, the input prices, and the environmental factors which affect the production cost of individual businesses. The data may cover a number of businesses at a particular time point (cross-sectional data), a business or an industry over a number of time periods (time-series data), or a number of businesses over a number of time periods (panel data).

A key issue in econometrically estimating a benchmark cost function is the selection of the explanatory variables. That is, the selection of the input, output, and environmental variables. These variables, as a group, are factors that systematically affect the benchmark costs of the sampled businesses and the subject industry. That is, the model should seek to capture determinants of costs that would be incurred by the sampled businesses if they were operating efficiently. Economic theory and industry knowledge suggest a number of cost drivers for energy networks, including the nature of the services provided, the prices of inputs, the quality of services provided, the customer served, and other relevant operating environmental factors.

As the conventional econometric approach to benchmarking does not allow for a random error term, the variables specified in the model should, as a group, be sufficient to fully explain the differences in benchmark costs between businesses that are due to differences in the characteristics and/or operating environment of the businesses. It is also important to ensure that the cost data used for benchmarking are consistent. This involves data corrections and adjustments, conducted in a transparent way prior to econometric estimations, to remove errors and/or the impact of unsystematic factors such as the extreme weather conditions exposed to one business in a particular season.

It is noted that the set of explanatory variables required to account for the differences in the cost performance of firms may differ from sample to sample. Any environmental conditions common to all of the sampled businesses can be omitted from the analysis as their cost impact can be captured in the intercept term. For example, this might apply to costs associated with: labour undertaking national service obligations; nationally prevailing weather conditions; or the prices of inputs with low transportation costs which are procured in a national or international market. Conversely, the greater the heterogeneity in the conditions faced by the businesses in the sample the larger the number of explanatory variables it may be necessary to include.

A wide range of explanatory variables have been used in benchmarking studies of electricity distribution businesses. Jamasb and Pollitt (2007) listed the different variables used in benchmarking studies. Burns, Jenkins, and Riechmann (2005) suggested that the different choices might reflect the fact that different studies were seeking to answer different research questions. They further argued that selected cost drivers/explanatory variables should:

- accurately and comprehensively explain the costs of a business;

- include those such as environmental factors that cannot be controlled by the business; and

- be captured by consistent data that can be collected with reasonable effort.

Prima facie, the selection of key cost drivers should be carried out independently of considerations of the available data.

However, a number of issues arise in relation to the quality of available data. First, there is a need to use more aggregated measures given the available data. In electricity distribution, the service provided is always, to at least some extent, personalised to each customer. At a minimum each customer has a geographically distinct connection point to the distribution network. In addition, customers can vary by their load profile, their responsiveness to price signals, the level of reliability they desire, the voltage at which they are supplied, or the presence of local generation facilities (such as solar panels). Analogously, inputs such as the labour input can be distinct individually or by skill and/or occupation. There is a trade-off between the level of information aggregation for the analysis and the precision of the results. In general, the greater the aggregation of the data used, the less precise the results, as they are likely to correspond to an average of two potentially different impacts of the disaggregated measures. Inevitably, some form of aggregation of the outputs and the inputs is necessary. For example, customers could be aggregated into groups on the basis of their geographic location and/or their usage profile.

However, problems arise with the aggregation of service capacity – how to express the capacity of an entire network which has the potential to deliver different volumes of electricity at different voltage levels at different geographic locations. Having simple measures such as throughput (MWh) and line length as a proxy for measures of capacity may fail to approximate the capacity of a network serving geographically heterogeneous customers.

Second, there can be a need to capture quality of services in the modelling as it is an important aspect of the services provided by an electricity distributor. However, in practice few studies have explicitly considered service quality as an output variable. Some of the studies are reviewed in Coelli, Gautier, Perelman and Saplacan-Pop (2010).

Issues may also arise with the measurement of the dependent variables if the 'total cost' approach is adopted. This is because, when a sunk investment of a long-lived asset is made, the allocation of the cost of that investment to any year of the life of the asset can be arbitrary and not well justified. The allocation used will affect estimates of year-to-year efficiency of the business. Lowry, Getachew and Hovde (2005) adopted a capital-service-price approach to measuring the cost of capital, which is added to labour and non-labour operating and maintenance (O&M) costs for the construction of the total cost measure. This approach, based on the original work by Hall and Jorgenson (1967), requires rigorous capital data to compute capital price and capital quantity measures under the assumption of the declining-balance depreciation. Similar problems associated with measuring capital quantity under total factor productivity analysis have been reviewed in section 3.2.

Another issue in using a benchmark cost function is that the number of estimated parameters changes depending on the functional form selected. Generally speaking, as the flexibility of the functional form increases, the number of required parameters also increases. That is, while the translog cost function is more flexible and provides fewer restrictions on the possible shapes of the underlying cost function, it also requires the estimation of a much larger number of parameters. The issue is further considered in Figure 4.1 below showing the different number of parameters used in different academic studies.

4.2.3 Advantages and disadvantages

The conventional econometric approach to benchmarking reveals information about the average industry cost structures, but measuring cost inefficiency relative to businesses operating on or close to a deterministic frontier. Even under COLS where cost performance is compared against the identified efficient business, the cost function is estimated on the basis of the sample average and as such the cost structure is of industry 'average' rather than frontier businesses. Assuming asymmetric distribution of inefficiencies, the use of MLE may give higher weights to the more efficient businesses in the estimation of the cost function (Rossi and Ruzzier, 2000).

The econometric approach to benchmarking also allows for the role of environmental factors affecting production and cost. To the extent that relevant exogenous factors are explicitly modelled, the estimated residual is net of the factors that are out of management control but affecting costs and thus attributable to management-controlled inefficiencies.

A potential shortcoming of the conventional econometric method is that there is no explicit separation of statistical noises from the true 'inefficiencies'. Rather than statistically decomposing between random error and inefficiency like SFA, the conventional approach may require a judgement call for the scope of true inefficiency relative to the measured residual. Without the random error term, greater variation in cost efficiency performance within the sample may be found than otherwise in the SFA.

Compared to the non-parametric DEA approach (discussed in Chapter 6), the econometric approach to benchmarking requires additional assumptions. For example, the econometric approach assumes that the functional form of the cost function used in the analysis is capable of modelling the cost structure of the sampled businesses. This is more likely as the flexibility of the functional form increases. The econometric results can be sensitive to the functional form specified.

As a parametric approach, statistical testing such as the specification of the functional form can be applied. A key drawback of non-parametric approaches is that this analysis cannot be carried out under standard DEA. A further difference is that DEA typically estimates the shape of the underlying production function rather than the shape of the cost function, using information on input and output volumes. Where additional information on input prices is provided, DEA can also be used to estimate the cost efficiency, defined as the ratio of minimum cost relative to observed cost subject to the estimated production technological constraints. The econometric approach, by directly focussing on estimating the cost function, may arguably be more appealing to regulators, compared with DEA.

4.3 Literature review of the econometric approach

Econometric estimation of the cost function has a long history. The Corrected Ordinary Least Squares approach was developed by Richmond (1974) and modified by Greene (1980). Its extension into Stochastic Frontier Analysis (SFA) approach was originally proposed by Aigner, Lovell and Schmidt (1977) and applied to panel data by Pitt and Lee (1981) and Schmidt and Sickles (1984). Kuosmanen (2011) has proposed a semi-parametric approach which combines elements of both parametric and non-parametric (DEA) techniques. This literature has been surveyed by Murillo-Zamorano (2004), Coelli, Rao, O'Donnell and Battese (2005) and Kumbhakar and Lovell (2000), *inter alias*. It has been discussed in relation to benchmarking of utilities in Coelli, Estache, Perelman and Trujillo (2003).

This chapter focuses on regression-based methods such as ordinary least squares and its variants, and does not cover the more advanced SFA method, which is analysed in Chapter 5, while Kuosmanen's development of a semi-parametric approach is discussed further in Chapter 6.

Bauer, Berger, Ferrier and Humphrey (1998) proposed a set of consistency conditions that different benchmarking methods should satisfy to be useful for regulators. In summary, they stated that the efficiency estimates derived from the different approaches should be consistent in their efficiency levels, rankings, and identification of best and worst firms, consistent over time and with competitive conditions in the market, and consistent with standard non-frontier measures of performance. The set of the principles set out (hereinafter 'the Bauer conditions') is discussed further at chapter 7 of this paper.

The econometric approach to the estimation cost functions for electricity and gas distribution sub-sectors has been used extensively. Jamasb and Pollitt (2001) listed some papers published in the 1990s that estimated cost functions for electricity distribution and transmission. Table 4.1 below identifies six more recent papers published in the 2000s. Further, Kaufmann and Beardow (2001) and Lowry and Getachew (2009b) identified issues involved in the application of econometric benchmarking in the energy sector.

Farsi and Filippini (2004) reported on the estimation of a cost function for 59 Swiss electricity distribution utilities using panel data. A key objective of the study was to determine whether or not the assessment of efficiency is sensitive to model specification when using panel data.

Farsi and Filippini (2004) assumed that the cost function with one output (electricity delivered) and three inputs (labour, capital and input power) takes the Cobb-Douglas form. They employed different econometric techniques to estimate the cost function: COLS and SFA (estimated by GLS, MLE and a 'fixed effects' model). Comparing the cost efficiency rankings using alternative estimation methods, the authors concluded that using different parametric estimation methods would significantly change the results, due to strong unobserved heterogeneity among distribution utilities. The authors recommended using the results of a benchmarking analysis as a complementary instrument in incentive regulation and not in a mechanical way.

Farsi and Filippini (2005) studied a sample of 52 Swiss electricity distribution utilities operating in 1994. The authors sought to test sensitivity problems of the benchmarking methods used in regulation. They assumed a Cobb-Douglas functional form to model the prices of capital, labour and input power as inputs and total electricity delivered as an output. The results indicated significant differences between COLS, SFA and DEA in terms of both efficiency scores and ranks. The differences were more pronounced between the parametric and non-parametric methods.

Jamasb and Pollitt (2003) studied a sample of 63 electricity distribution utilities in six European countries to assess the use of international benchmarking to assist energy regulators in carrying out incentive regulation. They considered ten different combinations of methods and model specifications – six variants of the DEA method, two COLS models and two SFA models. The two COLS and SFA models differ in that one uses a Cobb-Douglas cost function and the other a translog cost function. Comparing the results for consistency they found a high degree of correlation between the efficiency scores for the models which assume the same functional form (i.e., the two Cobb-Douglas function models or the two translog function models) and somewhat low correlation between the two COLS or the two SFA models. They considered that model specification form appeared to be more important for consistency or high correlation among the scores than the choice of parametric methods (p. 1620). They found very low or even negative correlation between DEA and SFA/COLS models. They concluded, 'from a regulatory point of view, substantial variation in the scores and rankings from different methods is not reassuring' (p. 1621).

They noted that a practical approach, in the absence of consensus over the appropriate methods, model specifications and variables, is to combine the results into a single value, using the geometric means of the efficiency scores from the preferred methods. They noted that this tends to reduce the possible bias in individual models. On the question of the feasibility of international benchmarking, they noted a number of issues relating to data and timing of reviews, and noted that international cooperation on data collection and discussion on appropriate model specification and functional forms should be carried out if international benchmarking were pursued.

Lowry, Getachew and Hovde (2005) estimated a translog cost function for a sample of 66 electricity distributors in the United States (US) over 12 years. This is one of the few papers that have focussed entirely on the use of econometric methods (rather than including them along with a discussion of other methods such as DEA or SFA) for cost benchmarking. They assessed four different variations of the model specifications, each with a different number of parameters, being translog and Cobb-Douglas functional forms and models that enforced hometheticity and homogeneity. They found a relatively high degree of consistency in the results across the four models. They proposed using the results to divide the regulated businesses into three categories based on their estimated efficiency.

Lowry, Getachew and Hovde (2005) concluded that benchmarking models of considerable sophistication can be developed for power distributors if a quality dataset of adequate size is available. They also concluded that statistical methods can be used in model specification and application, including tests of efficiency hypothesis. Such benchmarking can be applied to total cost or its components.

However, they noted that the smaller and less varied the sample, the more atypical the subject utility is from the sample used to appraise it, and the more poorly the cost model explains the data on which it is based. They noted that the use of hypothesis testing by regulators would encourage better benchmarking techniques, and the ability of a benchmarking method to facilitate such testing should be an important consideration in method selection.

A couple of academic papers have reviewed the use of benchmarking in specific regulatory practices. For example, Pollitt (2005) explored the application of benchmarking by the Ofgem in its 1999 and 2004 electricity distribution price control reviews. The type of econometric benchmarking used in the United Kingdom (UK) is detailed in the following section on regulatory practices. Pollitt (2005) concluded that, among other things, the lack of comparable data had limited the sophistication of the benchmarking undertaken; the benchmarking methods undertaken were open to question as other methods could have been used; and a comparison of the results from different methods could have been carried out more systematically. The author noted that the main methodological issues raised by the UK approach were the lack of attention to the use of input prices and prices for quality, and the modelling of capex-opex trade-offs (p. 288). It was also suggested that the small number of available data points (seven independent groups) would mean that either panel data or international benchmarking would be required.

Carrington, Coelli and Groom (2002) reported on benchmarking carried out by the IPART in New South Wales, which involved the application of international benchmarking to a sample of 59 gas distributors from Australia and the US. In this study, DEA was used to assign technical efficiency scores to each of the businesses in the study, while COLS (input distance function) was one of a number of techniques used to test the sensitivity of the results. The efficiency scores from COLS (along with SFA) were found to be lower than the DEA results. The authors noted that this is because parametric techniques bound the data less tightly than DEA. The authors concluded that, for the sample as a whole, the parametric techniques produced similar results to DEA. The study found a wide range of efficiencies in Australia compared to world best practice. The authors urged caution that non-modelled factors such as the operating environment could affect the performance of businesses and that 'greater effort is required to determine the actual influence of the operating environment on the efficiency of gas distribution' (p. 214).

Table 4.1: Summary of the Literature Applying the Econometric Method to Benchmarking Energy Networks*

Author/s	Country – sub-sector – period	NOB (firms * years)	Methods	Dependent variable	Inputs	Outputs (quantity)	Other variables	Functional forms	Estimation methods
Farsi and Filippini (2004)	Switzerland – Electricity distribution – 1988-1996	59 * 9	EM, SFA	Total cost	▪ Price of capital ▪ Price of labour ▪ Price of input power	▪ Electricity delivered (kWh)	▪ Load factor ▪ Size of service area ▪ Number of customers ▪ Dummy for high-voltage transmission network operation ▪ Dummy for share of auxiliary revenue (> 25 per cent) ▪ Dummy for serving forest area (> 40 per cent) ▪ Time trend representing technological progress	Cobb-Douglas	COLS
Farsi and Filippini (2005)	Switzerland – Electricity distribution– 1994	52 * 1	EM, SFA, DEA	Total cost	▪ Price of capital ▪ Price of labour ▪ Price of input power	▪ Electricity delivered (kWh)	▪ Load factor[51] ▪ Number of customers ▪ Size of service area	Cobb-Douglas	COLS
Pollitt (2005)	UK – Electricity distribution	14	EM, SFA, DEA	Opex (adjusted)[52]		▪ Composite scale variable[53]		Cobb-Douglas	COLS

[51] The load factor is defined as the ratio of average load to peak load.
[52] The Ofgem application adjusted the reported opex for any included capex, one-offs and other non-comparable cost elements (e.g., higher wages in London).
[53] The composite scale variable consists of customers served (25%), kWh distributed (25%), and network length (50%).

Author/s	Country – sub-sector – period	NOB (firms * years)	Methods	Dependent variable	Inputs	Outputs (quantity)	Other variables	Functional forms	Estimation methods
Lowry, Getachew and Hovde (2005)	US – Electricity distribution – 1991-2002	66 * 12	EM	Total cost	▪ Price of labour ▪ Price of non-labour O&M ▪ Price of capital	▪ Number of retail customers ▪ Volume of power deliveries ▪ Line miles	▪ Number of gas customers served ▪ Percentage of line miles overhead ▪ Average precipitation ▪ Measure of system age ▪ Value of transmission and generation plant ▪ Share of residential and commercial customers ▪ Average temperature	▪ Translog ▪ Homethetic ▪ Homogeneous ▪ Cobb-Douglas	MLE
Carrington, Coelli and Groom (2002)	Australia and US – Gas distribution	59	DEA, EM (input distance function), SFA		▪ Gas mains length ▪ O&M costs	▪ Gas deliveries (TJ) ▪ Residential customer number ▪ Other customer number		Translog	COLS
Jamasb and Pollitt (2003)	International – between 1997 and 1999	63 * 1	EM, SFA, DEA	Totex		▪ Electricity delivered ▪ Number of customers ▪ Network length		▪ Translog ▪ Cobb-Douglas	COLS

* The columns ‘Dependent variable’ to ‘Estimation methods’ of the table only present the summary information for the econometric method (EM).

4.4 Regulatory practices using the econometric method

Econometric benchmarking methods have been used by a number of energy regulators as part of price/revenue determinations for the electricity and gas distribution sub-sectors. Relevant regulatory practices are reviewed below.[54]

4.4.1 Regulatory practices review

Austria[55]

The Austrian energy regulator (E-control) has used an incentive-based approach for setting the revenue allowance of the electricity and gas distribution businesses (since 2006 and 2008 respectively). The E-control uses benchmarking methods to set a business-specific X factor which is deducted from the price cap formula. The X factor is the sum of a generic X factor for the industry and an amount proportional to the degree of inefficiency of the distribution business.[56] Compared to efficient businesses, inefficient distribution businesses are, in effect, provided with lower rate of real revenue change.

The E-control has used alternative benchmarking methods to assess the comparative efficiency of distribution businesses, including Modified Ordinary Least Squares (MOLS) and DEA. The E-Control noted a preference for MOLS over SFA due to the small sample size of 20 electricity and 20 gas distribution businesses in Austria. The E-control decision to aggregate the results of the two benchmarking methods and the decision on the weightings were based on compromise with the industry (WIK-Consult, 2011).

Electricity distribution

For electricity distribution, two DEA models and one MOLS model were estimated. The final set of efficiency scores was derived with a 60 per cent weighting from the DEA models and 40 per cent from the MOLS model.[57]

The relationship between costs and outputs was first investigated using an engineering reference model. The E-control then estimated a number of cost models using MOLS; the final cost model was:

$$\ln C = \beta_1 + \beta_2 \ln l_T + \beta_3 (\ln P_{MV})^2 + \beta_4 \ln P_{LV} \qquad (4.7)$$

where C is total expenditure (Totex) including opex and capex, P_{MV} is the peak load of the medium voltage level, P_{LV} is the peak load of the low voltage grid and l_T is the network length.

[54] As it is not possible to cover all countries, there may be other examples of energy regulators applying econometric benchmarking method that have not been captured in this paper and the supporting research. Haney and Pollitt (2009) also undertook an international survey of benchmarking applications by energy regulators.

[55] Refer to chapter 3.1 of WIK-Consult (2011).

[56] The formula for the business-specific X factor is $X = 1 - (1 - X_G) \cdot \sqrt[T]{ES}$ where X_G is an industry-generic factor, ES is the efficiency score for the business, and T is the number of years for two regulatory periods.

[57] Refer to section 6.4 for more information on the DEA models.

Gas distribution

The E-control has used a similar approach for the gas distribution sub-sector. Two MOLS and two DEA models were estimated. For the MOLS model a Cobb-Douglas cost function with the imposition of constant returns-to-scale technology restriction was used. The input variable was based on total costs including opex and capital cost. For the first model capital cost was measured as indexed historic costs and for the second model, capital cost was based on annuity cost. The output variables were the same for both models; these were: weighted network length, peak load of industrial customers and metering points for residential customers.

The E-control took an average of the two MOLS models to give a MOLS efficiency score and did the same for the DEA models. The final cost efficiency for each gas distribution business was a weighted average, with 60 per cent given to the higher score, MOLS or DEA and 40 per cent to the other.

United Kingdom[58]

Up until 2013, the UK energy regulator (Ofgem) has employed a price-control regime in the form of P_0 + RPI – X. For a regulated utility, the Ofgem determines the efficient costs in the base year (P_0),[59] which are then adjusted annually by the rate of the Retail Price Index (RPI)–X to provide the price path for the allowed revenue over the five-year regulatory period.

Electricity distribution

To determine the efficient costs of electricity distribution businesses in the base year, the Ofgem has employed econometric methods for cost benchmarking using historical data. The Ofgem's benchmarking applications have evolved substantially over the three five-year regulatory periods since it was first introduced in 1999, and continues to evolve with a new framework being introduced from 2013. The econometric methods have, to date, focussed on the opex component of total expenditure, with capex benchmarking conducted separately using other methods.[60]

In the 1999 and 2004 determinations, the Ofgem employed a relatively simple econometric approach, namely COLS.

The estimated cost function was:

$$\ln Opex_{it} = a_t + b_i \ln CSV_{it} \tag{4.8}$$

where:[61]

$$CSV = (\text{Customer numbers})^{0.5}(\text{Units distributed})^{0.25}(\text{Network length})^{0.25}$$

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[58] Refer to chapter two of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).
[59] That is the year immediately preceding the regulatory period.
[60] Totex (opex plus capex) benchmarking will be introduced from 2013 under the new regulatory framework.
[61] This was the formula used in 1999. In 2004 the weighting was changed slightly with a weight of 0.25 on customer numbers, 0.25 on units distributed, and 0.5 on network length.

For the 2009 determination, the Ofgem employed panel data regression techniques using a time-fixed effects approach,[62] and data covering 14 distribution businesses over the four years from 2005-06 to 2008-09. The Ofgem undertook 40 regressions using the log-log functional form. The 40 regressions covered three different levels of disaggregation (total opex, single opex categories and groups of opex categories), different combinations of included cost inputs, cost drivers (outputs), and weightings (where composite drivers were used).

From each of the 40 regression results, the Ofgem calculated a business-specific efficiency score based on the electricity distribution business's actual costs compared with the estimated efficient costs, which was then adjusted for the industry-average efficiency score. These 40 efficiency scores were then weighted to give a single score. The weightings were determined based on the Ofgem's judgement.

Gas distribution

The Ofgem also commissioned benchmarking studies to assess efficient opex for the gas distribution sub-sector. Regression benchmarking methods were employed to benchmark total opex and direct opex categories. Indirect opex categories were benchmarked using PPI methods (refer to section 2.4). The data used in the analysis covered eight gas networks (in four ownership groups) for the two years 2005-06 and 2006-07.

The total opex benchmarking was undertaken by Europe Economics. Two COLS models were estimated and given equal weighting. The input variable was total controllable opex for both models. The output variables were: volume of gas distributed for the first model and total number of customers for the second model. Europe Economics tested these models against a range of other models including two COLS models with a composite scale output variable, four DEA models and three multi-lateral TFP models. The benchmark efficient business was set at the upper quartile.

The direct opex benchmarking was undertaken by PB Power. PB Power undertook both engineering-based analysis and regression analysis. The regression analysis often included a composite scale output variable. The regression model was used to for benchmarking when the r-squared value was 0.7 or greater. The benchmark efficient business was set at the upper quartile.

The Ofgem primarily adopted the results of the disaggregated benchmarking (that is the direct and indirect opex categories), but then applied an uplift to these results based on the average difference between the disaggregated benchmarks and the total opex benchmarks.

Ireland[63]

The Irish energy regulator (the Commission for Energy Regulation – CER) used both econometric and PPI benchmarking methods (refer to section 2.4) to inform revenue decision for its single electricity distribution business, ESBN, for the period 2011 to 2015. A simple form of regression analysis was used to benchmark ESBN against 14

[62] This was done by including a dummy variable for each time period.
[63] Refer to chapter three of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

electricity distribution businesses in the UK. The dependent variable was defined as opex plus non-network capex (normalised to ensure that only activities were comparable and to take account of differences in capitalisation policies). The sole explanatory variable was a composite scale variable (CSV) consisting of customer numbers, electricity distributed and network length. The CER concluded that the ESBN's costs were 7.5 per cent above the upper quartile of the UK distribution business costs and 16 per cent above the efficiency frontier. The CER therefore ruled on a reduction of 11 per cent in controllable opex.

Ontario, Canada[64]

As discussed in sections 2.4 and 3.4, the OEB has employed incentive-based price-cap regulation for electricity distribution businesses since 2000. A key component of the price-cap formula is the X factor which is the productivity-offsetting factor. The X factor is composed of three parts: an estimate of industry-wide productivity change estimated by the index-number-based TFP method (refer to section 3.4.) and a stretch factor estimated by the combination of unit-cost (refer to section 2.4) and econometric benchmarking methods.

The econometric model developed by the OEB's consultant, PEG, employed data from 86 electricity distribution businesses in Ontario between 2002 and 2006. A double-log model with quadratic input price and output terms was used to model total opex. A time trend variable was also included. The statistically significant dependent variables were:

- output quantity variables – number of retail customers, total retail delivery volume, and total circuit of distribution line (kilometre); and
- an input price index – calculated as weighted average of sub-indices for labour prices and prices of miscellaneous inputs such as materials and services; and environmental variables – percentage of underground lines, a binary variable if most of the service territory is on the Canadian Shield and a measure of system age.

Statistical tests were conducted to test the hypothesis that each electricity distribution business was an average cost performer over the sample period. The businesses were then assigned as being either:

- a significantly superior performer, if test showed the business to be a significantly better cost performer than the average; or
- a significantly inferior performer, if test showed the business to be a significantly worse cost performer than the average; or
- an average cost performer, if the test showed the business was not significantly different from the average.

These results were then combined with the rankings from the unit-cost analysis (top quartile, middle two quartiles or bottom quartile) to form three final groups. Each final group was assigned a value for the stretch factor, a lower value for the relatively more efficient groups, which feeds into the X factor. The final groupings are re-assessed each year as new data become available, enabling regrouping and thus, the update of assigned stretch factor during the regulatory period.

[64] Refer to chapter six of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

California, the United States[65]

In the US state of California, regulated energy utilities have sometimes submitted cost-benchmarking analysis to the California Public Utilities Commission (CPUC) to support an application to increase rates. For example, San Diego Gas and Electric Company (SDG&E) engaged PEG to conduct an econometric analysis of the company's cost efficiency. This 2006 PEG study was summarised in Lowry and Getachew (2009c).

PEG developed an econometric cost model for each of the gas and electricity distribution services. The cost model for gas used data on 41 gas distributors in the US from 1994 to 2004. The total cost of gas distribution, including operation and maintenance expenses and the cost of gas plant ownership, was used as the dependent variable. The independent variables included: three input price indices for labour, non-labour operation and maintenance expenses, and capital services respectively; two output quantity variables for number of retail customers and volume of retail deliveries respectively; three business condition variables for the percentage of distribution main not made of cast iron, the number of electricity customers served (to reflect the degree of diversification), a binary variable reflecting high or low customer density; and a time trend variable to capture technological change. The flexible trans-log functional form was employed. The cost model for the 77 electricity distributors in the US from 1994 to 2004 was similar to the gas model, with the total costs of electricity distribution services estimated as a function of three input prices, two output quantities and ten business condition variables.

PEG used the cost models to estimate the percentage difference between SDG&E's actual cost relative to the 'efficient' cost predicted by the model and then rank SDG&E relative to the sample. The results formed part of SDG&E's evidence in its 2008-2011 General Rate Case public hearing and settlement processes. Based on the econometric cost analysis, SDG&E sought a stretch factor of zero (to apply to the gas and electricity business as a whole).

Australian Energy Regulator (AER)

For the revenue determination for NSW and the ACT electricity distribution businesses for the period 2009-10 to 2013-14, the AER's consultant, Wilson Cook, initially undertook PPI analysis using a composite size variable (refer to section 2.4). Following criticisms of this approach, Wilson Cook employed regression analysis to test the reasonableness of its bottom-up estimation of opex allowances (Wilson Cook, 2009, pp. 13-14). The dependent variable was opex and the explanatory variables were number of customers, line length, maximum demand, energy distributed and network type (urban or rural, based on customer density). Two models were considered to predict opex, a linear combination of the available variables and a linear combination of their log values. The data were based on 13 electricity distribution businesses within the AER's jurisdiction for the year of 2006-07. The AER (2009b, p. 176) noted that the results of the regression model were 'not materially different to those of the original analysis' and that this top-down analysis provides 'a useful test of the reasonableness of Wilson Cook's bottom up assessment'.

[65] Refer to chapter seven of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

A similar regression method was also applied by the AER as part of the assessment of Queensland and South Australian determinations for the regulatory period 2010-11 to 2014-15. As described in section 2.4, the opex assessment was primarily undertaken by consultant PB Australia focussing on a bottom-up engineering-based approach with consideration of the PPI benchmarking analysis as a cross check.

4.4.2 Summary of regulatory practices

The above review provides some examples of energy regulators that have employed econometric methods to determine the cost efficiency of energy networks operating in electricity and gas distribution sub-sectors respectively. While the AER and the Ontario, Austrian and Irish energy regulators combined the econometric results with the results of other benchmarking methods,[66] the UK energy regulator relied primarily on the results of the econometric method.[67]

Other than Ontario, each of the above regulatory applications reviewed had 20 or fewer distribution businesses that could be included in the sample. Notably none of these regulators included many explanatory variables in the regression models.

Turvey (2006) and Pollitt (2005) have questioned the theoretical basis of the UK benchmarking model used for the 1999 and 2004 price reviews. They argued against the simple but arbitrary model as it did not: include different input prices, sufficiently consider stochastic factors and consider the possible trade-off between capex and opex. The Irish model was based on the 2004 UK model. Similarly, the Austrian model was criticised by Turvey (2006) in that the small sample size could be the reason for other cost drivers being found to be statistically insignificant.

In contrast, with a sample of 86 electricity distribution businesses, the Ontario regulator was able to include a large number of explanatory variables, including environmental variables in addition to multiple outputs and an input price index (in linear and quadratic terms).

4.5 Issues arising from the review

There are a number of issues associated with the application of the conventional econometric method to benchmarking. These issues relate to the choice of: the functional form of the estimated cost function, explanatory variables included in the cost function, the method for the estimation, and the interpretation of the results.

4.5.1 Choice of functional form

As discussed, functional forms such as the Cobb-Douglas function suffer from a lack of flexibility compared to the translog functional form. That is, they restrict the possible range of estimated outcomes. While their results may reflect the underlying technology of the estimated industry, this is only the case if the underlying technology falls within the subset of possibilities captured by these functional forms. That is, less

[66] The CER informally combined the econometric results with the PPI benchmarking method results.

[67] The Ofgem did, however, compare the results of the econometric method with DEA analysis using the core model specifications for electricity distribution and with DEA and multilateral TFP analyses using similar model specifications for gas distribution.

flexible functional forms are less likely to yield results that approximate reality, compared to the translog functional form.

The translog functional form, although more flexible than the simple Cobb-Douglas function, still imposes restrictions on the range of possible cost functions. The choice of functional form is not benign. For example, the translog function rules out the possibility of: having zero values for one or some of the outputs and inputs specified; or discontinuities and other irregularities in the cost function.

Regardless of the flexibility of the functional form used, if the true cost function does not fit within the class of functions chosen, the resulting efficiency measurements can be misleading.

4.5.2 Choice of explanatory variables

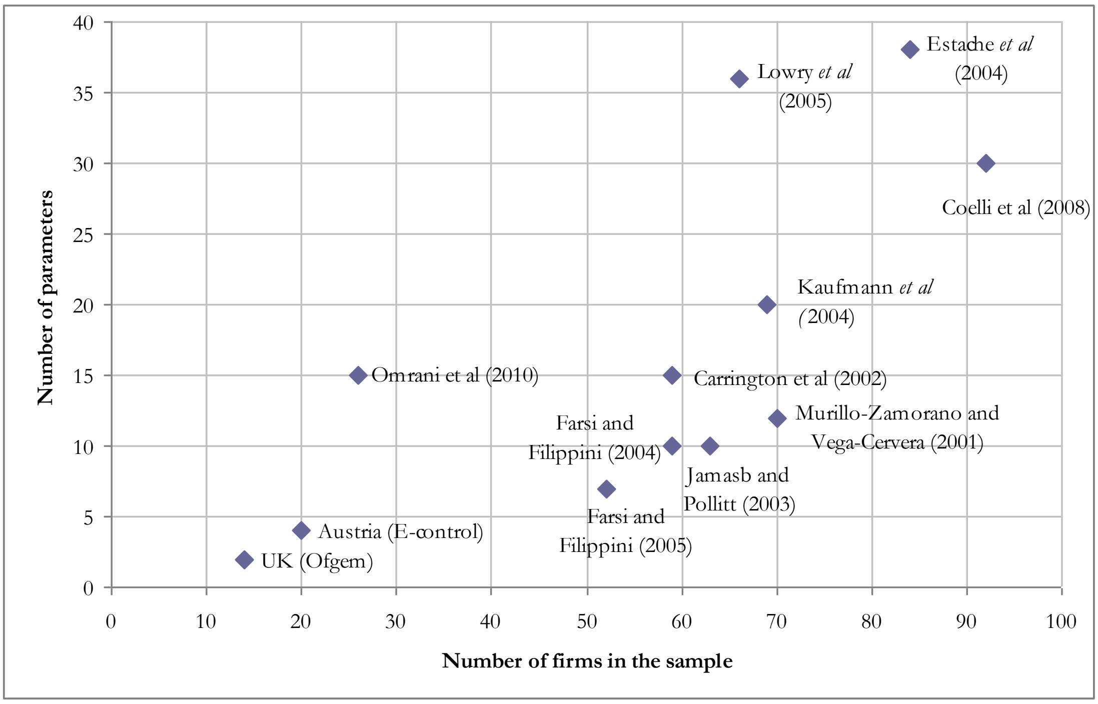
There are significant issues associated with the selection of outputs, input prices, and environmental variables to be used in the model. For example, some argue that there are limitations associated with measuring, aggregating and comparing variables such as network capacity which can vary across each geographic location in the network.

Further, some argue that issues arise in relation to the measurement of capital services.

There is not yet a consensus in the literature on the number or the set of variables needed to fully capture all of the legitimate differences between the sampled energy networks; for example, electricity distribution businesses. In general, the wider the range of conditions faced by businesses in the sample, the larger the number of variables required.

Figure 4.1 identifies the number of parameters in parametric benchmarking studies (using one or both of conventional econometric method and SFA) published since 2000. This is compared with the number of businesses used in the studies. Several features emerge. The two regulatory applications included on this chart (for Austria and the UK) use a smaller sample size: 20 businesses in the case of Austria and 14 in the case of the UK, and a correspondingly small number of parameters. Studies which use a larger number of parameters generally use data from a larger number of businesses. These studies also use panel data to increase the number of observations in the study (Lowry, Getachew and Hovde 2005; Coelli, Crespo, Paszukiewicz, Perelman, Plagnet and Romano 2008; and Estache, Rossi, and Ruzzier 2004). The panel-data studies are located at the top right corner of this chart.

Figure 4.1: Number of Parameters Modelled versus Number of Firms Sampled[68]



Source: compiled by ACCC staff.

One possible approach to choosing the relevant cost drivers is to explore the implications of an engineering-based model of the regulated businesses.[69] Examples include: the Network Performance Assessment Model (NPAM) used in Sweden between 2003 and 2007,[70] and the PECO basic network reference model adopted in Spain since 2009.[71] This approach takes, as inputs, data at the level of geographic location on customers, energy demand, voltage levels, and quality of supply, and then constructs a hypothetical radial electricity distribution network to service those customers with the required quality of supply. An alternative approach is to conduct a rigorous cost-driver analysis for the subject industry (Kaufmann and Beardow, 2001).[72]

4.5.3 Choice of estimation method

Another issue is the choice of estimation method. Studies have employed different econometric techniques when estimating the parameters in their cost models. This appears to have had a significant impact on the reported econometric results. Farsi

[68] Note that Figure 4.1 includes papers using the conventional econometric method and/or SFA method.
[69] Grifell-Tatje and Lovell (2003) compared managerial performance derived from DEA with engineering standards obtained from an 'ideal' network model for the Spanish electricity distribution businesses. They found lower costs for the ideal network due to superior network design and lower input prices. They also found that further cost savings could be achieved by the ideal network due to the presence of cost inefficiencies.
[70] The *ex post* price regulation using NPAM was strongly criticised by stakeholders and was followed by lawsuits. It was formally abandoned in January 2009. For details, see WIK-Consult (2011, p. 49).
[71] The PECO model is named after its main developer, Jesus Pascual Peco González. See González (2004) for details.
[72] Cost drivers are measurable exogenous factors that affect costs.

and Filippini (2004) estimated the same cost function with the same set of explanatory variables and the same set of parameters, using four different estimation methods, namely COLS, random-effects GLS, random-effects MLE, fixed-effects estimation. They found that the resulting efficiency scores were sensitive to the estimation method used. Given the theoretical differences and different underlying assumptions associated with the different estimation methods, this is not surprising, particularly when a simple functional form, such as the Cobb-Douglas function assumed in Farsi and Filippini (2004), is used.

While averaging results from different methods has been suggested in the literature (e.g., Jamasb and Pollitt, 2003) and adopted in regulatory practices, Pollitt (2005, p. 287) pointed out that inconsistent results cannot be reconciled merely by averaging if individual sets of results are not that satisfactory.

A potential shortcoming associated with this conventional econometric method is that business-specific inefficiency may be correlated with other variables in the model. Variations in efficiency may be attributable to, for example, business size or operating environments. That is, the assumption that the inefficiencies are independently and identically distributed is no longer held. The absence of independence calls into question the use of least-squares estimators commonly used for econometric analysis.

If the chosen variables fully capture the legitimate cost differences between businesses and if the true cost function fits within the functional form chosen, then recall equation 4.4:

$$\ln C_i = \ln \hat{C}(y_i, w_i, z_i) = \ln f(y_i, w_i, z_i|\alpha^*) + u_i \tag{4.9}$$

for some choice α^* of the parameters.

The best estimation method depends on the distribution of the disturbance term. The simplest approach is to assume that the disturbance is independently and identically distributed with zero mean and constant variance, and thus uncorrelated with the explanatory variables. Under this assumption it is appropriate to use simple Ordinary Least Squares (OLS) to estimate the values of the parameters α.[73] Given independence, it is possible to use a GLS technique if the distribution of the disturbance is unknown or to use MLE if non-homoscedastic distribution is assumed (See for example, Schmidt and Sickles, 1984; Lowry, Getachew and Hovde, 2005). With heteroscedasticity, OLS point estimates remain unbiased but inefficient while statistical testing is no longer valid due to biased estimates of standard errors of the coefficients.

However, if the inefficiency term *u* is correlated with explanatory variables in the model, the above estimation methods result in biased estimates of the parameters and the measured inefficiencies. As suggested by the literature (see for example, Schmidt and Sickles 1984 and Kumbhakar and Lovell 2000), having access to sufficiently long panel data may assist as some panel-data estimation methods (e.g., fixed-effects) do not require the independence assumption.

[73] Under classical assumptions, the OLS estimator is the best linear unbiased estimator of the parameters.

Another cause of the violation of the independence assumption is the 'omitted variable' problem. If a variable that should be modelled as part of cost structure is left out and this variable is correlated with other variables in the model, then the estimation results are biased. This problem can be avoided by careful consideration of model specification and conducting model-specification tests.

4.5.4 Interpretation of the results

Without allowing for the effects of random error term, the conventional econometric method attributes the entire residual differential to cost inefficiency difference between businesses. Depending on the estimation methods and sometimes involving judgement call by the researchers and/or regulators, the efficient business is determined and is benchmarked against to derive the cost inefficiency measure.

The approach relies fundamentally on careful consideration of the appropriate model specifications (covering what variables to model and in what form, error distribution) and suitable estimation methods (including the proper benchmarks), as well as quality data that are relatively free of statistical noises. If there is a need to model both the random error term and the inefficiency term, then the approach known as Stochastic Frontier Analysis (SFA) should be considered.

4.6 Conclusions

Many regulators have sought to use some form of econometric approach to benchmarking. According to the international surveys conducted by Jamasb and Pollitt (2001) and Haney and Pollitt (2009), among the statistical benchmarking methods, the econometric approach to benchmarking is second in popularity only to Data Envelopment Analysis in regulatory practice.

This approach has the potential to provide an important insight into the relative performance of businesses. However, the selection of the explanatory variables, the functional form, and the best estimation method need to be considered carefully.

In practice, these techniques may mix any measurement of inefficiency with 'noise' in the data itself. It is not possible to separate out these factors by examining the results of a benchmarking study alone. To this end, the SFA method is recommended as it explicitly accounts for the random error term in the modelling.

However, it may be possible to improve the credibility or reliability of a benchmarking study through careful attention to a number of steps. The first step is to identify a list of explanatory variables, at the outset, which can explain the key differences in costs incurred by regulated businesses. Several recent papers (such as Burns, Jenkins and Riechmann 2005 and Turvey 2006) have emphasised the importance of careful independent assessment of the likely cost drivers and factors affecting differences in costs. Kaufmann and Beardow (2001) pointed out the importance of also understanding the impact of service quality and other business conditions on cost.

The second step is to establish the basic shape of the cost function. As emphasised above, there are no *a priori* grounds in economic theory for assuming that the cost function of, say, an electricity distribution business can be represented as a Cobb-

Douglas or translog function. Instead, engineering models and economic analysis should be used to determine the basic shape of that function.[74]

The third step is to establish a large enough dataset of comparable businesses. Although there are only a limited number of independent comparable businesses in Australia, there are many hundreds of such businesses overseas. *A priori* there appears to be no reason why electricity distribution businesses in, say, the US – which supply similar services using similar underlying technology – cannot be compared to electricity distribution businesses in Australia.[75]

A final step is to interact and co-operate with the industry stakeholders (service providers and customers) to further refine and improve the choice of variables, the quality of the data, the choice of functional form, and so on. Benchmarking is likely to be an iterative process.

[74] There is some academic work in this area. Lowry, Getachew and Hovde (2005) pointed to the seminal article by Neuberg (1977) and contributions by Hjalmarsson and Veiderpass (1992), Salvanes and Tjotta (1998) and Yatchew (2000).

[75] Kaufmann and Beardow (2001) emphasised the importance of collecting data particularly on rural distribution utilities, since 'Australia has a significant number of distribution businesses that operate under very rural conditions'. See also Lowry, Getachew, and Hovde (2005).

Chapter 5 Evaluation of the parametric SFA method

5.1 Introduction

Stochastic Frontier Analysis (SFA) is an extended econometric method that can be used in cost benchmarking analysis. SFA enables the estimation of a cost frontier, from which actual costs incurred by businesses can be compared. SFA is similar to other econometric cost models in that it specifies a functional form that relates costs to outputs, input prices, and environmental factors.[76] However, it differs from traditional econometric approaches in two main ways. First, SFA focuses on estimating the cost frontier representing the minimum costs rather than estimating the cost function representing the 'average' business. Second, SFA aims to separate the presence of random statistical noise from the estimation of inefficiency.

SFA has been widely applied by academic researchers to estimate and compare the cost efficiency of energy networks in one jurisdiction or between jurisdictions. The results have often been compared with results from other benchmarking methods such as Data Envelopment Analysis (DEA) or Corrected Ordinary Least Squares (COLS).

SFA has been applied by a limited number of energy regulators. Germany and Finland have applied the SFA method to assess the relative cost efficiency of energy businesses and Sweden has applied SFA to assess industry-wide productivity changes over time.

The remainder of this chapter is organised as follows. A description of the SFA method is provided in section 5.2. A summary of the academic applications of SFA to the energy sector is provided in 5.3 and a summary of regulatory applications is provided in 5.4. Section 5.5 discusses the potential issues associated with the application of SFA and conclusions are drawn in section 5.6.

5.2 Description of the SFA method[77]

As discussed in chapter 4, the econometric approach is traditionally estimated using Ordinary Least Squares or its variants, such as corrected or modified least squares. This estimation process identifies the residuals from the modelling in one term. The residuals are then used to identify relative efficiency of the businesses. That is, the residuals capture departures of a business's actual costs from the estimated cost function.

The problem with the traditional econometric approach is that while the departure from the estimated cost function may be an indication of inefficiency, it may also be due to random statistical noise, or because of other reasons that are not related to the management-controllable inefficiency.

SFA addresses this shortcoming by isolating business-specific inefficiencies from the effects of random statistical noise. SFA separates the composite residuals into two components: random error term and a term capturing 'other departures from the

[76] Environmental factors are either included directly in the cost model or indirectly as explanatory variables for estimating the one-sided error term (discussed in more detail in section 5.2.1).
[77] For detailed description of SFA methods, refer to Kumbhakar and Lovell (2000).

frontier'. It is these 'other departures from the frontier' which are assumed to be management-controllable inefficiencies.

As with conventional econometric methods, the stochastic cost frontier approach involves estimating the costs that a cost-minimising business should incur for the production of a given set of outputs, assuming given input prices, technology and circumstances. It differs from conventional econometric methods in that the structure of the cost frontier estimated represents 'best-practice' for businesses. In contrast, the estimated cost structure under the traditional econometric approach represents the cost structure of an *average* business (with an adjusted intercept).

5.2.1 Mathematical illustration

As discussed in Chapter 4, the production costs can be represented by:

$$\ln C_i = \ln \hat{C}(y_i, w_i, z_i) = \ln f(y_i, w_i, z_i | \alpha) + u_i \tag{5.1}$$

for some choice α^* of the parameters. The dependent variable, C_i, is the costs of business i and $u = \ln(e) \geq 0$ represents the inefficiency term, assuming that the variables in the model fully capture the cost differences between businesses. The vector of independent variables, y_i, w_i and z_i represent output quantities, input prices and business conditions respectively. These are the cost drivers of business i.

When statistical noise is included explicitly under SFA, the model becomes:

$$\ln C_i = \ln \hat{C}(y_i, w_i, z_i) = \ln f(y_i, w_i, z_i | \alpha) + v_i + u_i \tag{5.2}$$

This approach suggests that the differences between the observed costs and the estimated efficient costs for a business are captured by the sum of the two separate terms, $v_i + u_i$.

The term v_i captures the effect of random factors such as unusual weather conditions and unexpected variations in labour or machinery performance. This term is assumed to be symmetric and normally distributed with mean zero and variance σ_v^2. These assumptions are also made in relation to the error term for the OLS model (as discussed in section 4.2).

The term u_i captures inefficiencies that are management controllable. It is assumed that this variable has a one-sided, non-negative distribution, with non-zero mean and variance σ_u^2. The term u_i is one-sided because a business cannot, by definition, minimise costs beyond the minimum possible costs for the production of a given set of outputs at the given input prices.[78]

The composite error term ε_i, where $\varepsilon_i = v_i + u_i$, is therefore asymmetric and positively skewed.

[78] For a production frontier, the mean would be negative and values could only be zero or negative as the business can only operate on or below the production frontier.

Environmental factors (z_i) can be modelled in two ways under SFA. They may be included as explanatory variables in the estimated cost model. Alternatively, they may be included as explanatory variables when estimating the mean of the one-sided inefficiency term. This is discussed further below.

Model assumptions

The SFA method requires a number of assumptions regarding the:

- functional form of the cost function;
- distribution of each of the error terms; and
- independence between the error terms and variables in the model.

SFA cost functions are commonly estimated using Cobb-Douglas or translog functional forms. As discussed previously, the strength of the Cobb-Douglas functional form lies in its relative simplicity. The problem is that if the underlying production technology of the industry is more complex, then the un-modelled complexity will impact the error term. That is, misspecification of the functional form could lead to biased estimates of business inefficiency.

Translog functional form is more flexible than the Cobb-Douglas function as it provides a second-order approximation to a well-behaved underlying cost function at the mean of the data. Further, multiple outputs can be better modelled using the translog.[79] The translog functional form is often used in empirical studies. However, flexible functional forms, such as the translog, increase the number of parameters in the model. As the number of input and/or output variables in the model specification increases, the number of parameters that must be estimated for the translog function increases disproportionately, and thus require large amount of data to estimate the model. As a consequence, models using a translog functional form may suffer from multi-collinearity.[80]

The econometric results vary depending on the assumptions in relation to the distribution of the inefficiency term (u_i). The distribution of the one-sided inefficiency term directly influences the distribution and the sample mean of the efficiency estimates. The one-sided distribution is commonly assumed to be half-normal or truncated-normal. A half-normal distribution assumes that the mean parameter associated with u_i is zero.[81] A truncated-normal distribution provides a more flexible representation of the pattern of inefficiency but also requires estimation of the mode (μ) of u_i. Environmental factors can be used to estimate μ. This estimation of additional parameters means that the truncated-normal distribution requires more data points than the half-normal distribution. The one-sided error term may also be specified as

[79] The translog cost functions allow for multiple outputs without necessarily violating curvature conditions associated with cost functions.

[80] Multi-collinearity arises when explanatory variables have approximate linear relationship, making estimation of their separate effects difficult.

[81] That is, the mean of the normal distribution prior to truncation.

exponentially distributed or two-parameter gamma distributed, although these are less common.[82]

The SFA approach also requires the following independence assumptions. First, the terms v_i and u_i are independent of each other. Second, each of the terms is independent of the explanatory variables. Violation of these independence assumptions may lead to biased results. This is because, in the case where u_i is correlated with w_i, the inefficiency error term will be affected by variation in the cost drivers. However, where u_i is correlated with v_i, it will be affected by statistical noise. The possible correlation of u_i with environmental factors may lead to the environmental factors (z_i) being excluded from the estimation of the cost function and instead included as explanatory variables when estimating the mean of the one-sided inefficiency term, u_i.

Finally, as with other econometric methods, if some cost drivers, or business-specific heterogeneity, are not taken into account in the model specification, then this can create bias in the inefficiency estimates.

5.2.2 Data requirements

Estimation of an SFA cost model requires the following information at the business level:

- costs, such as opex, capex or both;
- quantities of each output produced;
- input prices; and
- factors that capture the operating environments that may affect costs.

Estimation of the SFA cost model is more computationally demanding than the equivalent specification under the conventional econometric method. This is because of the estimation of the two separate error terms in the SFA model. This requires additional data compared to the econometric approach.

The SFA model can be estimated using either cross-sectional or panel data. As discussed previously, cross-sectional data are data for many businesses collected at the same point in time. Panel data are also data for many businesses collected for multiple time periods. Compared with cross-sectional data, models using panel data are preferred as they are more likely to distinguish random statistical noise from systematic differences in businesses' costs because of managerial inefficiency.

The use of panel data provides the additional benefit of increasing the estimation techniques that can be used. For example, the fixed-effects or random-effects estimation methods may be applied to the panel-data model.[83]

[82] The exponential distribution is a relatively simple distribution and has the same statistical properties as the half-normal distribution, but with a different density (shape). The gamma distribution provides a more flexible representation of the pattern of inefficiency by generalising the one parameter exponential distribution by introducing an additional parameter. The more flexible distribution requires more data points to estimate the additional parameter.

The fixed-effects technique, also known as the 'within estimator' technique, is a superior estimation method where the inefficiency term u_i is time invariant. That is, if business-specific levels of inefficiency are assumed not to change over the sample time period, then the fixed-effects technique provides more accurate estimations. Other benefits include:

- other assumptions in relation to the distribution of u_i are not required;
- assumptions in relation to the independence of u_i relative to the cost drivers and the independence of u_i relative to v_i are not required; and
- parameter estimates are consistent as the sample size or time period increases.[84]

However, the fixed-effects technique:

- assumes that at least one business in the sample is 'fully efficient'. All other businesses are then assessed relative to this 'fully efficient' business;
- cannot accommodate explanatory variables that are time-invariant. For example, it may not be appropriate to include environmental factors that have an impact on costs but remain constant over time.

In the alternative, the random-effects estimation method can be applied in conjunction with the generalised least squares (GLS) estimation procedure.[85] The inefficiency error term is random such that it is not correlated with independent variables. The benefits of using the random-effects estimation technique include:

- the possible inclusion of time-invariant cost drivers in the model;
- assumptions about the distributional shape of u_i are not required, except that u_i is non-negative and is randomly distributed with a constant mean and variance; and
- the estimated parameters are consistent as the sample size and time period increases.

The random-effects estimation method, however, does require the assumption that u_i is independent of v_i and is independent of the explanatory variables of the model.

As with other econometric models, the longer the time period covered by the panel data, the more likely that technology will change over time and affect the results. The introduction of a time-period dummy variable can control, and provide an estimate for, the effects of technical change over time.[86]

[83] Variants of both the random- and fixed-effects models will also be available.
[84] In this context, 'consistency' means that as more businesses or more time periods are included, the distribution of the parameter estimates tightens around the expected value.
[85] GLS is estimated first using OLS, then the parameter estimates are re-estimated using an econometric technique called feasible generalised least squares.
[86] See, for example, Hattori (2002) as reviewed in section 5.3.

5.2.3 Advantages and disadvantages

SFA contains many of the strengths and weaknesses of econometric methods more generally.

The strengths of the SFA benchmarking method include:

- The statistical significance and magnitude of each cost driver variable within the model may be assessed. Further, the error terms may be examined to determine the appropriateness of assumptions made in relation to the error terms. This is not possible with non-parametric models such as DEA or PPI;

- The results distinguish random statistical noise from management controllable inefficiencies. That is, some of the variation from the estimated cost frontier will be due to random statistical noise which is beyond the control of the business and therefore is excluded from the measure of inefficiency. This is not possible with either OLS or DEA; and

- Using panel data, it smoothes out differences between businesses that are occurring at one point in time but may not impact on dynamic differences between the businesses over a longer term.

The weaknesses of the SFA benchmarking method include:

- High information requirements for all the costs, input prices and environmental factors that may affect the business. The omission of key costs drivers in the model may lead to biased results. This information requirement is comparable to other econometric models but greater than the DEA or PPI approaches;

- A large number of data point is required to facilitate the decomposition of the unexplained cost variation into random and efficiency-related components;

- A specific functional form of the cost function must be selected. Misspecification may lead to biased results;[87]

- The assumption that u_i is independent of w_i or v_i. If this assumption is not true, the results are likely to be biased;

- Outliers in the data may affect the estimation of the curvature of the cost frontier. In this case, estimates are likely to be biased, particularly where the sample size is small (Syrjänen, Bogetoft and Agrell, 2006);

- The distribution and the sample mean of the efficiency estimates is sensitive to the distribution of the error terms chosen. The basic assumptions underlying the distribution of the error terms are: v_i is symmetric and normally distributed with mean zero and variance σ_v^2; and u_i is one-sided, with a non-negative distribution, and non-zero mean and variance σ_u^2. The one-sided inefficiency term may assume different distributions.

[87] This is because the inefficiency term will capture the variation in costs from the frontier due to mis-specification of the frontier.

The SFA benchmarking method also sets the benchmark at the 'frontier'. This is similar to the DEA method. The frontier represents the minimum, optimised, level of costs that a business will incur based on the most efficient business in the industry, to produce a given set of outputs for a given set of input prices. In contrast, when estimated by OLS, the econometric method estimates the cost function which is derived from the 'average' business in the sample. Based on this function, the benchmark cost frontier may then be shifted to place the business that is deemed to be efficient at the frontier.[88]

5.3 Literature review of the SFA method

A review of the literature shows that the SFA method has been applied to benchmarking the energy sector in a number of different ways. A sample of the relevant literature is provided in this section. Many of the studies have focussed on comparing the consistency of efficiency results across different benchmarking methods including SFA, DEA and/or econometric methods. Similarly some studies have used the SFA method only and assessed the consistency of results with respect to alternative estimation methods or functional forms. Other studies have used SFA simply for sensitivity analysis to test the robustness of efficiency estimates obtained through other benchmarking methods. A summary of the findings of these studies is provided below. For each empirical study in relation to energy networks, table 5.1 contains summary information on the estimation methods, functional forms, inputs and outputs included in the main model and the data employed.

5.3.1 SFA for primary analysis

Hattori (2002) used data covering 12 American and nine Japanese electricity distribution businesses between 1982 and 1997 to estimate their comparative efficiency performance. The author employed SFA to estimate the level of technical inefficiency for each business in each year of the sample under four different SFA model specifications, each of which included a different set of control variables on operating environments. Data limitations prevented the inclusion of the ratio of overhead to underground lines as an output variable, the inclusion of which the author considered could enhance the study. The author found that the Japanese electric utilities were on average more efficient than the utilities in the United States (US) and had lower variation in efficiency. Inefficiencies appeared to be increasing over time and the annual rate of technical change had a decreasing trend.

Gong and Sickles (1989) undertook an experimental analysis to explore the sensitivity of SFA results to different functional form assumptions and different estimation methods. The authors used Monte Carlo simulations to generate data that approximated the following functional forms – the CES-translog, the translog and the generalised Leontief. The authors then estimated business-specific technical inefficiencies using three estimation methods, namely maximum likelihood, random effects (by generalized least squares) and fixed effects (the within estimator). By comparing the estimated inefficiency with assumed inefficiency, the authors found that the SFA approach is sensitive to the form of the underlying technology. SFA is very good when the underlying technology is very simple (e.g., Cobb-Douglas or CES) but this ability to

[88] For example, if Corrected Ordinary Least Squares and Modified Ordinary Least Squares are used.

accurately estimate inefficiency decreases as the underlying technology becomes more complex. However they found that the performance of the three estimation methods was similar, giving quite stable efficiency scores across estimation methods. The authors noted a preference for the fixed-effects (within estimator) estimation as it allows for weaker assumptions regarding the independence of outputs and technical efficiency, and is computationally easier.

Farsi, Filippini and Kuenzle (2007) undertook an empirical study of the cost structure of 26 gas distribution utilities operating in Switzerland from 1996 to 2000. The authors tested the sensitivity of the cost efficiency scores estimated by SFA under four different estimation methods, two MLE and two random-effects (GLS) procedures. The authors found that while the efficiency estimates were reasonably robust to estimation method and showed a strong correlation, the 'best' and 'worst' utilities identified change across methods. The authors suggested that individual efficiency estimates cannot be directly used to set the X factor in the price-cap formula.

In response to proposals to set the rates of electricity delivery equal to average distribution costs in Switzerland, Filippini and Wild (1998) examined the scale and cost efficiency of a sample of 30 Swiss electricity distribution businesses between 1992 and 1996 using SFA. They estimated an average-cost frontier model using the random-effects procedure rather than a fixed-effects procedure, which was precluded due to one of the environmental factors, size of service area, being fixed over time. Two cost models with different input and output variables were estimated. The authors found the existence of economies of output, customer density and scale, and that the majority of Swiss electricity utilities were cost inefficient. They concluded that the average-cost frontier model could be used to benchmark distributors and control the level of rates proposed.

Filippini, Hrovatin and Zoric (2002) analysed the cost structure of Slovenian electricity distribution businesses with respect to the cost and scale efficiency of the industry. The study was based on data from five electricity distributors between 1991 and 2000. Applying the SFA method to panel data, the authors estimated total costs as a function of energy delivered, customer numbers, and capital and labour input prices. The authors noted that, due to the small sample size, the translog model could not be considered and therefore the Cobb-Douglas functional form was imposed. Similarly the small sample size limited the inclusion of a larger set of explanatory variables. The authors noted that the interpretation of the results should take into account the small sample size. Nevertheless the authors considered that the analysis could be used by the Slovenian regulator to increase the informational basis for more effective price-cap regulation.

The Finnish regulator (the Energy Market Authority – EMA) commissioned a report on alternative benchmarking methods to DEA for measuring business-specific efficiency. The EMA was concerned about a number of weaknesses with the DEA method, including potential estimation errors caused by noise in the data, problems related to exceptional businesses and the inability to formally analyse the choice of inputs, outputs and environmental factors. The consultancy report, Syrjänen, Bogetoft and Agrell (2006), considered 24 different input-output combinations and four different functional-form specifications and compared the results using both the SFA and DEA methods. The authors found that the SFA frontier was more stable over time than the DEA frontier, the SFA model indicated no clear biases treating different sized companies fairly, the SFA scores were higher than the DEA scores, and changes in efficiency scores are mostly caused by changes in an individual company's inputs and outputs. The authors considered the two benchmarking methods are complementary such that the weaknesses of one benchmarking method are the strengths of the other and vice versa. The authors therefore suggested that the SFA and DEA scores are averaged to filter out potential mistakes relating to each method and would lead to lower efficiency-change targets than DEA alone.

Kopsakangas-Sovolainen and Svento (2011) used panel data on 76 Finnish electricity distribution businesses between 1997 and 2002 to estimate the impact on inefficiency scores if observed and unobserved heterogeneity are taken into account in the SFA modelling. The authors estimated five models, some of which account for observed heterogeneity only and others which also take into account unobserved heterogeneity. The authors found that both ways of accounting heterogeneity (observed or unobserved) tended to diminish the inefficiency estimates and notably that the models resulted in very different efficiency ranking of businesses.

Knittel (2002) used SFA to investigate the effect of alternative regulatory programs on the technical efficiency of coal and natural gas generation units in the US. The data are an unbalanced panel of generator-specific inputs and outputs for a large sub-set of investor-owned utilities in the US covering the years 1981 to 1996. Noting a preference of SFA over OLS, Knittel (2002) went on to test the SFA results using the OLS method and found consistency in terms of sign and statistical significance.

Growitsch, Jamasb and Pollitt (2009) used SFA to estimate the efficiency of around 500 electricity distribution businesses from European countries. The authors focussed on the impact of quality of services on efficiency and optimal business size. They estimated a multi-output translog input distance function rather than a cost or revenue function as the latter models require behavioural assumptions that may be violated. They estimated two models, the first where total expenditure was driven by three output variables and the second where quality of service, measured as customer minutes lost, is included as an input. They found that large businesses may be better able to improve service quality by increasing costs, while smaller businesses cannot substitute costs and quality to the same extent.

5.3.2 SFA for comparison with other benchmarking methods

Burns and Weyman-Jones (1996) used panel data from electricity distribution businesses in England and Wales to identify principal cost drivers, evaluate cost efficiency performance, examine the impact of privatisation and assess the sensitivity of the results to model specification and estimation method. The primary benchmarking methods employed were SFA and OLS. First the authors compared the OLS and SFA results using pooled cross-sectional time-series data and found little difference between the results. However, once panel-data estimation were used, a number of the explanatory variables become statistically insignificant and the final model specification suggested operating costs depended only on the number of customers, maximum demand and factor prices. The authors rejected the cross-sectional and fixed-effects panel-data estimation methods in favour of the random-effects estimation method. The authors also tested three different distributional assumptions for the inefficiency error term, namely exponential, half-normal and truncated-normal, and found little change in the efficiency rankings.

Jamasb and Pollitt (2003) undertook an international benchmarking study of 63 electricity distribution and regional transmission businesses from six European countries. The authors examined frontier-oriented benchmarking methods, including DEA, COLS and SFA. They found that the choice of benchmarking method, model specifications, and choice of variables could affect the efficiency scores as well as the efficiency ranking of the businesses. While there was strong correlation between the non-parametric and parametric methods, they found that the mean and minimum efficiency scores in DEA were significantly lower than the SFA and COLS methods when constant returns-to-scale technology was assumed. The correlation was weaker when variable returns-to-scale technology was assumed. The SFA method also led to higher estimated efficiency scores than the COLS method. The authors considered that substantial variations in the scores and rankings from different methods were not reassuring from a regulatory point of view and therefore a one-to-one translation of efficiency scores to the X factor was not justified. They suggested that a practical approach, in the absence of consensus on the most appropriate benchmarking method, model specification, and variables, was to combine the results from different methods. For example using the geometric mean of the scores of the preferred methods as this tends to reduce the possible bias in individual methods.

Noting that DEA and SFA were the two most commonly-used frontier-based methods, Estache, Rossi and Ruzzier (2004) used the two methods to estimate the efficiency of 84 South American electricity distribution businesses between 1994 and 2001. They compared the results from two SFA models (an input distance function and an input requirement function) and four DEA models (two input distance functions, one with variable returns-to-scale and another with constant returns-to-scale, and two input requirement functions, one with variable returns-to-scale and another with constant returns-to-scale). The efficiency scores across the six models were found to be statistically significantly different (based on the Kruskal-Wallis non-parametric test). The authors considered that regulators should not directly translate efficiency scores to the X factor. Mixed results, including inconsistency between DEA and SFA in identifying the top and bottom performers, were found when testing the correlation in the rankings between pairs of benchmarking methods. The authors suggested that consistency in identifying efficient businesses is crucial, otherwise only a 'mild' form of benchmarking should be relied on by regulators.

Farsi and Filippini (2004) measured the cost efficiency of 59 electricity distribution utilities operating in Switzerland between 1988 and 1996. The authors considered different frontier-based methods, including SFA and COLS, and compared the efficiency scores and rankings across different models. The authors focussed on parametric methods because of the ability to undertake statistical testing of the significance of variables. The authors found that while the average inefficiency score was not sensitive to the model chosen, the rankings varied significantly from one model to another, possibly attributable to the unobserved heterogeneity among the distribution utilities. Furthermore, the findings confirmed that the lack of robustness of efficiency results reported in the previous literature was not limited to cross-sectional data. The authors therefore considered that a direct use of inefficiency estimates in regulation may be misleading and sensitivity analysis should be used to study the robustness of the efficiency results, and the limitations of different models.

Farsi and Filippini (2005) used a sample of 52 electricity distribution utilities in Switzerland to assess the efficiency scores and ranks across alternative benchmarking methods, namely COLS, SFA and DEA. Efficiency scores from COLS were six per cent lower on average than the other methods, but the average estimates between DEA and SFA were quite similar. There was a high correlation between SFA and COLS in terms of both efficiency scores and rankings; however, the correlation with the DEA efficiency scores and rankings was relatively low. Given the sensitivity of efficiency scores to the benchmarking method employed, the authors recommended against using the inefficiency estimates in a mechanical way, and instead suggested that benchmarking analysis should be used as a complementary instrument in incentive regulation.

Agrell and Bogetoft (2007) developed benchmarking models for the German electricity and gas distribution upon request of the national regulator, Bundesnetzagentur (BNetzA). The authors noted that, from a benchmarking perspective, Germany was unique as there were a large number of distribution businesses and a large set of data available on these, and the data were generally of good quality. This allowed for the exploration of several benchmarking methods, DEA, SFA and OLS, under a range of model specifications. The preliminary results showed similar cost efficiency rankings and levels across the benchmarking methods. However, for gas distribution the authors found that SFA performed in a more robust manner to data errors than DEA.

Coelli, Crespo, Paszukiewicz, Perelman, Plagnet and Romano (2008) estimated input distance functions using SFA and DEA methods for a sample of 92 French electricity distribution businesses over a three-year period. The purpose of this study is to investigate the possibility of incorporating the quality of service in efficiency benchmarking. Both DEA and SFA were used and consistency of the results across methods was examined. The mean technical efficiency score was found to be similar between the two models both with and without the inclusion of the quality measure. The authors therefore concluded that the inclusion of the quality variable had no significant effect upon mean technical efficiency scores for the given sample.

In a review paper by Kaufmann and Beardow (2001), alternative methods for benchmarking electricity distributors, namely index-number-based TFP, econometric cost function, SFA and DEA, were evaluated.. The authors found that econometric techniques (such as econometric cost functions and SFA) had significant advantages over DEA.

5.3.3 SFA for sensitivity testing

In 1999, the IPART commissioned London Economics to undertake a benchmarking study of NSW electricity distribution businesses. In the study of London Economics (1999), SFA was used for testing the sensitivity of the results derived from the primary benchmarking method, DEA. The efficiency scores from the SFA and DEA methods were compared in terms of the mean score, the scores and the ranking of businesses. The study concluded that while there were some differences, the two benchmarking methods gave sufficiently similar results.

Carrington, Coelli and Groom (2002) measured the technical efficiency of Australian gas distributors relative to the US gas distribution businesses primarily using DEA. SFA and COLS were then used to test the sensitivity of the DEA results with respect to method. The inclusion of the US sample for international benchmarking has enabled estimation of the 'data hungry' SFA and DEA benchmarking methods. The SFA assumed a translog functional form with variable returns-to-scale technology, and a one-sided error term distributed as truncated normal. The parametric methods were found to lead to lower efficiency scores because the frontiers bounded the data less tightly than DEA. However the parametric methods produce results similar to the DEA results. Because SFA recognises that some of the distance to the frontier is due to random events or statistical noise, there were fewer efficient distribution businesses identified, compared with the other benchmarking methods. Overall it was found that the choice of benchmarking method had not unduly affected the efficiency scores.

5.3.4 Data used in academic studies

A number of academic studies carried out have used SFA to estimate the efficient frontier. The number of explanatory variables and parameters vary between the studies based on the purpose of the benchmarking study and the assumed technology underpinning the production or cost function. In each instance, panel data for several years or more are used. The number of observations used for each study is high. In several cases, panel data for between 50 and 90 businesses are used. The length of panel data is also longer where a smaller number of utilities is sampled in a study. For example, Filippini, Hrovatin and Zoric (2002) used panel data for ten years in their study of five electricity distribution businesses in Slovenia, while Burns and Weyman-Jones (1996) used panel data for 13 years in their study of 12 electricity distribution businesses in the United Kingdom (UK).

5.3.5 Conclusion on literature review

The use of SFA as a benchmarking method for estimating cost frontiers and inefficiency is common in the academic literature. Much of this research has focussed on the comparison of various SFA results, derived from different estimation methods (e.g., panel versus cross-sectional data), different distributional assumptions and/or different functional forms. Many studies have focussed on comparing the SFA method with different benchmarking methods such as DEA and COLS. In many cases significant differences in terms of the efficiency estimates and/or resulting business ranking, between different benchmarking methods and between different SFA specifications, were found. SFA has been used by some academics and by the German and Finnish energy regulators as a primary method to benchmark cost efficiency. All of these studies have used large samples of businesses and, where available, multiple observations on the same business over time.

Table 5.1: Summary of the Literature Applying SFA to Benchmarking Energy Networks*

Author/s	**Data**	**Method**	**Estimation method**	**Functional form**	**One-sided Error**	**Dependent variable**	**Inputs**	**Outputs**	**Environmental variables**
SFA as primary benchmarking method									
Hattori (2002)	12 US and 9 Japan electricity utilities 1982 to 1997 N[89] = 329	SFA – Input distance function	MLE	Translog	Half-normal		Number of employees, Transformer capacity (MVa)	Electricity for residential customers, Electricity for commercial and industrial and other customers	Load factor, Customer density, Consumption density, Country dummy, Time trend, Product of country dummy and time trend
Farsi, Filippini and Kuenzle (2007)	26 gas distribution businesses 1996 to 2000 N = 129	SFA	MLE, Random-effects (GLS)	Cobb-Douglas	Half-normal	Total cost	Labour price, Capital price, Purchase price of natural gas	Gas delivered	Load factor, Number of terminal blocks, Service area size, Customer density
Filippini and Wild (1998)	30 electric distribution businesses 1992 to 1996 N ~ 150	SFA	Random-effects	Translog	Time-invariant inefficiency	Model 1 – Average cost per kWh Model 2 – Average cost per kW	Labour price, Capital price	Model 1 – Total number of kilowatt hours delivered Model 2 – Maximum demand	Customer numbers, Service area size

[89] N denotes number of observations.

Author/s	Data	Method	Estimation method	Functional form	One-sided Error	Dependent variable	Inputs	Outputs	Environmental variables
Filippini, Hrovatin and Zoric (2002)	5 electricity distribution businesses 1991 to 2000	SFA[90]	MLE	Cobb-Douglas	Half-normal	Total cost	Labour price, Capital input prices	Electricity delivered (kWh)	Customer density Load factor
Syrjänen, Bogetoft and Agrell (2006)	91 electricity distribution businesses in 2004 *N* = 91	SFA	MLE	Various – linear, Cobb-Douglas, translog and normed linear	Truncated-normal distribution with mean as a function of environmental factors	Total direct costs (opex + depreciation + Interruption costs)		Value of energy delivered, Number of customers, Network length	Percentage of underground cables, Interruption time
Kopsakangas-Sovolainen and Svento (2011)	76 Finnish electricity distribution businesses 1997 to 2002 *N* = 419	SFA	2 Random-effects 2 Fixed-effects 1 combined fixed- and random-effects	Cobb-Douglas	Various including a non-normal time-varying error component	Total annual costs per kWh output	Labour price, Capital price, Price of input power	Annual output (GWh), Number of customers	Load factor
Growitsch, Jamasb and Pollitt (2009)	499 electricity distribution businesses from eight European countries in 2002	SFA – input distance function	MLE	Translog	Truncated-normal distribution with mean as a function of environmental factors		Totex, Totex and service quality	Energy delivered, Number of customers	Country dummies, Customer density

[90] A three-stage estimation method proposed by Coelli (1996) was employed.

Author/s	Data	Method	Estimation method	Functional form	One-sided Error	Dependent variable	Inputs	Outputs	Environmental variables
SFA for comparison with other benchmarking methods									
Burns and Weyman-Jones (1996)	12 electricity distribution businesses in England and Wales 1980-81 to 1992-93 *N* = 156	SFA	MLE, Random-effects GLS), Fixed-effects	Translog	Various, including the truncated normal and exponential	Operating costs	Price of capital, Price of labour	Number of customers, Maximum demand	Privatisation dummies
Jamasb and Pollitt (2003)	63 electricity distribution businesses from 6 European countries *N* = 63	SFA, DEA, COLS		Cobb-Douglas and translog	Normal and truncated normal distributions	Total costs	Totex,	Electricity delivered, Number of customers, Network length	
Estache, Rossi and Ruzzier (2004)	84 electricity distribution businesses 1994 to 2001 *N* = 367	SFA – Input distance function and input requirement function, DEA	MLE	Translog	Truncated normal distribution		Number of employees, Transformer capacity (MVa), Distribution network (kilometre)	Number of final customers, Energy supplied to final customers (GWh), Service area (sq km)	Residential sales' share GNP per capita
Farsi and Filippini (2004)	59 electricity distribution businesses in Switzerland 1988 to 1996 *N* = 380	SFA, COLS	Random-effects (GLS and MLE), Fixed-effects	Cobb-Douglas	Half-normal distribution	Total costs	Labour price, Capital price, Price of purchased power	Electricity delivered (kWh), Number of customers	Load factor, Service area, Dummy variables for share of operating transmission lines

Author/s	Data	Method	Estimation method	Functional form	One-sided Error	Dependent variable	Inputs	Outputs	Environmental variables
Farsi and Filippini (2005)	52 Swiss electricity distribution businesses in 1994 *N* = 52	SFA, COLS, DEA	MLE	Cobb-Douglas	Composite half normal distribution	Total costs	Labour price, Capital price, Price of purchased power	Total delivered energy in kWh, Number of customers	Load factor, Service area
Agrell and Bogetoft (2007)	• 328 electricity distribution businesses • 294 gas distribution businesses	COLS, SFA, DEA		Translog	Truncated normal distribution	Total direct cost		*Service:* Number of meters, Service area (by voltage) *Capacity:* Coincidental load (by voltage), Transformer (HS/MS, MS/NS), Feed-in power of decentred generation	N/A
Coelli, Crespo, Paszukiewicz, Perelman, Plagnet and Romano (2008)	92 electricity distribution businesses in France over three years *N* = 276	SFA – input distance function, DEA	MLE	Translog	Truncated normal distribution		Capital (gross replacement value), Opex, Total number of interruptions (quality variable)	Energy supplied, Number of customers, Network length (or service area)	Time-period dummies

Author/s	Data	Method	Estimation method	Functional form	One-sided Error	Dependent variable	Inputs	Outputs	Environmental variables
SFA for sensitivity testing									
London Economics (1999)	196 distributors from Australia, New Zealand, England and Wales, and the United States	DEA, SFA – input distance function	MLE	Translog	Truncated normal distribution		Total O&M expenditure, Network length, Transformer capacity	Energy delivered, Number of customers, Peak demand	Customer density, Load density and system loading, Customer mix
Carrington, Coelli and Groom (2002)	59 distributors from Australia and the United States	DEA, SFA– input distance function, COLS	MLE	Translog	Truncated normal distribution		Gas mains length, O&M costs	Gas deliveries (TJ), Residential customer number, Other customer number	Age of network, Climate

* The columns 'Estimation method' to 'Environmental Variables' of the table only present the summary information for the SFA method.

5.4 Regulatory practices using the SFA method

5.4.1 Regulatory practices review

Energy regulators in Germany, Finland, and Sweden have applied the SFA benchmarking method using data on electricity and/or gas distribution businesses to either develop business-specific efficiency scores or estimate industry-wide productivity change. The following information on the application of SFA by the above regulators has been primarily drawn from WIK-Consult (2011).[91]

Germany[92]

Incentive regulation, via a revenue cap, was introduced in Germany in 2009. The new revenue cap requires existing cost inefficiencies to be linearly removed over two five-year regulatory periods. The national energy regulator, Bundesnetzagentur (BNetzA), used cost benchmarking to determine the existing cost inefficiencies for each of the 198 electricity distribution businesses and 187 gas distribution businesses under the BNetzA's jurisdiction.

The cost benchmarking was undertaken at the total cost level with no further disaggregation of costs. The BNetA considered two different measures of total cost, where the difference related to the measurement of capital costs. The first measure of capital cost was based on the values reported from the utilities' annual reports. The second measure was based on a standardised cost of capital. The two different measures of total cost were benchmarked using both SFA and DEA methods, therefore resulting in four sets of cost inefficiency estimates for each business sampled.

The large number of distribution businesses in the sample enabled the BNetzA to include a large number of output variables.

For electricity distribution, the same 11 variables were used for the four alternative analyses. These were: number of connection points for high-, medium- and low-voltage levels, circuit of cables (high and medium), circuit of lines (high and medium), total network length (low), service area (low-voltage level), annual peak load (high/medium and medium/low), number of transformer stations across all three voltage levels, and installed capacity of distributed generation across all three voltage levels. The first seven of the output variables captured end-user-related aspects and the last four captured capacity-related aspects.

For gas distribution, the benchmarking included the same ten output variables for the four alternative analyses. These were: number of exit points to end-users, number of potential exit points to end-users, service area, pipeline length (≤ 5 bars and > 5 bars), annual peak load, potential peak load, volume of pipelines, population in 1995 and population in 2006. The first five of the output variables captured end-user-related aspects and the last five captured capacity-related aspects.

[91] There can be other examples of energy regulators applying SFA benchmarking methods. Haney and Pollitt (2009) undertook an international survey of the current benchmarking applications by 40 energy regulators.

[92] Refer to chapter 3.4 of WIK-Consult (2011).

To provide for flexibility in SFA model estimations, the BNetzA assumed normalised linear cost functions with constant returns-to-scale and a truncated-normal distribution of inefficiency. For the DEA models, however, non-decreasing returns-to-scale was assumed to ensure that small distribution businesses were only compared with other small distribution businesses. These functional forms were applied to both gas and electricity.

The outcomes of the four models (two SFA and two DEA models) were combined by setting the business-specific efficiency score as the maximum (most favourable) value of the results if this was no less than 0.6; otherwise, 0.6 was applied. The identified cost inefficiency for each utility is linearly deducted from the allowed revenue over two five-year regulatory periods, such that by the end of the second period only the efficient costs will be used to set the allowed revenue.

Finland[93]

In Finland, the 88 electricity distribution businesses are entitled to set their own tariffs, but must follow the methods relating to opex and capex that are described *ex ante* by the Finnish energy regulator, the Energy Market Authority (EMA). The EMA has employed cost benchmarking since 2008 to set the individual efficiency targets for opex. Both SFA and DEA methods were used because it became clear that both DEA and SFA have some strengths and weaknesses.

For the regulatory period 2009 to 2011, the EMA considered that total-cost benchmarking was most suitable as previous experience indicated that benchmarking based on opex only created perverse incentives for regulated utilities to focus only on controllable opex at the expense of other costs. The EMA measured total costs as the overall costs to customers, comprised of operating costs, depreciation (straight line) and the outage costs.[94] The rationale for including outage costs was to prevent cost-cutting at the expense of service quality. The same measure of total cost was used for both SFA and DEA. The data were based on the average value of the cost inputs between 2003 and 2006.

In contrast to the BNetzA, the EMA only included a few output variables. For the SFA method, these were total urban network length, total other network length, number of users and value of energy distributed to consumption. The non-decreasing returns-to-scale technology was assumed and the 'linear functional form' (Energiamarkkinavirasto, no date, p. 58) was used.

The outcomes of the two methods (SFA and DEA) were combined by taking a simple average of efficiency scores from the two methods. The resulting business-specific efficiency target indicates how much a business should reduce operating costs to achieve an efficient cost level under the prescribed opex method.

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[93] Refer to chapter 3.3 of WIK-Consult (2011).
[94] The outage cost measure appears to be a payment or rebate to customers following outages.

Sweden[95]

Commencing in 2012, the Swedish regulator, the Energy Market Inspectorate (EI) applies new *ex ante* incentive-based regulatory framework (revenue cap) to electricity distribution. This new framework replaces an engineering-based reference model that was used from 2003. Sweden has around 170 electricity distribution businesses.

The EI employed SFA, DEA and regression methods to analyse industry-wide productivity change of electricity distribution businesses between 2001 and 2008. The model consisted of controllable operating cost as the input variable and three output variables, namely number of customers, length of lines and cables, and installed capacity of transformers. The EI considered that there was no need to incorporate other business environment variables as the focus was to estimate the industry-wide productivity and not to compare utilities (WIK-Consult, 2011, p. 51). The EI used this model to estimate an industry-wide efficiency target which is to be applied to controllable operating costs only and therefore feed through into allowed revenue.[96] No benchmarking has been undertaken to set business-specific efficiency targets.

5.4.2 Summary of regulatory practices

This review has identified only a limited number of energy regulators that have used SFA for cost benchmarking. Sweden, Germany and Finland all have a relatively large number of distribution businesses, which has facilitated the use of SFA. Germany, with over 180 distribution businesses in both gas and electricity, was able to include a large number of dependent variables in their modelling. With 88 electricity distribution businesses in Finland, the smaller sample size limited the number of output variables that could be included in the model. All the three European regulators combined the SFA benchmarking method with the use of other benchmarking methods such as DEA and regression.

A number of other regulators such as the Ofgem (the UK energy regulator) and the Dutch Energy Regulator, have considered but been advised against the use of the SFA method for cost benchmarking by their consultants. This has been due to data limitations resulting from the small number of regulated utilities, 14 electricity distribution businesses in the UK and around 20 in the Netherlands. Similarly, Austria ruled out SFA due to its relatively small sample of 20 gas and 20 electricity distribution businesses.

5.5 Issues arising from the review

The review of the SFA method for the purpose of cost benchmarking, as covered in the previous sections, includes the theory behind SFA, the empirical applications of SFA by researchers mostly in the context of the energy sector, and by energy sector regulators.

The key issues arising from this review are:

- the need for extensive data to undertake the modelling;

[95] Refer to chapter 3.7 of WIK-Consult (2011).
[96] There is no further information available from WIK-Consult (2011) on how the results from different methods were combined.

- the assumptions that must be made in relation to the choice of the functional form, the distribution of the error terms and the independence of the error term and the explanatory variables; and
- the limited number of studies undertaken by regulators.

5.5.1 Data requirements

The SFA cost frontier model requires the following data: costs, output quantities, input prices and business environmental conditions. Input quantities and cost share data may also be required (Kumbhakar and Lovell, 2000). A mis-specification of the model, where not all the relevant variables that determine the costs modelled are included, may lead to the estimation of an incorrect cost frontier and biased estimates.

SFA also requires more data points than the conventional econometric methods in order to estimate the two separate residual terms, namely the statistical noise term and the inefficiency term. Without a large amount of data, the SFA method may not be able to estimate all necessary explanatory variables based on the desired functional form. This may result in a model misspecification error and a biased estimation of the cost function.

In order to undertake SFA, a large sample size (by including utilities in other countries or using panel data) is required. Given the small number of Australian businesses in each of the energy sub-sectors, the sample size may be enlarged by including comparable businesses in comparator countries.

Construction of a panel dataset requires data on the same businesses to be collected repeatedly over time. The collected data must be consistent and directly comparable over time. Data on the same businesses over time can also improve the separation of statistical noise from estimated management-controllable inefficiency, and enable more consistent estimation of the model parameters and the inefficiency term.

However, potential data issues may arise from the use of international benchmarking and/or panel data. This is covered in Chapter 7.

5.5.2 Required assumptions

The SFA method requires that assumptions are made regarding the functional form of the model. If the simpler Cobb-Douglas function is assumed for the production technology, this risks biased estimation of the inefficiency term as the inefficiency estimate may capture the departure of observed costs from the estimated frontier that is due to technological factors left out of the model. As discussed in Chapter 4, the translog model, while more flexible, requires considerably more data points. This is particularly important as the number of parameters for estimation increases disproportionately with the rise in the number of cost drivers. Similarly, other flexible functional forms are data-intensive.

The SFA method also requires an assumption in relation to the one-sided inefficiency error term. Empirical applications have tended to assume either the half-normal or truncated-normal distributions to represent the pattern of inefficiency. While there is no consensus on the appropriate specification, there does appear to be some early evidence suggesting that different distributions may not have significant effect on the efficiency or accuracy of the results (Kumbhakar and Lovell, 2000, p. 90).

Finally, most of the SFA estimation methods, including MLE and random effects, still require the assumption that the inefficiency error term is uncorrelated with the cost drivers included in the model. However, in some cases this assumption may seem counterintuitive. A violation of this independence assumption may lead to biased estimation of both the inefficiency term, and the parameters of the cost drivers included in the model.

5.5.3 Limited regulatory applications

The review of regulatory practices has identified three regulatory applications of SFA.[97] Both Germany and Finland used SFA to determine the cost inefficiency of each individual business. However, neither of these two regulators relied solely on the SFA method. The German regulator applied the most favourable efficiency score derived from four models; two models using SFA and two using DEA. The most favourable efficiency score from the four models, if no less than 0.6, was applied. The Finnish regulator averaged the results of two models; one estimated by SFA and the other by DEA. Both regulators directly incorporated the identified inefficiency (relative to the frontier) into the allowed revenue (for Germany) or operating cost method (for Finland).

Sweden relied on SFA, together with econometric analysis and DEA, to determine the industry-wide productivity change for controllable opex. This industry-wide efficiency target feeds into the annual revenue allowance via the annual adjustments to the efficient controllable operating costs.

All three of these European energy regulators have a large sample of utilities under their jurisdictions. Germany and Sweden had over 170 utilities and Sweden also had used panel data. Finland had 88 utilities and was not able to include many cost drivers due to this relatively smaller sample size.

It is also important to note that the application of cost benchmarking in each of these three European countries is relatively new. It was introduced in 2008, 2009 and 2012 for Finland, Germany and Sweden respectively. Indeed, it may be premature to draw lessons from these experiences.

5.6 Conclusions

SFA has many desirable properties which lend well to cost benchmarking. In particular, the separation of statistical noise from the estimation of management controllable deviations from the cost frontier would seem appropriate in a regulatory context. In addition, SFA retains many of the desirable properties of other econometric methods including allowing for statistical testing of the model parameters, explanatory power of variables and the error assumptions.

[97] A number of energy regulators from the OECD countries have been reviewed. An international survey by Haney and Pollitt (2009) also identified Belgium, Portugal and Norway as applying the SFA benchmarking method in the most recent price review.

However, SFA is a data-intensive benchmarking method and failure to include sufficient data points for the estimation can lead to biased and/or inconsistent estimation of the parameters in the model and, therefore, the estimated inefficiency term. Most academic or regulatory applications of SFA have involved substantial data points.

Similar to other econometric methods, SFA requires the imposition of assumptions regarding functional form, the distribution of the error terms, including the one-sided error term and the independence of the one-sided error term with all of the output variables included in the model. Violation of these assumptions can lead to biased estimation of the inefficiency term.

Given these potential issues, it would seem that the use of the SFA method to benchmark cost efficiency for regulatory applications should be approached with caution. Ideally, multiple periods of data on a large number of energy businesses in a sub-sector would be available for the analysis. In addition it may be prudent to follow the approach of academics and regulators that have applied the SFA benchmarking method. That is to undertake cross-checking of the SFA efficiency or productivity estimates (or rankings) against different model specifications and assumptions, and against different benchmarking methods such as DEA, OLS and its variants.

Chapter 6 Evaluation of the non-parametric DEA method

6.1 Introduction

Data Envelopment Analysis (DEA) is a technique that compares the efficiency and productivity of businesses that produce similar outputs using similar inputs. Unlike other parametric techniques, DEA does not require *ex ante* assumptions about the shape of the underlying production function or cost function. Information about the shape of the real-world production technology is inferred from observations of the input-output combinations used by the businesses.

At the heart of DEA is a set of assumptions about how observed input-output combinations from real-world businesses can provide information about the set of possible input-output combinations available to the businesses in the industry. That is, this approach relies on data in relation to the output levels of businesses in the industry and the amount of inputs to produce that output (the 'input-output combinations'). Sophisticated mathematical techniques are employed to calculate efficiency levels for each business, given their relative scale, output levels, output mix, and use of inputs. That is, possible 'input-output combinations' are derived and compared with actual input-output combinations so that the business-specific level of efficiency is calculated. Different approaches to DEA differ in the assumptions about the space of feasible input-output combinations from observations of the actual input-output combinations achieved by individual businesses.

Once all possible input-output combinations are determined, the efficiency score for each business is determined. Under the input-oriented version of this approach, the efficiency score provides an answer to the following question: How much can the inputs used by that business (holding the output constant) be scaled down and still have an input-output combination which is feasible? The output-oriented version of this approach asks: How much can the output of the business (holding the inputs constant) be scaled up and still have an input-output combination which is feasible?

DEA is relatively simple and intuitive, and has been widely applied in practice. Many academic papers relate to the theory or the applications of DEA. This body of research covers a wide range of sectors. Scores of papers relate to the application of DEA in public utility industries. Many economic regulators have applied DEA to electricity and gas distribution companies as part of their regulatory processes.

The remainder of this chapter is structured as follows: section 6.2 describes the DEA method in more detail. Section 6.3 reviews the academic literature on DEA and section 6.4 reviews the regulatory practices which have used DEA. Section 6.5 discusses issues that arise in the application of DEA, and conclusions are drawn in section 6.6.

6.2 Description of the DEA method

6.2.1 Method

The DEA method constructs a space of feasible input-output combinations starting from observed input-output combinations of sample businesses. Different DEA approaches make different assumptions in extrapolating from specific observed input-output combinations to the set of all possible feasible input-output combinations.

If a business produces the vector of N outputs $y = (y_1, y_2, \ldots, y_N)$ using the vector of M inputs x= $(x_1, x_2, \ldots, x_M)$, the input-output combination $f = (y, x)$ is said to be *feasible*. A sample of such observations yields a set of discrete feasible input-output combinations $f^1, f^2, \ldots, f^S$, where S is the number of businesses.

From this observed set of feasible input-output combinations, the next step is to extrapolate to the full space of feasible input-output combinations. The most common approach to DEA is to assume:

- Free disposability: If (y, x) is a feasible combination then so is (y', x') where $y' \leq y$ and $x' \geq x$;[98] and

- Scalability and combinability of peer observations: If (y^i, x^i) is a set of feasible combinations, then so is $(\sum_i \lambda^i y^i, \sum_i \lambda^i x^i)$ where, under the assumption of constant returns-to-scale (CRS), the weights of peer observations in forming the surface of feasible input-output combination λ^is are allowed to be any non-negative real number.

Other assumptions may include:

- the businesses have decreasing returns-to-scale (DRS), where the weights are allowed to be any non-negative real number which sums to less than or equal to one; or

- the businesses have variable returns-to-scale (VRS) where the weights are allowed to be any non-negative real number which sum to the value of one.

Given the set of feasible input-output combinations constructed, the DEA score for a business under an input-oriented model is a measure of how much, for a given set of outputs, the inputs used by the business could be proportionally scaled down while still remaining within a space of feasible input-output combinations. Alternatively, the output-oriented approach asks how much the output of the business could be scaled up, holding the inputs constant, while still remaining within the space of feasible input-output combinations.

The following description of the DEA method is based on an input-oriented model as it is perceived to be appropriate for modelling electricity distribution, where businesses may have less discretion over the output quantities supplied relative to the inputs used. One could argue that capital inputs are fixed in the short run in electricity distribution, as assumed in a number of DEA studies including London Economics (1999). This requires the modelling of capital as the non-discretionary input. For simplicity, this is not illustrated in the description below.

[98] A vector y is said to be less than or equal to a vector y' if and only if every element of the first vector is less than or equal to the corresponding element of the second vector.

Mathematically, given a particular business with input-output combination (y^0, x^0), DEA measures technical efficiency of the business; that is, it provides the answer to the following linear optimisation problem for an industry with a CRS technology:

Min θ subject to:

$$y^0 \leq \sum_i \lambda^i y^i \text{ and } \theta x^0 \geq \sum_i \lambda^i x^i \text{ where } \lambda^i \geq 0.^{99} \qquad (6.1)$$

Here θ is just a positive number which reflects how much the inputs of the business in question can be scaled down. The λ^is are a set of non-negative numbers which reflect how much the input-output combinations of the sampled businesses should be weighted up or down before being combined.

If the inputs of a business cannot be scaled down at all with its input-output combination remaining within the feasible set, that business is assigned an efficiency score of one. For business with an efficiency score of less than one, there is some combination of other businesses which can produce the same or more output with less inputs.

The example below will make this clearer.

Suppose that observations are made on the input-output combinations of two firms. Firm 1 produces 100 units of service A and 8.9 units of service B at a cost of $100 m, while firm 2 produces 50 units of service A and 60 units of service B at a cost of $150 m. There is a third firm producing 20 units of service A and 20 units of service B at a cost of $60 m.

		Firm 1	Firm 2	Firm 3
Outputs	Service A	100	50	20
	Service B	8.9	60	20
Inputs	Cost	$100 m	$150 m	$60 m

Under the assumptions of the CRS technology, it is possible to produce the output of firm 3 using 0.036 copies of firm 1 and 0.328 copies of firm 2. This combination of firms could produce the output of firm 3 at a cost of only $52.8 m. As a result, firm 3 is assigned an efficiency score of 0.88 (equal to 52.8/60).

Firm 3 in this example is much smaller than the other two firms. It can be as inappropriate applying DEA under the CRS assumption, to comparing firm 3 to a scaled down combination of firm 1 and 2. For example, in the industry in question smaller utilities may be disadvantaged relative to larger utilities – a form of non-decreasing returns-to-scale technology.

[99] In addition, in the case of decreasing returns to scale or DRS there is an additional constraint $\sum_i \lambda^i \leq 1$; in the case of variable returns to scale or VRS the additional constraint is $\sum_i \lambda^i = 1$. Other possible assumptions are discussed in Bogetoft (1997).

The conventional way in DEA to handle an alternative technology to CRS is to impose a new constraint on the way that the space of feasible input-output combinations is formed. Specifically, whereas the standard CRS assumption above allows the input-output combinations of the sampled businesses to be weighted up and down of any scale while still being feasible, the VRS assumption limits the feasible set to firms of similar size and the non-decreasing returns-to-scale assumption would not consider *weighted-down* versions of the input-output combination. Using the example above, for the industry facing non-decreasing returns-to-scale technology, it would be found that the output of firm 3 could not be constructed from any combination of the output of the other firms of much larger size and it would be concluded that the efficiency score for firm 3 is one.

This is an illustration of a general principle: Where the standard assumptions in DEA analysis do not appear realistic (e.g., where the input-output combinations of businesses cannot be weighted up or down at will to make new feasible combinations), it is possible to change those assumptions – usually by relaxing these assumptions in some way. This can make the analysis more credible or realistic but also results in more observations being found to have an efficiency score of one as the reference set is constrained in some way.

As with all benchmarking methods, the selection of the input and output variables is of fundamental importance. In principle, the input and output variables should capture the relevant aspects of production, including quality of service. In addition to inputs and outputs, however, business performance can differ due to operating or environmental condition factors which are out of management control.[100] The geographical location of electricity distribution businesses (e.g., percentage of forest coverage, customer density, and customer type) may affect their operational costs.

There are a variety of approaches for incorporating environmental variables into the standard DEA analysis.[101] One approach is simply to add these variables as additional inputs or outputs. However, treating environmental variables as regular inputs or outputs might give rise to problems with the scalability assumptions mentioned above. Some environmental factors can be non-discretional, and thus cannot be scaled proportionally, as with regular outputs and inputs. For example, an electricity distributor operating in an area with low customer density cannot change its operating environment.

Another approach is to restrict the set of comparators to only those which have the same or less favourable environment. Under this alternative, the environmental variables are included as non-discretionary variables so that their inclusion limits the comparator set for the input-output combination considered. Nillesen and Pollitt (2008) commented that this approach of limiting the comparison to those with the same environment 'does not handle continuous environmental variables well and reduces the size of the sub-samples to unacceptably low levels in most

[100] This point is emphasised by Turvey (2006, p. 105): 'The frequency and intensity of storms, the saline content of the atmosphere, the proportion of overhead lines that pass through wooded areas, the length of cabling in dense urban areas and the accessibility of lines and substations are all factors which affect the required maintenance effort.'
[101] These are summarised by Coelli, Rao, O'Donnell and Battese (2005) and Nillesen and Pollitt (2008).

circumstances'. To broaden the comparator set, the direction of the impact of the environmental variable must be known in advance. In addition, businesses with extreme environmental conditions are automatically determined to be efficient. As the number of environmental variables increases, so does the number of businesses deemed to be efficient.

A more commonly adopted approach to incorporating environmental variables is to carry out the analysis in two or more stages. In the first stage a standard DEA method is performed. In the second stage, the DEA efficiency scores are regressed against various possible environmental factors, typically using Tobit regression,[102] to assess the contribution of the environmental factors to the level of gross inefficiency. Ray (1991) adopted second-stage regression to identify key performance drivers in school districts. Banker and Natarajan (2011) provided a framework for the evaluation of environmental variables by considering appropriate estimation methods and statistical tests for a variety of data-generating processes. However, if the variables in the first stage are correlated with the variables in the second stage the results are likely to be biased. See for example, discussion in Coelli, Rao, O'Donnell and Battese (2005) and Barnum and Gleason (2008).

Simar and Wilson (2007) criticised this approach on various statistical grounds and, instead, proposed a three-stage process in which SFA is used to decompose the source of the apparent inefficiency of a business. Nillesen and Pollitt (2008) adopted the two-stage approach, on the basis of the results of Yang and Pollitt (2008) which found a high correlation between the scores arising from the two-stage method and the theoretically preferable three-stage method. Another criticism, due to Kaufmann and Beardow (2001), is that in order to carry out this second-stage regression some assumptions must be implicitly made about the shape of the underlying function – which undermines one of the claimed advantages of DEA.

As an aside, it is worth noting that it is possible to use the DEA method to obtain an estimate of the cost efficiency as follows. Given a set of input prices w, the cost function derived from the DEA method $C^{DEA}(y|w)$ can be defined as (Agrell, Bogetoft and Tind, 2005):

$$C^{DEA}(y|w) = \min \sum_i \lambda^i w x^i$$

subject to: $y^0 \leq \sum_i \lambda^i y^i$ and $x^0 \geq \sum_i \lambda^i x^i$ where $\lambda^i \geq 0$ (6.2)

(and, in the case of non-decreasing returns to scale, $\sum_i \lambda^i \geq 1$; in the case of variable returns to scale, $\sum_i \lambda^i = 1$).

Alternatively, if cost measures are used to model inputs, then cost efficiency performance across businesses is also considered.

A set of input-output combinations at a given point in time is assumed to define the production possibility set at that point in time. Given a set of input-output combinations at different points in time the change in productivity of a firm over time

[102] The Tobit regression method is used because the DEA efficiency score is truncated from above.

can be computed. In principle, the business performances at time zero can be computed using the production-possibility set from time one and vice versa. These DEA scores can then be combined into a form of 'Malmquist Index' of productivity change of the firm over time and its decomposition into efficiency change and technical change. Coelli, Rao, O'Donnell and Battese (2005) provides a detailed description of the computation of the Malmquist Index using DEA and SFA.

6.2.2 Data requirements

The standard approach to DEA focuses on the establishment of a production-possibility set – the space of all feasible input-output combinations. As such, DEA requires information on a set of input and output quantities. As noted above, if data on input prices are also available or cost measures are used to model inputs, DEA can be used to directly estimate a benchmark cost for each business.

As in all benchmarking methods, a key issue is the selection of the explanatory variables – that is, the input, output, and environmental variables – which should, as a group, be sufficient to model the production and thus the performance of the businesses considered.

That is, the explanatory variables must account for all of the legitimate differences in the cost performance of the businesses, including all the differences in cost that are due to differences in the nature of the services provided, the customers served, the quality of service provided, the weather conditions, operating environment, input prices, and other factors that are out of management control.

The number of explanatory variables required to completely account for all of the legitimate differences in the cost performance of businesses will differ from industry to industry and study to study. Any variables which are common to all of the businesses in the sample can be omitted from the analysis.[103] Conversely the greater the heterogeneity in the business conditions faced by the sample, the larger the number of variables that will likely be necessary to account for that heterogeneity.

In modelling electricity distribution, the problems in relation to the selection of inputs and outputs, as discussed in earlier chapters, are also relevant to the DEA method. Ideally each distinct service provided should be treated as a different output and each unique factor of production used should be separately modelled as an input. However, as the number of inputs and outputs increases, the number of dimensions in which the sampled businesses needed to compare with each other accelerates. A general rule of thumb is that the sample size should be no less than, the product of the number of inputs and number of outputs, or three times the sum of the number of inputs and outputs, whichever is larger (Cooper, Seiford and Tone, 1999, p. 252). Dyson, Allen, Camanho, Podinovski, Sarrico and Shale (2001) suggested a stricter guideline requiring a sample size at least double the product of the number of inputs and number of outputs. According to Coelli (2012), the information requirements for DEA can be greater than SFA:

[103] For example, this might apply to, say, national service standard obligations, nationally prevailing weather conditions, or the prices of inputs with low transportation costs which are procured in a national or international market.

> Given that DEA frontiers are arguably more flexible than a second-order parametric frontier, such as the translog, one would expect that the data requirements for DEA are greater than those of SFA. Hence, I believe that the existing rules of thumb used in the DEA literature are generally too low. I would suggest that the construction of bootstrap confidence intervals for DEA efficiency scores could provide some useful information regarding the degree to which these DEA results obtained from small samples can be relied upon.

As with other benchmarking methods, there is a need to use more aggregated input and output measures under the DEA method.

Generally speaking, broad categories of outputs and inputs capable of capturing all essential aspects of electricity distribution should be modelled. As discussed in earlier chapters, there are a number of problems in measuring inputs and outputs for electricity distribution, including that:

- little consensus on which input-output variables best describe the production;
- difficulties in modelling service quality;
- problems with the aggregation of service capacity; and
- difficulties with measuring the volume of capital input.

In addition, data are also required for modelling the set of environmental variables needed for a two or three-stage DEA analysis.

6.2.3 Advantages and disadvantages

DEA is a relatively simple and intuitive technique.[104] Its strength is that it requires relatively little detailed knowledge of the shape of the underlying cost function. What is required is the knowledge regarding (a) the key cost drivers – the factors that can legitimately affect the volume of outputs produced from a given set of inputs and (b) the basic shape of the technology (such as whether there are increasing returns to scale). Unlike other benchmarking methods, DEA provides a clear picture of the comparator business or business against which any given business is being compared.

Various possible disadvantages of DEA have been raised:

- DEA neglects the possibility of errors in the measurement of the output and input variables. As a result, the DEA measure is sensitive to the presence of outliers or errors in the measurement of the data (see, for example, Pedraja-Chaparro, Salinas-Jiménez, and Smith, 1999). In particular, the DEA efficiency measure is sensitive to the input-output combinations for those (few) businesses which define the boundary of the feasible space. Furthermore, adding more

[104] Nillesen and Pollitt (2008, p. 20) emphasised that DEA is easy to communicate: ‘The great thing about DEA is that it has a major advantage over other potential methodologies. It is easy to communicate with managers. This is because it involves an engineering, rather than a statistical, approach and all performance can be visually represented. Managers are in general much more comfortable with direct estimates of efficiency and with fixed adjustments for potential, rather than “letting the data decide” in an opaque way such as is the case with an econometric efficiency technique such as Stochastic Frontier Analysis’.

observations to the sample will result in a tendency for the DEA scores to decrease.

- DEA does not easily control for differences in business conditions. As discussed in section 6.2.1, the alternative approaches to incorporating environmental variables have their own problems. Kaufmann and Beardow (2001) argued that the treatment of service quality is particularly difficult under DEA.

- Standard DEA allows for no internal validation of the model chosen, or whether the resulting efficiency scores are statistically different from one. As Pedraja-Chaparro, Salinas-Jiménez, and Smith (1999) emphasised:

  > The user of data envelopment analysis (DEA) has little guidance on model quality. The technique offers none of the misspecification tests or goodness of fit statistics developed for parametrical statistical methods. Yet, if a DEA model is to guide managerial policy, the quality of the model is of crucial importance.

- A related disadvantage is that it is not possible to know what sample size is required to obtain a reasonable estimate of relative efficiencies.

- Kaufmann and Beardow (2001) argued that a disadvantage of DEA was its use of input volumes rather than input prices, given the difficulty in measuring the volumes of capital services consumed.

Some of the disadvantages of DEA are addressed by recent developments in DEA, including the development of statistical inference in DEA (Simar and Wilson, 1998, 1999, 2000; Kneip, Simar and Wilson, 2009), window analysis (see for example, Webb 2003) and stochastic DEA. In a series of papers by Simar and Wilson, the bootstrapping method has been applied to DEA modelling so that statistical inferences can be made. In a recent paper Kuosmanen (2011) has further developed the nonparametric DEA model by combining it with aspects of Stochastic Frontier Analysis. Kuosmanen (2011) recommended replacing the use in Finland of an average of DEA and SFA efficiency scores with the StoNED estimator, which combines a nonparametric frontier with stochastic inefficiency and noise terms. The resulting model was claimed to be a generalisation of both the classic DEA and SFA models. The key idea is that the standard 'least squares' regression model is itself a form of constrained-optimisation problem, similar to the classic problem. In principle, a set of linear combinations of businesses which minimises the sum of the squared deviation of the actual from the estimated costs can be found for a given set of data on costs and outputs.

6.3 Literature review of the DEA method

The idea of measuring technical efficiency by a radial measure representing the proportional input reduction possible while staying within the production possibility set is due to Farrell (1957). The application of linear programming methods to measuring technical efficiency under the CRS assumption (and the name Data Envelopment Analysis) was first proposed by Charnes, Cooper and Rhodes (1978) and extended to the VRS model by Banker, Charnes and Cooper (1984).[105] DEA is also discussed in several surveys on productivity and efficiency measurement, such as the article by Murillo-Zamorano (2004) or the textbook by Coelli, Rao, O'Donnell and Battese (2005).

A number of academic papers have applied some form of DEA method to electricity and gas distribution. Early contributions in this area were made by Charnes, Cooper, Divine, Ruefli and Thomas (1989) and Miliotis (1992).

Charnes, Cooper, Divine, Ruefli and Thomas (1989) applied DEA to 75 Texas electric cooperatives and compared the results to ratio and regression-based analyses used for evaluating management efficiency. They considered DEA to be superior to ratio analysis and decided to adopt DEA to assist the regulator to determine which cooperatives might best be audited, provide reference businesses to judge the performance of others and supply information as to source and magnitude of any inefficiency that might be present.

Miliotis (1992) applied DEA to evaluate the relative efficiency of 45 electricity distribution districts for the Greek Public Power Corporation. Miliotis (1992) used eight input-output factors and considered four different DEA models, each with a different combination of inputs and outputs. It was noted that, when using DEA, inputs and outputs should be disaggregated up to a level where all the basic idiosyncrasies of the system being modelled are represented, taking into account that excessive breakdown of inputs and outputs may result in loss of discriminative power, especially when the total number of businesses is relatively small. Miliotis (1992) concluded that DEA scores appeared to be more reliable than simple productivity ratios. The paper noted that the difference in DEA results between the businesses might be due to the management of resources controllable by the business, the efficiency of the design of the supply system or, finally, environmental aspects not explicitly identified in the model.

Later development in this area covers DEA applications to a large number of countries, such as Australia, the United Kingdom (UK), Finland, Norway, and Switzerland. Table 6.1 summarises relevant empirical studies on energy networks in terms of the sample, method, DEA model specification and assumptions.

Relatively few studies have taken into account quality of service measures when carrying out DEA benchmarking. Among the few exceptions are Giannakis, Jamasb, and Pollitt (2005) and Coelli, Crespo, Paszukiewicz, Perelman, Plagnet, and Romano (2008). Giannakis, Jamasb, and Pollitt (2005) extended the DEA benchmarking of electricity distribution businesses by including quality of service measures – indexes of security of supply and reliability of supply – as an *input* variable. The authors investigated the impact of the inclusion of quality of service measures as inputs into the DEA model, and also the impact of including a measure of totex or opex. The authors found that there were performance variations when quality of service indicators were included in the model, which might indicate a possible trade-off between the costs and quality of service.

[105] A further problem is that there may be increasing returns to scale over some output levels and decreasing returns to scale over others. Appa and Yue (1999) proposed a further extension to the basic model to address this issue.

Coelli, Crespo, Paszukiewicz, Perelman, Plagnet, and Romano (2008) used annual data on 92 French electricity distribution businesses and included the total number of interruptions as an input in the DEA model to account for quality of service.[106] They found that the inclusion of a quality variable had no significant effect upon mean technical efficiency scores.

Several academic papers sought to assess whether or not DEA and other benchmarking methods satisfy the consistency conditions proposed by Bauer, Berger, Ferrier, and Humphrey (1998). Estache, Rossi and Ruzzier (2004) applied DEA and SFA methods to 84 South American electricity distribution businesses and found a high correlation in the efficiency ranking of utilities using CRS and VRS DEA models, but a low correlation between SFA and DEA efficiency measures. Farsi and Filippini (2005) applied DEA, SFA, and COLS methods to a sample of 59 Swiss electricity distribution utilities.[107] They found that although there was quite high correlation between the COLS and SFA efficiency scores, the correlation with the DEA estimates are relatively low. They concluded that the Bauer consistency conditions were difficult to satisfy in the context of electricity distribution. Other papers include Murillo-Zamorano and Vega-Cervera (2001), and Omrani, Azadeh, Ghaderi, and Aabdollahzadeh (2010).

Several academic papers discussed the pros and cons of DEA (along with other benchmarking methods). These include: Kaufmann and Beardow (2001), and Ajodhia, Petrov and Scarsi (2003) in the context of the regulation of electricity distribution; Burns, Jenkins and Riechmann (2005), and Lowry and Getachew (2009b) in the context of public utility regulation more generally.

Kaufmann and Beardow (2001) evaluated alternative methods for benchmarking the performance of power distributors, including DEA, SFA and econometric methods. The authors considered that econometric techniques (such as econometric cost functions and SFA) had significant advantages over DEA. The authors believed that DEA was not well suited for electricity networks, particularly in countries like Australia, where there are relatively limited data on domestic energy networks. The authors considered a number of problems associated with implementing DEA for energy networks, including problems with capital measurement, dealing with distance and service quality, and the impact of non-comparable variables in international datasets.

In another series of papers, Bogetoft (1997, 2000) set out a proposal for using DEA mechanistically to determine the revenue allowance for a regulated business. This proposal involves setting a revenue allowance for the regulated business which is a weighted average of its past cost out-turns and a DEA score. Agrell, Bogetoft and Tind (2005) applied this notion to the UK electricity distribution businesses.

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[106] Coelli, Crespo, Paszukiewicz, Perelman, Plagnet, and Romano (2008) expressed concerns with the Giannakis, Jamasb, and Pollitt (2005) paper – specifically, the use of totex contains capex measures 'which need not reflect the actual amount of capital services consumed in a particular year' and the small sample size problem. Coelli, Crespo, Paszukiewicz, Perelman, Plagnet, and Romano (2008) got around these problems by applying DEA to a set of 92 electricity distribution businesses all operated by EDF Réseau Distribution in France. See also Lassila, Honkapuro, Viljainen, Tahvanainen, Partanen, Kivikko, Antila, Mäkinen and Järventausta (2005).

[107] Discussion of Farsi and Filippini (2005) appears earlier in this paper at section 4.3.

Bogetoft (1997) investigated the use of DEA in regulatory environments with technological uncertainty. He found that regulatory schemes incorporating a component of DEA estimated cost reductions would induce the regulated businesses to minimise costs and minimise their information rents. Bogetoft noted many benefits of DEA: it requires very little technical information; it allows a flexible, non-parametric modelling of multi-input multi-output production process; and its cost estimates are conservative or cautious because they are based on an inner approximation of the production possibilities. Bogetoft (2000) similarly found that the use of DEA could play a role in future planning and provide incentives to cost minimisation.

Agrell, Bogetoft and Tind (2005) investigated the introduction of yardstick competition in the Scandinavian countries and the use of DEA as a comparator. They noted that using a DEA-based yardstick model compares favourably to the use of a CPI–X model as it addresses issues relating to: the risk of excessive rents; the ratchet effect; the arbitrariness of the parameters CPI and X; and the inability to accommodate changes in the output profile. They noted that dynamic DEA yardstick modelling is a potentially promising technique to address challenges facing a regulator in a liberalised electricity market.

Overall, the academic literature on benchmarking using DEA urges a cautious approach. Ajodhia, Petrov and Scarsi (2003, p. 270) considered that the main lesson from the Dutch regulatory experience with DEA benchmarking is 'perhaps that regulators should take into account the limitations of benchmarking'. They further argued for the use of benchmarking results as an informative tool rather than mechanically to feed directly into the X factor. Lowry and Getachew (2009b) suggested a number of improvements to make for using DEA as a regulatory benchmarking tool. These include: the need to account for business conditions; and the use of bootstrap method for statistical testing of DEA score. They considered that benchmarking could either be used for prudence review in regulation or to aid in rate-setting directly.

Table 6.1: Summary of the Literature Applying DEA to Benchmarking Energy Networks*

Author	Country, sub-sector, years	*N*[108]	Method	Inputs	Outputs	Other factors	Returns-to- scale assumption
London Economics (1999)	NSW (Australia) – Electricity distribution – 1995 – 1998	219	DEA	O&M expenditure (1997-98 $AUS), Route kilometres, Nameplate transformer capacity	Energy delivered (GWh), Total customers, Peak demand (MW)	Customer density, Load density and system loading, Customer mix	VRS, CRS
Charnes, Cooper, Divine, Ruefli and Thomas (1989)	Texas (United States – US) – Electricity distribution – 1983	75	DEA	**Variable expenses:** Opex, Maintenance expense, Consumer accounts expense, Administrative and general expense **System characteristics:** Customer density, Line Loss,[109] Average hours outage per customer (reliability), Load factor, Total plant (system size) **Other:** salaries, inventory	Net Margin, Total electricity sales (kWh), Total revenue received from sales of electricity		CRS
CEPA (2003)	UK – Electricity distribution – 2001-02	14	DEA, COLS, SFA, TFP, PFP, Parametric programming	Opex	Customer numbers, Electricity distributed, Network length		CRS, VRS

[108] *N* denotes number of observations.
[109] This is also treated as an undesirable output by taking the reciprocal of this value.

Author	Country, sub-sector, years	N[108]	Method	Inputs	Outputs	Other factors	Returns-to- scale assumption
Korhonen and Syrjänen (2003)	Finland – Electricity distribution –1998	106	DEA – Stepwise approach to test the impact of adding variables to the model	Opex	Interruption time, Delivered energy	Network length, Number of customers	CRS, VRS
Syrjänen, Bogetoft and Agrell (2006)	Finland – Electricity distribution – 2004	91	DEA, SFA, COLS	Opex, depreciation and interruption costs	Value of energy,[110] Network length, Number of customers	Geography (topology, obstacles), Climate (temperature, humidity, salinity), Soil (type, slope, zoning), Density (sprawl, imposed feed-in locations)	VRS, DRS, NDRS, CRS
Miliotis (1992)	Greece – Electricity distribution	45	DEA	Various:[111] Network - total length (kilometre), Capacity of installed Transformation points (kVa), General expenses, Administrative labour - (hrs), Technical labour - (hrs)	Various – Network - total length (kilometre), Capacity of installed Transformation points (kVa), Number of customers, Energy supplied (kWh), Service area (km square)		Not specified

[110] This measure is based on the amount of energy delivered to consumption (MWh) on three voltage levels. For each voltage level, the amount of energy is multiplied by the national average distribution price.
[111] This study used four differently configured models, and considered the following items as inputs or outputs depending on the configuration chosen.

Author	Country, sub-sector, years	N[108]	Method	Inputs	Outputs	Other factors	Returns-to- scale assumption
Kittelsen (1999)	Norway – Electricity distribution	173	DEA	Labour hours, Energy loss, Transformers (Number and capacity of local transformers and main transformers), Lines (Voltage level and length), Goods and services	Maximum power in kW, Energy delivered to other electricity utilities and energy intensive industry (MWh);, Energy delivered to other industry and commerce (MWh), Energy delivered to others (households and agriculture) (MWh), Number of customers	Environmental constraints: Distance index; Corrosion index; Climatic index.	CRS, VRS
Agrell, Bogetoft and Tind (2005)	Sweden – Electricity distribution – 1996 – 2000	238	DEA	Capex, Opex, Network loss (MWh)[112]	Coincidental peak load (MW), Number of high-voltage connections, Number of low-voltage connections, Net delivered high-voltage energy, Net delivered low-voltage energy	Climate, Normalised network length (km)	CRS (long run), VRS (short run)
Giannakis, Jamasb and Pollitt (2005)	UK – Electricity distribution – 1991-92 – 1998-99	14	DEA	Various:[113] Security of supply, Reliability of supply, Totex, Opex	Customers, Energy delivered, Network length		CRS, VRS

[112] In this study, net loss is treated as an output in the short-run model and an input in the long-run model.
[113] Four tests were used and then results were compared for modelling outputs with: Opex; Totex; Service quality; and both Totex and Service quality.

Author	Country, sub-sector, years	N[108]	Method	Inputs	Outputs	Other factors	Returns-to- scale assumption
Coelli, Crespo, Paszukiewicz, Perelman, Plagnet, and Romano (2008)	France – Electricity distribution – 2003 – 2005	92	DEA, SFA	Capital, Opex, Number of interruptions	Energy supplied, Number of customers, Network length (or service area)		VRS
Pahwa, Feng, and Lubkeman (2002)	US – Electricity distribution – 1997	50	DEA	System losses, O&M expenses, Capital additions expenses, Distribution line transformers, Distribution lines	System peak load, Retail sales, Retail customer		CRS
Tanure, Tahan and Lima (2006)	Brazil – Electricity distribution	924 consumer units (60 distribution businesses)	DEA, dynamic clusters	Line length (km), Installed transformers, Number of transformers, Number of switches, Type of switches, O&M costs	Service quality measured by the regulators (DEC and the FEC)		Not specified
Jamasb, Nillesen, and Pollitt (2004)	US – Electricity distribution – 2000	28	DEA	Opex	Electricity delivered, Number of customers, Network length		CRS

Author	Country, sub-sector, years	N[108]	Method	Inputs	Outputs	Other factors	Returns-to- scale assumption
Agrell and Bogetoft (2007)	Germany – Electricity distribution	328	DEA, SFA and OLS analytic cost model	Total direct cost (as specified in the regulation)	**Service provision:** Number of meters, Service area (by voltage – high, medium, low) **Capacity provision:** Coincidental load (voltage – high, medium, low voltages; transformer – HS/MS, MS/NS), Feed-in power of decentred generation		CRS, DRS, NDRS, VRS
Wang, Ngan, Engriwan and Lo (2007)	Hong Kong – Electricity distribution – 1994 – 2003	2	DEA – Malmquist TFP	Capex, Labour	Electricity delivered, Customer density		CRS
Cullmann and von Hirschhausen (2007)	Germany, Poland, the Czech Republic, Slovakia and Hungary – Electricity distribution – 2002	84	DEA	Number of employees, Length of electricity grid	Total sales in GWh, Number of customers.	Structural variable to account for regional differences: Inverse Density Index (IDI) – in km^2 per inhabitant	CRS
Carrington, Coelli and Groom (2002)	Australia and the US – Gas distribution	59	DEA, PPI, OLS, COLS, SFA	Length of distribution mains (km), O&M cost (covering labour, contracting, network marketing, etc.)	Total yearly deliveries (as a proxy for capacity to deliver gas), Customer numbers (as a proxy for connection points) by residential and other customers	Climate, Age of network	VRS, CRS

Author	Country, sub-sector, years	N[108]	Method	Inputs	Outputs	Other factors	Returns-to- scale assumption
Goncharuk (2008)	Ukraine and the US – Gas distribution – 2005	74	DEA	Material cost, Number of employees, Amortisation (proxy for fixed capital), Accounts payable (proxy for financial capital)	Operating revenues, Trade accounts payable	Scale (number of employees), Regional location, Property category, Other factors	VRS, CRS
Jamasb and Pollitt (2003)	Italy, the Netherlands, Norway, Portugal, Spain and the UK – Electricity distribution – 1999	63	DEA (6 tests), COLS (2 tests), SFA (2 tests)	**DEA – 1CRS, 1VRS & 1E:**[114] Totex (PPP) **DEA – 2CRS:** Opex (PPP), Network length, Transmission and distribution losses **DEA –- 2VRS:** Opex (PPP), Network length, Transmission and distribution losses **DEA – 1OP:** Opex (PPP)	**DEA – 1CRS, 1VRS & 1E** Power delivered, Number of customers, Network length **DEA – 2CRS:** Power delivered, Number of customers **DEA – 2VRS:** Power delivered, Number of customers **DEA – 1OP:** Power delivered, Number of customers, Network length		VRS, CRS

[114] DEA-1E used Totex as an input converted into Euros using Purchasing Power Parities (PPP).

Author	**Country, sub-sector, years**	***N*[108]**	**Method**	**Inputs**	**Outputs**	**Other factors**	**Returns-to- scale assumption**
Estache, Rossi and Ruzzier (2004)	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, Venezuela – Electricity distribution – 1994 – 2001	84	DEA, SFA	Number of employees (ideally divided into subcategories such as skilled labour, unskilled labour and management), Transformer capacity (MVa), Distribution network (km)	Number of final customers, Energy supplied to final customers (GWh), Service area (square km)	Residential sales' share, GNP per capita	CRS, VRS
Kuosmanen (2011)	Finland – Electricity distribution		Method combining DEA and SFA	Cost	Customer numbers, Network length, Amount of energy transmission (GWh)	Proportion of underground cables	CRS, NDRS, VRS
Omrani, Azadeh, Ghaderi and Aabdollahzadeh (2010)	Iran – Electricity distribution – 2003–2006	26	DEA, COLS, Principal component analysis (PCA)	Network length, Transformer capacity, Number of employees	Number of customers, Total electricity sales		CRS, VRS

* The columns 'Inputs' to 'Assumption regarding returns-to-scale' of the table only present the summary information for the DEA method.

6.4 Regulatory practices using the DEA method

DEA benchmarking methods have been used by a number of energy regulators in the determination of price and revenue requirements for electricity and gas distribution businesses in countries, for example, Finland, Norway, the Netherlands, Germany, and Austria; and in New South Wales, Australia.[115]

Haney and Pollitt (2009) also noted that,[116] DEA had been considered in some form by energy regulators in Belgium, the UK, Slovenia, Iceland, Norway, Argentina, Brazil, Colombia, and Mexico. These countries are not reviewed here.

6.4.1 Regulatory practices review

Germany[117]

As discussed in section 5.4, the German regulator, the Federal Network Agency (BNetzA) computed efficiency scores for the 198 electricity distribution businesses and 187 gas distribution businesses under its jurisdiction using both DEA and SFA benchmarking methods.

For electricity distribution both the DEA and SFA methods used totex as the input variable (measured in two different ways). The output variables were: number of connection points for high, medium and low-voltage levels, circuit of cables (high and medium), circuit of lines (high and medium), network length (low), service area (low-voltage level), annual peak load (high/medium and medium/low), number of transformer stations across all three voltage levels, and installed capacity of distributed generation across all thee voltage levels. The DEA model assumed non-decreasing returns-to-scale (NDRS) technology.

Similarly, for gas distribution, the DEA and SFA methods, included totex as the input variable and ten output variables: number of exit points to end-users, number of potential exit points to end-users, service area, pipeline length (≤ 5 bars and > 5 bars), annual peak load, potential peak load, volume of pipelines, population in 1995 and population in 2006.

Finland[118]

The Finnish regulator (EMA) also used both DEA and SFA methods (as discussed in section 5.4) to set the opex method which must be followed by 88 electricity distribution businesses when they set their tariffs. The data used in the opex benchmarking for the current regulatory period were taken from the average values for the years 2003 to 2006. By using average values, the EMA hoped to smooth the effects of random variation.

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[115] As it is not possible to cover all countries, there may be other examples of energy regulators applying DEA benchmarking method that have not been captured in this paper and the supporting research.
[116] Haney and Pollitt (2009) undertook an international survey of benchmarking applications by 40 energy regulators.
[117] Refer to chapter 3.4 of WIK-Consult (2011).
[118] Refer to chapter 3.3 of WIK-Consult (2011).

The DEA model used four variables – one input variable and three output variables. The input variable was the overall costs to customers, composed of the sum of total of controllable operational costs, depreciation and outage costs. The output factors were total length of the electricity network, number of users of the network operator and the value of energy distributed for consumption. The EMA adopted an input-oriented version of the DEA model under NDRS.

The efficiency score results of the SFA and DEA methods were combined by taking a simple average, which provides the efficiency target for the business to reduce costs to achieve an efficient cost level under the prescribed opex method.[119]

Austria[120]

As discussed in section 4.4, the Austrian energy regulator (E-control) used an incentive-based approach to set the revenue allowances for electricity and gas distribution businesses in 2006 and 2008 respectively. The E-control used benchmarking methods to set a business-specific X factor which is deducted from the price cap. The X factor is the sum of a generic X factor for the industry and an amount proportional to the degree of business-specific inefficiency.[121] Inefficient distribution businesses were, in effect, provided with lower rates of increase in real revenues.

The E-control used both DEA and MOLS benchmarking methods to assess the relative efficiency of each distribution business. The decision to aggregate the results of the three benchmarking models and the decision on the weightings were based on compromise with the industry (WIK-Consult, 2011).

Electricity distribution

For electricity distribution, total expenditure (totex) was the sole input variable, (which was the sum of opex, excluding the costs for the usage of upstream networks, plus capex). Two DEA models were estimated with different combinations of output variables; both models assumed CRS. The E-control also estimated a MOLS model which is described in section 4.4. The output variables for the models were chosen based on analysis of an engineering-based reference model.

The first DEA model – DEA(I) - had three output variables: peak load of the medium voltage level (P_{MV}), peak load of the low voltage grid (P_{LV}), and an aggregate network length variable (l_T)calculated as a weighted sum of network lengths at the three voltage levels:

$$l_T = 5.83 \cdot l_{HV} + 1.66 \cdot l_{MV} + l_{LV} \qquad (6.3)$$

The second DEA model – DEA(II) – used five output variables: the two peak load variables (P_{MV}, P_{LV}) and the three network length variables (l_{HV}, l_{MV}, l_{LV}) separately.

[119] The use of averages of efficiency scores derived has been criticised by Pollitt (2005).
[120] Refer to chapter 3.1 of WIK-Consult (2011).
[121] The formula for the X factor is provided in section 4.4.

With only 20 observations, the E-control considered that DEA(II) (with six variables) was not able to fully discriminate between the efficiency performances of different businesses. The final business-specific efficiency score was a weighted average of the two DEA scores and the MOLS score, with less weight applied to the DEA(II) model.

Gas distribution

The E-control used a similar approach for the gas distribution sub-sector. Two DEA and two MOLS models were estimated. The DEA models assumed CRS with a 75 per cent limit on the maximum input/output contribution. The input variable was based on total costs including opex and capex. For the first model capex was measured as index historic costs and for the second model, capex was based on annuity. The output variables were the same for both models; these were: weighted network length, peak load of industrial customers, and metering points for residential customers. Each model was estimated by DEA and MOLS, resulting in four sets of efficiency results.

The E-control took an average of the two DEA models to give a DEA efficiency score and did the same for the MOLS models. The final efficiency score for each gas business was a weighted average, with 60 per cent given to the higher score, DEA or MOLS, and 40 per cent to the other.

Norway[122]

With 150 electricity distribution businesses, Norway was one of the first European countries to introduce incentive regulation based on efficiency benchmarking. For the most recent regulatory period, 2007 to 2012, the Norwegian Water Resources and Energy Directorate (NVE) set a revenue allowance which was a weighted average of the out-turn cost (weight = 0.4) and a benchmark cost determined through a DEA analysis (weight = 0.6). The data for both the out-turn costs and the DEA model were from two years prior to the start of the five-year regulatory period.

The DEA model used a single input, six outputs, various environmental variables and assumed CRS. The input variable was total costs covering operating costs, capital costs, and quality costs (measured by the value of lost load). The output variables were energy delivered, customers, cottage (small) customers, high voltage lines, network stations (transformers), and interface.[123] Environmental variables included measures of snow, forest, and coastal climate.

The model used by the NVE was for super-efficiency score analysis,[124] such that the scores may be higher than 100 per cent. The DEA efficiency estimates were calibrated such that the cost-weighted-average efficiency score was 100 per cent. This implied that a representative utility, with an average efficiency score, is allowed to earn the normal rate of return, and an efficient utility can earn more than the normal rate of return.

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[122] Refer to chapter 3.5 of WIK-Consult (2011).

[123] The interface variable is the cost weighted sum of equipment in the interface between distribution and transmission networks.

[124] This method is first proposed by Andersen and Petersen (1993) and has often been used to provide a ranking system that allows for comparison of efficient businesses.

Since 2009, the NVE's efficiency benchmarking model has also controlled for factors influencing the efficiency level rather than the production technology. The amendment involved correcting the DEA scores *ex post* through regression analysis. The regression analysis aimed to estimate the efficiency effect of the number of connections to regional networks, installed capacity for small hydro power generators connected to the grid and the number of remote islands supplied.

The Netherlands[125]

When incentive regulation was introduced in the Netherlands from 2001, the energy regulator, DTe, employed DEA benchmarking methods to assess the relative efficiency of around 20 electricity distribution businesses.[126] It was intended that the DEA efficiency scores would form one aspect of X factor, which also included an estimate of industry-wide general efficiency change (refer to section 2.4). The relative efficiency scores would only be included for the first two regulatory periods to provide up to six years for inefficient distribution businesses to 'catch-up' with efficient businesses.

Using data based on 20 local electricity distribution businesses in 1999,[127] the DEA model employed by the DTe included:[128]

- Total controllable costs (opex, depreciation and standardised capital costs) as the input variable;
- Energy delivered, number of large customers, number of small customers, peak demand at distribution level, and peak demand at transmission level as the output variables; and
- Number of transformers and network route length as the environmental variables.

Efficient businesses were assigned a DEA score of one and inefficient businesses a DEA score of less than one. The business-specific DEA score was then multiplied by the actual costs of the business to derive efficient costs in the base year (i.e., 2000).

In the first regulatory period (2001 to 2003), however, the DTe's inclusion of the relative efficiency component in the X factor was overturned in subsequent litigation and only the industry-wide general efficiency component of the X factor remained. As a result, the DTe sought a legislative change to allow the inclusion of the individual efficiency component in the second regulatory period (2004 to 2006).

125 Refer to chapter five of 'Regulatory Practices in Other Countries' (ACCC/AER, 2012).

126 It was the DTe's consultants, Frontier Economics, who recommended the use of DEA rather than econometric methods on the basis of the small sample size.

127 The initial analysis by Frontier Economics included data on both electricity distribution and supply businesses in 1996. Frontier Economics intended to separate out the 20 distribution businesses from supply businesses and update the analysis for 1999 data. As the final report is not publicly available, secondary sources of information are used in this paper to confirm the use of 20 distribution businesses but not the time period.

128 It is unknown which returns-to-scale assumption was employed by the DTe.

Australia

In 1999, the Independent Pricing and Regulatory Tribunal of NSW (IPART) reviewed the relative efficiency of NSW Australian electricity and gas distribution businesses against other Australian and international distribution businesses. The IPART used a building-block model to determine allowable revenues for each regulated business and the results of the cost benchmarking analysis were used to inform the assessment of their efficient costs.

Electricity distribution

London Economics (1999) was commissioned to report on the efficiency of NSW electricity distribution businesses. DEA was used to benchmark the NSW utilities against Australian and international utilities. The sample included 219 electricity distributors from Australia, England, Wales, New Zealand and the United States (US), with the sample periods slightly different for each country.

The inputs used in the DEA model were total O&M expenditure (in 1997-98 $AUS), route kilometres and nameplate transformer capacity. Outputs were total energy delivered (in GWh), total customers and peak demand (in MW). VRS was assumed. A second-stage Tobit regression was employed to adjust the gross DEA efficiency scores to account for environmental differences.

Various other benchmarking methods were used for sensitivity analysis including Tornqvist TFP and SFA. IPART (1999) considered that the deviation between the results was expected due to the known characteristics of the different methods.

Gas Distribution

Following the London Economics (1999) study, IPART (1999) conducted its own efficiency benchmarking of seven Australian gas distribution businesses against 51 gas distribution businesses in the US using similar methods.

IPART (1999) estimated a DEA model with the VRS assumption. The input variables were O&M costs and capital costs (measured by the length of distribution mains). The output variables considered were the amount of gas delivered (TJ), the number of residential customers and the number of other customers. Environmental factors considered were climate and age of the network. Two methods of incorporating these were explored, the first of which was the direct inclusion of environmental factors into the DEA model and the second method used a second-stage Tobit regression. These are ultimately found to have minimal impact on the results.

Sensitivity analysis was conducted on the results using an alternative DEA model specification incorporating quality of services, and the COLS and SFA methods. The alternative DEA model used the same inputs but considered the amount of gas delivered, the total number of customers and the reciprocal of unaccounted-for gas for the outputs.

6.4.2 Summary of regulatory practices

DEA benchmarking methods have been applied by a number of the European regulators. DEA has also been applied in the Australian context by combining the data on Australian distribution businesses with comparable international distribution businesses to increase the sample size.

Austria, Germany and Finland all combined the efficiency scores from the DEA method with the efficiency scores derived from alternative methods such as modified ordinary least squares and SFA. Both London Economics (1999) and IPART (1999) undertook extensive comparisons of the results of DEA models against the results of COLS and SFA methods. The Dutch and Norwegian regulators, however, only considered the result from DEA analysis. In the Netherlands, a sample size of 20 distribution businesses was considered to be insufficient to confidently employ econometric methods.

With data on 198 electricity and 187 gas distribution businesses, the German regulator was able to include a large number of dependent variables in the DEA model, 11 and ten for electricity and gas respectively. Similarly, the Norwegian regulator with 150 electricity distribution businesses included nine variables. The Austrian and Netherlands regulators, with only 20 distribution businesses in their samples, included fewer variables in the model.

6.5 Issues arising from the review

The above sections review the use of the DEA method for efficiency analysis of energy utilities in a sub-sector. The review covers the theoretical foundation of DEA, empirical applications by researchers, mostly in the context of the energy sector, and regulatory applications by sectoral regulators.

A number of issues seem to arise in the application of DEA to benchmarking electricity and gas networks. The choice of variables, the model specification and the size of the sample are critical factors in determining how much weight can be put on the DEA results.

6.5.1 The choice of variables

As already emphasised, the selection of the input and output variables is of critical importance.[129] Unfortunately there is no consensus on how these variables should be chosen.

As shown in Jamasb and Pollitt (2001) and noted by Giannakis, Jamasb and Pollitt (2005), choosing the input-output specification is an important step in DEA, but the literature has shown a lack of consensus on which variables best describe the operation of electricity distribution utilities. Burns, Jenkins and Riechmann (2005) instead considered that the range of models largely reflected the particular research questions to answer. For example, the model specifications can differ depending on whether the short-term performance or long-term performance is modeled. They

[129] Note that much of the discussion on the choice of variables is also applicable to other benchmarking methods reviewed in this paper.

recommended a systematic approach for variable specification involving both theoretical analysis (e.g., model network analysis, intuition and heuristics) and empirical analysis (e.g., regression analysis).

Coelli, Crepo, Paszukiewicz, Perelman, Plagnet, and Romano (2008) provided some justifications for its chosen three-output and three-input model specification in their DEA study of French electricity distribution businesses. They followed the literature of electricity distribution benchmarking to model standard output characteristics, such as energy supplied (in MWh), number of customers and network size (e.g., service area or network length), but specifically incorporated a quality measure as an input to examine the impact of modelling quality of services on efficiency benchmarking. They highlighted the difficulties in selecting just a few variables for accurately capturing all of the relevant differences in inputs and outputs. Instead, their study focussed on capturing the key aspects of output heterogeneity and input variations.

Specific issues arise with respect to individual choices of variables: For example, while the number of customers is usually considered as an output, should the network length (in kilometre) be considered an input or an output? In one view, poles and wires are capital inputs into the final service (delivery of electricity to the location of the customer) and therefore should be treated as inputs. In another view, length of network showing the scope of operation can be used as a proxy for customer density – a legitimate driver of costs. However, viewing network length as an output runs the risk that a network that increases its length of lines is rewarded even if there is no impact on the real-world delivery of service to customers. In their survey of 20 benchmarking studies of energy network, Jamasb and Pollitt (2001) reported that size was treated as an input in 11 studies and as an output in four other studies. Jamasb, Nillesen and Pollitt (2004, p. 830) commented that ‘in extremis certain variables may be used as inputs in one regulatory model, whereas in other regimes they are used as outputs’.

Another issue concerns the use of the ‘quantity of electricity delivered’ (usually measured in GWh). The use of this throughput measure is quite common in DEA studies of electricity distribution as it is often considered as the only homogeneous product of the electricity distribution (Kittelsen, 1999, p. 16). According to Jamasb, Nillesen and Pollitt (2004), Allas and Leslie (2001) reported that about 85 per cent of costs varied with the number of customers and the units of energy delivered. However, Turvey (2006) criticised the use of volume of electricity delivered as an output and argued for the use of a capacity measure:

> The throughput of a network of pipes and wires … is not determined by the enterprise and should not be regarded as its output. … What the enterprise provides is not gas, electricity, water or messages; it is the capacity to convey them. It follows that, to compare efficiencies, it is necessary to compare differences in capacities with differences in costs.

Another concern relates to the specification of inputs. Most studies recognise the difficulty of measuring the supply of services from capital assets. In practice this is reflected in the arbitrariness of the choice of the allocation of capital costs into a single period.[130] Many benchmarking studies simply chose to exclude consideration

[130] Turvey (2006) went into some detail on the measurement of capital services using what was described as ‘heroic assumptions’.

of capital costs and focus entirely on operating and maintenance expenditures. Unfortunately, an exclusive focus on operating costs ignores the possibility of trade-offs between capital and operating expenditure and will not identify the most efficient firm from the total cost perspective. In addition, benchmarking studies which ignore capital expenditure will tend to favour businesses with young assets, even when that asset replacement decision is socially inefficient overall.[131]

Another issue relates to the difficulty of measuring the quality of labour inputs. Even where data are available on number of hours worked, different workers and different types of workers presumably provide different services. A common solution to this problem is to value all inputs at their cost, and to use an aggregated input cost measure in the benchmarking. A difficulty with this approach is that labour input price can vary across businesses. Using this cost measure as an input, a business in a high labour-price location would appear less productive than a business in a low labour-price location for no fault of its own.[132] In this case, (labour) price deflators at the regional level, if available, need to be used to deflate the labour cost.

Issues also arise in choosing the total number of input and output variables. DEA may find many of the sampled businesses efficient where the number of input-output variables (or operating condition variables) is large relative to the size of the sample, (Coelli, Rao and Battese, 1998, p. 181). Burns, Jenkins and Riechmann (2005) noted the lack of an ability to discriminate between businesses by DEA relative to econometric analysis. However, they emphasised that the solution was not to reduce the number of input-output variables which might result in mis-specification or under-specification of the benchmarking model.

Increasing the number of input-output variables will tend to capture more dimensions of input and output combination that firms can be compared with each other and will also tend to make more firms appear on the frontier. As pointed out by Kittelsen (1999), non-parametric DEA methods have problems with collinearity or irrelevant variables. In fact, the inclusion of a purely irrelevant factor (such as a random number) will still make some businesses appear to be efficient. Kittelsen (1999) went on to suggest stepwise DEA that uses statistical tests to evaluate sensitivity of efficiency results with respect to variable disaggregation and addition and to assist the determination of model specification.

It might be argued that a possible solution to input-output specification is through testing of a number of alternative model specifications, with different input, output and environmental variables. However as noted earlier, DEA offers no internal mechanism for validating the selection of particular variables. The use of bootstrap methods for statistical testing of DEA efficiency scores may offer some useful information regarding the degree to which DEA results obtained from small samples can be relied upon.

[131] This assumes that the operating and maintenance expenditures per transformer or per kilometre of line depend, in part, on the age of the underlying assets.

[132] Another issue relates to the treatment of network losses. Very few benchmarking studies of distribution businesses include losses at all, but network losses are, in principle, controllable by the distribution business in the long run.

6.5.2 The specification of the DEA model

In any application of the DEA method, decisions must be made as to the construction of the set of feasible input-output combinations. This involves the consideration of two issues: input- or output-orientation and the nature of returns-to-scale.

The choice of input-orientation and output-orientation model depends on whether the business has most control over the inputs or the outputs. If the business is considered as having greater control over input quantities relative output quantities, then an input-oriented model with input-reduction focus should be used. Conversely, if the business is considered to have greater control over output quantities, then an output-oriented model with output-expansion focus should be used. For the regulated electricity distribution utilities, the outputs are generally assumed to be exogenously given. An input-oriented model is therefore generally used. By definition, the orientation assumption has no impact on the efficiency results only under a CRS model. Empirically the choice of orientation may only have a minor impact upon the efficiency scores estimated (see for example, Coelli and Perelman, 1999).

The most common approach to DEA assumes that feasible input-output combinations can be scaled and combined without constraint. This excludes the possibility of alternative assumptions to CRS technology. This assumption can be weakened but doing so may weaken the ability of the DEA model to discriminate between businesses. For example, the variable returns-to-scale (VRS) model effectively compares a business only with businesses of a similar size rather than all sampled businesses regardless of their size.

The choice of constant or variable returns-to-scale model may, in part, depend on the nature of returns-to-scale in the industry. Jamasb, Nillesen and Pollitt (2004, p. 834) noted that there had been empirical evidence of the presence of economies of scale in electricity distribution networks. They cited a number of studies on Switzerland, Norway, New Zealand and Canada, which estimated the minimum efficient firm size to be around 20 000 to 30 000 customers. However, in practice CRS is more commonly assumed. Both the Dutch and Norwegian regulators have used CRS DEA models by assuming that electricity distribution utilities can freely adjust their scale of operations through mergers and acquisitions. In contrast, the UK regulator has consistently applied VRS DEA by taking the number and the size of electricity businesses in the industry as given. The German and Finnish regulators have assumed NDRS in their DEA models, under which small networks were only compared with other small networks. This would penalise too large networks operating at sub-optimal scale in the short-run. The choice may also affect the long-term structure of the industry.

6.5.3 Importance of data quality

As a deterministic technique that has no account for measurement errors, DEA is particularly sensitive to outlying observations (i.e., observations with usually large or small values). Therefore, there is a strong need to screen for potential outliers when assembling the data used for DEA analysis. Necessary steps of assessments include:

- Use descriptive statistics (including tabular and graphical analysis) to identify outlying observations for further checking.

- Correcting outlying observations if they are found to have been incorrectly entered.

- Use super-efficiency DEA or other modified DEA, under which certain observations (including the business under evaluation and/or outlying observations identified) can be excluded from form the reference production set. The super-efficiency DEA was first proposed by Andersen and Petersen (1993) to provide a ranking for efficient businesses.

A related problem in regulatory applications has been identified by Jamasb, Nillesen and Pollitt (2004). According to their paper, since the DEA measure depends strongly on the input-output combinations of a few boundary businesses, there can arise scope for strategic action taken by regulated utilities to manipulate the location of the boundary through, for example, mergers, or collusion in the reporting of results. Their analysis of the US utility data suggested that strategic behaviours by regulated businesses could have significant effects on the measured firm performance and profitability. They considered that the regulators should note the importance of ensuring reliability of regulatory data and conducting sensitivity analysis with respect to method and model specification.

6.5.4 Validation of a DEA model

As already noted, one of the key drawbacks of the DEA method is that it is impossible to interpret the validity of the results within the framework of the model itself.[133] Unlike econometric methods, DEA does not offer diagnostic statistics to test for the possibility of model misspecification or to assess the overall goodness of fit of the model. Pedraja-Chaparro, Salinas-Jiménez and Smith (1999) noted that a DEA model might offer misleading results as a result of model mis-specifications (due to incorrect variable inclusions or exclusions and an incorrect returns-to-scale assumption) and/or inadequate data. In their views, the performance of a DEA model depends on amongst other things, the distribution of efficiencies, the number of factors included in the analysis, the size of the sample, and the degree of correlation between factors. They emphasised that whether a DEA model specification is adequate depends on the research question to answer. Based on their simulation study, they rejected the use of simple rules of thumb (e.g., number of inputs and outputs relative to sample size) to guide on the reliability of the results obtained.

One way to validate the model specification and results is to examine the DEA peers of each business to see if the model is producing sensible benchmarks (i.e., comparator businesses).

Most importantly, the validation of a DEA model should come from external sources – that is, from a careful independent assessment of the necessary variables and cost drivers, together with a careful choice of the assumptions underlying the DEA method. The need to use economic theory and industry knowledge to choose model specification should not be forgotten when some specification issues can be driven by

[133] CEPA (2003, pp. 64-65) stated that: 'One of the key drawbacks of the DEA methodology is that it is difficult to assess the significance of the results ... Overall we believe that DEA is a theoretically appealing benchmarking technique that is easy and practical to implement ... However it cannot be relied upon in isolation due to the difficulty in assessing the significance of the results obtained.'

data. These choices may also be informed by careful engineering industry studies. Finally, as large a dataset as possible must be compiled.

6.6 Conclusions

DEA is a straightforward technique that uses observations of feasible input-output combinations to create a set of feasible input-output combinations against which the performance of other businesses can be assessed. The basis for an efficiency score for any individual business can be reasonably easily communicated. It is particularly useful where there are a large number of comparable businesses producing essentially homogeneous outputs.

The validity of any particular application of DEA rests on the assumptions made – that is, the choice of the input, output and environmental variables and the returns to scale assumptions. It is therefore important that any application of DEA carefully considers and justifies the use of a particular set of variables. It is also important that the largest possible data sample be used – including distribution businesses in other countries if necessary.

For a DEA benchmarking study to have a degree of authority, four steps should be carefully followed: First, the input, output, and environmental variables should be carefully chosen to capture all of the important aspects of operations run by electricity distribution utilities. This should normally be based on sound economic theory and industry knowledge and probably be carried out using careful engineering analysis. Second, the basic features of the underlying production function need to be determined – such as the presence of economies of scale and the ability of individual businesses to scale up or down the activities of other businesses. Third, as large a dataset as possible needs to be compiled – while it is not possible to know what sample size is required to obtain a reasonable estimate of relative efficiencies, larger sample size relative to the number of input-output dimensions modelled would increase the discriminatory power of a DEA model. Finally, the DEA benchmarking should generally be an iterative, collaborative process with industry participants (regulated businesses and customers), which allows for progressive improvement in the model specification and the enumeration of the factors necessary to differentiate different firms.

A credible DEA study is likely to shed some light on the shape of the cost function underlying distribution businesses and may shed some light on key cost drivers and the rate of technological change. At least, DEA may play a role in identifying a particular group of actual observations, which, in combination, produce more efficiently than a business under evaluation. This information could possibly be used as the basis for further investigation aimed at identifying business best practices which should be and could be copied by other businesses in the industry.

Chapter 7 Common issues in benchmarking of energy networks

7.1 Introduction

Benchmarking of energy networks, particularly those operating in electricity distribution, has been conducted in both academic literature and regulatory practices. As surveyed by Jamasb and Pollitt (2001) and Haney and Pollitt (2009), a variety of benchmarking methods have been used by energy regulators across the countries and jurisdictions reviewed, with a notable preference for the non-parametric methods. There are a number of technical issues for benchmarking. Researchers and regulators often consider that benchmarking should be used with caution and its limitations should be recognised; for example, Ajodhia, Petrov and Scarsi (2003), Shuttleworth (2005), and Farsi and Fillipini (2004).

Based on the review of alternative benchmarking methods in chapters 2 to 6, this chapter summarises major technical issues in benchmarking of energy networks, such as data and model-specification issues. The following chapter will consider regulatory challenges in applying benchmarking.

The rest of the chapter is structured as follows. Section 7.2 provides a summary of the review of alternative benchmarking methods. Potential data issues and model-specification issues are discussed in sections 7.3 and 7.4 respectively. Section 7.5 provides some insights into benchmarking of energy networks before drawing conclusions in section 7.6.

7.2 Summary of alternative benchmarking methods

The foregoing review of alternative benchmarking methods, namely partial performance indicators (PPI), index-number-based Total Factor Productivity analysis (TFP), econometric method (EM), Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), examines method, model and data requirements, as well as advantages and disadvantages relative to each other.

There is no clear consensus in the literature in relation to which benchmarking approach should be used by economic regulators. As identified previously, each method has relative strengths and weaknesses.

Table 7.1 below summarises key characteristics of the five benchmarking methods reviewed.

The advantage of PPI and index-based TFP methods is their relatively simple theoretical basis and their relative ease of calculation. Unlike EM, SFA and DEA, the PPI and TFP methods do not involve the estimation of an underlying cost or production technology of the industry.

PPI has been used by Australian energy regulators, including the AER. In the regulatory context, TFP has been used, or at least considered, for determinations of an X factor, or its frontier-shift component in: the Northern Territory (Australia), New Zealand, Canada, the Netherlands and Austria.

However, the relative theoretical simplicity of the PPI and TFP methods is also a weakness. PPI may fail to properly model a multiple-input and multiple-output production process because the partial approach to performance measurement can be too simplistic. That is, the PPI may not be capable of modelling the overall performance of the business or the industry. The TFP method has a rigorous grounding in economic theory. However, the TFP is relatively information intensive as it requires price and quantity data for both input variables and output variables.

The parametric approaches, EM and SFA, require the estimation of a specific functional form that is sufficiently flexible to capture the structure of the underlying production process. The problem is that estimation of a functional form that is not sufficiently flexible will result in biased results.

A strength of EM and SFA, from an economic perspective, is their relatively strong theoretical basis. EM and SFA use economic theory to attempt to capture the industry's underlying cost and production processes. Further this parametric approach provides statistical testing of estimated parameters. This provides an additional insight into the significance of cost drivers and of the role of technology in the industry.

The strength of SFA over EM is that it incorporates a separate random error term and explicitly estimates an inefficiency term. That is, a shortcoming of EM is that it merely assumes that all residuals in the estimation procedure (relative to a benchmarking) represent inefficiencies, and does not explicitly account for the possibility of random errors.

Finally, DEA requires the computation of a production frontier using a non-parametric approach. It can provide a relatively clear comparison of efficiency performance of businesses. However, like EM, DEA is not able to provide for random errors within its framework. Further, at least one business is assumed not to have scope for additional productivity improvements. That is, DEA will always identify at least one business maximising outputs given its inputs even if all the sampled businesses operate inefficiently.

As discussed, the data requirements differ across methods. PPI is the least information-intensive while TFP is relatively information-intensive as it requires both price and quantity information on inputs and outputs. Technically, TFP only requires two observations of the same business at different points in time to measure productivity changes. However, this approach is often used for long-run analysis which, by definition, requires data over a sufficiently long time period. The parametric approach (EM and SFA) needs a large number of observations in the sample. DEA also has a small sample-size problem as it may lead to a self-identification problem when the number of observations is not adequately large relative to the number of inputs and outputs specified. Time-series data are more commonly used for PPI and TFP methods, while cross-sectional and panel data are primarily used for EM, DEA and SFA.

TFP is generally used for the estimation of firm- or industry-level productivity changes, while other statistical methods (other than the PPI) have been used in various studies measuring comparative performance of sampled utilities.

DEA has been used extensively by regulators in Finland, Germany, the United Kingdom (UK), the Netherlands, Norway and Texas, the United States (US).

Parametric approach, such as EM and SFA, seems to be less commonly used for regulatory purposes. However, there are a few regulatory applications, including the use of simple forms of EM by regulators in the UK, Ireland and Austria and the use of SFA in Germany, Finland and Sweden. It is noted that regulators tend not to rely solely on a single method for benchmarking. The benchmarking outcomes are determined either jointly by two or more methods or primarily on the basis of one preferred method with sensitivity analysis to test the robustness of the results from alternative methods.

Table 7.1: Summary of Alternative Benchmarking Methods

	PPI	TFP	EM	SFA	DEA
Type	Non-parametric	Non-parametric	Parametric	Parametric	Non-parametric
Presence of random error	No	No	Yes (one composite error term)	Yes	No
Presence of inefficiency	No	No	Yes (one composite error term)	Yes	Yes
Presence of optimal behaviour	No	Yes	Yes, cost function	Yes, cost frontier	Yes, frontier firm(s)
Statistical testing allowed	No	No	Yes	Yes	Possible
Measurement	Single factor productivity and unit costs	Productivity changes	A benchmark cost function	A benchmark cost frontier	A set of all the feasible input-output combinations
Information requirements	Quantities or prices of inputs or outputs	Quantities and prices of inputs and output	Volume of outputs and prices of inputs	Volume of outputs and prices of inputs	Volume of inputs and outputs
Number of inputs	Single (or a composite scale variable)	Multiple	Multiple	Multiple	Multiple
Number of outputs	Single (or a composite scale variable)	Multiple	Multiple	Multiple	Multiple
Sample size requirement	A minimum of two observations	A minimum of two observations	As large a dataset as possible	A large number of data points (more than the equivalent econometric model).	As large a dataset as possible (some rules of thumb recommended in the literature)

	PPI	TFP	EM	SFA	DEA
Dataset requirements	• Cross-sectional • Time-series	• Cross-sectional • Time-series • Panel	• Cross-sectional • Time-series • Panel	• Cross-sectional • Panel	• Cross-sectional • Panel

7.3 Data issues in benchmarking

7.3.1 General data requirements

The cost benchmarking methods require price and/or quantity information on input and/or output, and sometimes information on various costs and business conditions, for a sufficiently large number of cross-sectional and/or time-series observations. They have been used in benchmarking analysis to establish some reference performance for the sampled businesses – such as own past performance (e.g., trend) or current industry best-practice or average performance on a regional, country or international level.

Regardless of the methods used, the availability of a high-quality, reliable and sufficiently large dataset that covers comparable businesses at a point in time or over a period of time is essential for the proper application of benchmarking, which involves an assessment of the efficiency and productivity performance at the business or industry level.

7.3.2 Potential data problems

Data-point availability can be an issue for each of the benchmarking methods reviewed. It is a particular issue for the relatively data-demanding parametric approach (EM and SFA) requiring a large sample size relative to the number of parameters estimated (i.e., the degree of freedom) – higher degree of freedom for estimating a regression model means that a larger amount of information is available so that a better estimate can be derived.

Therefore the choice of the method can be, in part, dependent on the availability of data. For example, the limited number of regulatory applications of SFA identified, including Sweden (electricity), Germany (electricity and gas) and Finland (electricity), takes place in countries where there are a large number of utilities operating in the sub-sectors. In the UK, the regulator has applied the OLS-type regression analysis to a relatively small set of 14 utilities. DEA has also been used as a cross-check against the regression results. As for jurisdiction-based distribution determinations in Australia, a combination of assessments, particularly the PPI method, has often been used, possibly due to the very small number of distribution businesses in a state.

A challenge to relying upon even the simple PPI method and placing a greater weight on benchmarking distribution businesses in regulatory determinations is the compatibility of the regulatory data for the utilities compared.

Obtaining high-quality and consistent information across utilities and over time is equally important for other benchmarking methods to allow like-with-like comparison and/or to establish representative industry frontier or average performance.

The presence of data errors or noises can also influence the choice of the benchmarking method. Methods with no account for random errors (e.g., DEA) may not be suitable for data of low quality. Nevertheless, prior to the application of benchmarking method, sufficient data checking needs to be done to identify potential data errors and thus improve data quality.

Data availability and quality is one of the considerations for possible benchmarking application. The choice of model specifications is often constrained by data availability and quality. This is particularly the case for academic researchers working with data in the public domain. In general, the more disaggregated specifications on potentially heterogeneous inputs and outputs result in more accurate benchmarking results. For example, specifying skilled labour and unskilled labour separately may allow better estimation of their respective contribution to the production than an estimate of their average contribution when an aggregate labour measure is used. However, it can be very difficult obtaining disaggregated information data and the quality of such disaggregated information can be a major issue given the potential cost-allocation problem (i.e., the allocation of shared/common costs to individual services). Generally, aggregating the inputs and/or the outputs to an extent that provides a reasonable categorised representation of the resources used for the provision of the range of output services is required.

As with other industries, the main categories of resources used for electricity distribution are labour, capital, and material and other input. The major categories of outputs can be more difficult to specify and requires a good understanding of the nature of the network services provided by the electricity distributors (as discussed in subsection 7.4.2 below).

7.4 Model specification issues

7.4.1 Model specifications

To the extent that data are available, there are some common model-specification and measurement issues for the benchmarking methods other than the PPI method.

As discussed previously, the appropriate input-output specification and functional form used in benchmarking should be informed by a combination of sound economic theories, good industry knowledge and rigorous 'cost driver' analysis.

In practice, a range of explanatory variables have been used in different benchmarking studies of electricity distribution businesses. Jamasb and Pollitt (2007) tabulated the variables that had been used in previous academic studies. Burns, Jenkins and Riechmann (2005) noted that 'it is sometimes suggested that the wide variety of cost drivers that are used in benchmarking analyses imply that there is no clear set of variables that should be used for benchmarking'. They went on to argue that different choices of variables in different models primarily reflected the fact that different studies were seeking to answer different questions. They highlighted three characteristics that the cost drivers/explanatory variables should satisfy:

- Describing the cost drivers that most accurately and comprehensively explain the costs;
- Exogenous environmental factors that affect the costs; and
- For which data can be collected consistently across all businesses and with a reasonable effort.

Regulatory practices for electricity distribution show similarities in the model specifications, though no two countries reviewed applied benchmarking analysis in the same manner. Jamasb and Pollitt (2001, p. 125) provided a list of model specifications that were used by regulators at that time. The most common outputs modelled are power delivered and customer numbers. The most common input is opex, either as an aggregate measure, or in a less aggregated form by type of expenditures such as wages, maintenance, etc. Some measures of physical quantity of inputs can also be modelled instead of the value-deflated measures. There appears to be less consistency in environmental variables modelled.

In principle the selection of the key cost drivers should be carried out independently of considerations of the available data. The practice of choosing the number of explanatory variables to suit the data has been heavily criticised by Turvey (2006, p. 104):

> Cost comparisons between enterprises can only illuminate differences in their efficiency in doing what they do if the magnitudes of their tasks can be compared. This is a platitude, yet failure to articulate it has led some authors to scrabble around among available data to select a set of 'explanatory' variables without displaying any understanding of what the enterprises actually do and how they do it. Applying different econometric methods to find which method and which of such variables give the 'best' results is very different from understanding the industry sufficiently well to identify and describe the determinants of short-run or long-run costs. Unfortunately, data concerning these true determinants are usually lacking, resort being had by econometrists to using whichever of the limited available data that they consider most relevant.

One possible approach to choosing the relevant cost drivers is to explore the implications of an engineering-based model of the regulated businesses. Burns, Jenkins and Riechmann (2005) described a method previously used in Austria for selecting cost drivers based primarily on an engineering-based simulation model of a hypothetical electricity distribution network. Turvey (2006) highlighted the Network Performance Assessment Model (NPAM) previously used by the energy regulator in Sweden.

To the extent that data are available, some aggregation and/or approximations are required to facilitate the high-level benchmarking at the potential cost of generating errors in measurement. Furthermore, Jamasb and Pollitt (2001, p. 128) concluded that 'the issue of choosing the most appropriate benchmarking methods and model specification cannot be settled on theoretical grounds' and suggested sensitivity analysis to test the robustness of the results with respect to model specification and method.

The major issues arising from the review of literature and regulatory practices, as discussed below, include:

- Output specification and measurement;
- Input specification and measurement, particularly for the capital input;
- Cost measures;
- Operating environment factors; and
- Functional form.

7.4.2 Output specification and measurement

Demand-side versus supply-side of network services

The output specifications for the multi-dimensions of energy network services generally cover the demand-side of services (i.e., electricity delivered and/or customers connected), but may not necessarily cover the supply-side (e.g., coverage and capacity of the network) and the quality-of-supply (e.g., frequency and duration of outages) aspects of network operation.

In conducting a benchmarking analysis, a decision as to whether to consider outputs based solely on demand-side or supply-side models or a mixture of the two has to be made. In doing so, one has to recognise that the model selected may be biased towards particular business types.

The demand-side models tend to favour urban distributors with dense networks while the supply-side models tend to favour rural distributors with sparse network (e.g., long line length). Some studies (e.g., those by Dr Denis Lawrence) consider it important to account for both supply and demand in the TFP analysis and adjust for different operating conditions. However CEPA (2003, p. 88) considered that the inclusion of network length as an output variable (or account for network density) might introduce perverse incentives by encouraging network expansion solely to improve relative performance.

Turvey (2006, p. 110) pointed out the difficulty of aggregating the concept of service capacity into a few variables for the purpose of comparing electricity distribution networks responsible for providing and maintaining the capacity to meet the maximum demands upon the various parts of the networks with different voltage levels and at different locations. He questioned the common use of available data on electricity distributed (MWh) as a proxy for maximum demand and on network length per customer as customer density variable to explain maximum demand. In his view, the relevance of these measures depends on networks having similar customer and load factors. Network efficiencies may be inaccurately estimated because of business-specific circumstances not adequately described by the available data.

Quality of services measures

Quality of services can be an important issue as these may exhibit substantial quality differences across utilities or quality changes over time.

A more recent research theme in the academic literature is the incorporation of quality of services in benchmarking of energy networks, which has been briefly reviewed in Coelli, Gautier, Perelman and Saplacan-Pop (2010). Of the small number of reviewed empirical studies quantifying the impact of cost-quality modelling, both the DEA study by Giannakis, Jamasb and Pollitt (2005) and the SFA study by Growitsch, Jamasb and Pollitt (2009) found that incorporating quality of services into cost benchmarking would affect the measured productivity significantly. They argued for the integration of quality-of-service measures into regulatory cost benchmarking. On the contrary, Coelli, Crespo, Paszukiewicz, Perelman, Plagnet and Romano (2008) found that the inclusion of the number-of-interruption measure had no significant effect upon mean technical efficiency scores estimated from DEA and SFA respectively.

It is rare in regulatory practices to directly incorporate quality into cost benchmarking. Instead most of the countries reviewed run separately a quality-of-service reward/penalty regime. The exceptions may include the Energy Market Authority (EMA), the Finish regulator, who has taken outage costs (i.e., the cost to consumers caused by electricity supply outages) into account as part of the total cost for efficiency benchmarking by DEA and SFA for the determination of business-specific efficiency target for the regulatory period 2008 to 2011 (see WIK-Consult 2011, pp. 20-26).

Consistent cross-sectional and time-series data measuring one or more of the three aspects of quality of services – reliability of supply (SAIDI, SAIFI, CAIDI, MAIFI), technical quality of services (e.g., number of complaints, distribution network loss or cost of loss), quality of customer services (e.g., call centre performance) are generally not available to the economic regulators or the researchers as they have not been systematically reported by the energy networks.

In addition, there are two reasons for the failure to incorporate quality of services in the index-number-based TFP analysis: first, the method does not incorporate 'bad outputs' (i.e., a decrease in the measure represents an increase in service-quality output) easily; and second, it is difficult to value quality improvement to consumers in order to weigh the quality-of-service output appropriately.

7.4.3 Input specification and measurement

Capital input measures

Of the inputs modelled, capital input is most problematic to measure, which may explain the common practice of benchmarking opex as opposed to the 'total cost' approach. The calculation of the periodic capital input in terms of physical quantity (and cost) is important for benchmarking analysis, particularly in a capital-intensive network industry. For production analysis, the proper measure of capital input is the flow of capital services during a period. A proxy can be the measure of capital stock in place, which is assumed to be in proportion to the flow of capital services, regardless of the age of assets. For electricity distribution, physical quantities of two main distribution assets are commonly modelled – network line length (in route/circuit kilometres) and installed transformer capacity (in MVa).[134] It assumes constant provision of services at full productive efficiency until the end of the service life of an asset ('one-hoss shay').[135] Other depreciation profiles may also be assumed in the empirical studies; for example, a declining-balance approach to depreciation called perpetual inventory method (PIM) has generally been adopted in the PEG studies (see for example, PEG 2004) to construct the constant-dollar replacement cost of utility assets using detailed capital data over time.

[134] The network line length measure models transmission of energy to customer, and the installed transformer capacity measure captures transformation of high voltage energy to low-voltage energy.

[135] A number of researchers in the area consider the one-hoss shay depreciation pattern reasonably reflect the depreciation process in the electricity distribution. See for example, Makholm and Quinn (2003, p. 5) and Lawrence and Diewert (2006, p. 217). For a definition of the term, see OECD (2012).

There is an on-going debate in the literature, as well as in the regulatory work, as to whether capital input is better measured in terms of physical quantity or monetary value. Some, such as PEG (2004), have argued that the deflated asset value method provides a better estimate of total capital input as it incorporates other types of major fixed assets than distribution lines and transformers. Lawrence (2005b) argued against the use of deflated asset value method for the TFP analysis for Victorian electricity distribution networks for two main reasons:

- The method usually assumes the declining-balance approach to depreciation, which may overstate the rate of physical depreciation for electricity distribution networks whose true depreciation profile is more likely to reflect the 'one-hoss shay' or 'light bulb' assumption. Therefore, the method is likely to underestimate the quantity of capital used and overstate the rate of TFP growth (Lawrence, 2005b, p. 12).

- The method is better suited to more mature systems where the asset valuations are very consistent over time and across utilities, which is not the case for the Victorian sub-sector.

Analogously, Coelli, Crespo, Paszukiewicz, Perelman, Plagnet and Romano (2008) measured capital stocks using gross (not depreciated) replacement value. They chose this in preference to net replacement measure to avoid identifying a business with significant amount of recent investment as inefficient because of their relative high net capital stock. They noted two implicit assumptions made in using this measure: first, the asset age was assumed not to significantly affect service potential; and second, all operators were assumed to have assets with similar life spans and hence that annual service potential was proportional to the stock. In their views, these assumptions were arguably reasonable in their study as all the data came from a single distribution business who defined and managed very similar policies for investment, operations and network asset development across the various local distribution units.

In their book on efficiency measurement for network regulators, Coelli, Estache, Perelman, and Trujillo (2003) includes an entire appendix on capital measurement. They also recommend the use of undepreciated replacement value measure, if relevant data are available (Coelli, Estache, Perelman, and Trujillo, 2003, p. 119).

Capital input price can be measured either directly (i.e., annual user cost of capital that takes account of depreciation, opportunity costs and capital gains) and indirectly (i.e., realised residual between total revenue and operating and maintenance costs), which may also drive differences in the measured TFP or other performance measures. For example, in its critical review of PEG (2004), Lawrence (2005b) considered that the direct measure reported by PEG appeared to underestimate the true cost of capital. Nevertheless, the direct measure is more desirable as it approximates the *ex ante* cost of capital. However, it is information-intensive and has many measurement problems with the individual estimation of the depreciation rate, the opportunity cost and the expected capital gains.

Other input measures

Another major category of inputs is labour. Physical quantity of labour input is generally measured at the aggregate level; for example, the number of full-time-equivalent (FTE) staff or total hours worked. The aggregate measure does not make a distinction between labours of different skills and thus assumes uniform skill distribution across comparable businesses. Labour quantity can also be measured as the labour cost deflated by an appropriate labour price index, which may reflect many inter-business differences, such as skill distribution and wage rate. Depending on how labour quantity is measured, the labour price can be measured either directly using a suitable labour price index or indirectly as the total labour cost divided by the labour quantity measure.

The 'other input' variable is generally a 'catch all others' category containing material, fuel and other office expenses. The constant-dollar value measure is generally used for measuring this variable. For individual expense items within this category, their respective share to total costs is generally small and therefore does not warrant separate categorisation and consideration. Specific categorisation may be needed for some types of expense items (e.g., outsourcing cost) that are sufficiently large and changes differently from other types of expenses. The increased use of contract labour also complicates the modelling of labour input as a separate category.

7.4.4 Cost measures

For cost benchmarking, one or more of the four cost measures – operating expenditure (opex), capital expenditure (capex), total expenditure (totex – the sum of opex and capex) or total costs incorporating the cost of capital – may be considered. Potential issues arising from benchmarking opex, capex, totex and total costs are further discussed in Chapter 8.

It is worth noting that the total-cost approach to benchmarking has been adopted by the Dutch energy regulator, DTe, in its regulation of electricity transmission and distribution network (Ajodhia, Petrov and Scarsi 2003). The total cost is the sum of operating expenditure, depreciation and a standard return on assets. It is used as the single input factor in the DEA benchmarking. The total cost approach is considered to be preferable as it creates incentives to improve performance in both the short term and the long run. However, as noted above, it can be very difficult to measure the price and quantity of the capital input, and thus their product – capital costs – is extremely difficult to measure for benchmarking purposes.

7.4.5 Operating environment factors

In addition to the modelling of inputs and outputs in the production, there is also a need to consider the role of exogenous environmental factors that are out of management control but may influence business performance. Some benchmarking methods, such as the parametric approach, allow relevant environmental factors to be directly included in the modelling. Other methods (e.g., TFP and DEA) generally use second-stage regression analysis to test the influence of environmental factors on the estimated raw efficiency and productivity performance.

For electricity distribution businesses, key operating environment conditions may include (but not be limited to) geographical conditions such as energy density, customer density, network density, customer mix and underground relative to overhead network. The literature on TFP studies suggests that energy density and customer density are generally found to be the two significant operating environment variables in energy distribution studies. See for example, AEMC (2008) and Lawrence, Diewert and Kain (2007). In their study of the productivity of the Swiss gas distribution sub-sector using SFA, Farsi, Filippini and Kuenzle (2007) pointed out the importance of environmental and output characteristics such as customer density and service area size.

7.4.6 Functional forms

For non-parametric methods (TFP and DEA), no specification of a functional form for the production or cost function is required. For a parametric approach (EM or SFA), an appropriate functional form for the production or cost function is used to capture the underlying production technology. A variety of functional forms have been used in empirical studies. The most commonly adopted forms are the simple Cobb-Douglas function and the more complex transcendental logarithmic function (translog for short).

The Cobb-Douglas functional form is a restrictive representation of the underlying production technologies. That is, the limitation of the Cobb-Douglas is that it automatically imposes restrictions on resulting substitution possibilities between inputs *a priori*, regardless of whether it is desirable. This will generate results that are biased if the underlying industry technology is not Cobb-Douglas in nature. This problem is referred to in the literature as a 'lack of flexibility' in the functional form.

The translog function is a direct generalisation of the Cobb-Douglas function, allowing for all squared and cross-effects terms for output quantity and input prices variables to be included in the cost function (or all squared and cross-effects terms for input quantity variables in the production function). This functional form is more flexible such that it provides a second-order approximation to any well-behaved underlying cost function at the mean of the data (Kumbhakar and Lovell, 2000, p. 143). That is, the substitution possibilities between inputs, such as capital and labour, can be better identified without restrictions or limitations. This means that the translog functional form is more likely to generate results that are consistent with neo-classical microeconomic theory, with fewer providing biased results.

The translog function is capable of producing an estimated model of an industry that includes the following important underlying economic properties:

- Domain: the cost function is a positive real-valued function defined for all positive input prices and all positive producible output.
- Monotonicity: the cost function is non-decreasing in output and non-decreasing in input prices.
- Continuity: the cost function is continuous from below in output and continuous in input prices.
- Concavity: the cost function is a concave function in input prices.
- Homogeneity: the cost function is linear homogenous in input prices.

Following the estimation of the model, these properties can be tested. Estimated translog models may not contain these economic properties. This may suggest problems with data. In this case, the translog results would not be persuasive. In addition, translog functions may fail to produce statistically significant results for some samples due to the potential multicollinerity problem.[136]

The translog functional form has become popular in recent applied production studies. However, flexible functional forms tend to have an increase in the number of parameters to estimate econometrically,[137] requiring a higher number of data points for estimation. Therefore there is a trade-off between the extent to which an econometric functional form imposes few restrictions on the underlying production process and the number of data points that is needed to estimate that function.

Some empirical studies have used statistical testing (e.g., the generalised likelihood-ratio test) to determine whether the Cobb-Douglas or the translog functions are best suited (Coelli, Rao, and Battese, 1998, p. 201).

Using Monte Carlo simulations, Guilkey, Lovell and Sickles (1983) compared three flexible functional forms, namely translog, generalised Leontief, and generalised Cobb-Douglas – and found that the translog form performed at least as well as the other two and provided 'a dependable approximation to reality, provided that reality is not too complex'.

Nevertheless, specifying a particular functional form limits the range of technologies that can be characterised. Depending on the existing knowledge about the underlying production technology in energy networks, an appropriate functional form or alternative functional forms may be chosen for the cost benchmarking.

7.5 Insights into benchmarking of energy networks

7.5.1 Addressing potential data issues

As noted in section 7.3, data availability and quality are considerations for the possible benchmarking application. Effort should be made by researchers or regulators to access larger datasets and improve the quality of benchmarking data. According to Lowry, Getachew and Hovde (2005, p. 91), this can be achieved by the accumulation of panel data and the greater use of international benchmarking.

Panel-data analysis

Quality panel data covering several energy utilities over a period of time, if available, will not only increase the sample size, but also address some shortcomings with the use of cross-sectional data. However, the lack of quality panel data to facilitate such an analysis often limits the use of benchmarking methods.

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[136] Multicollinearity is only a problem if accurate estimates of individual parameters (e.g., price elasticities in a demand function) are needed. For benchmarking analyses using econometric methods, the research interest is the efficiency estimates, which are linear combinations of a large number of estimated coefficients. Multicollinearity in a benchmarking model may not affect the model's efficiency prediction performance.

[137] For example, for a Cobb-Douglas production with n+1 parameters, the corresponding translog production function has a total of (n+1)(n+2)/2 parameters.

With one-year data where some observations may be strongly influenced by unexpected events (e.g., severe weather condition) or one-off major capital expenditure made, the benchmarking results may not reflect the longer term performance of these utilities or the overall performance of the sub-sector examined. Furthermore, panel data can also be used to measure business- and industry-level performance changes over time, such as TFP changes and its sources such as technical changes (i.e., frontier shift) and efficiency change (i.e., catch-up).

In the academic literature there have been mixed views regarding the usefulness of panel data for benchmarking analysis. Burns and Weyman-Jones (1996) found panel data to be useful in addressing the shortcomings of cross-sectional data. In particular, some variables that are particularly important for cross-sectional comparison may not be required for panel-data analysis. In their study in relation to applying SFA to electricity distribution in England and Wales, panel data suggested two main determinants of opex – customer numbers in an area and simultaneous maximum demand. A series of papers involving Farsi and Filippini (e.g., Farsi and Filippini (2004), Farsi, Filippini and Greene (2006)) examined whether some limitations of frontier models can be overcome with panel data for the Swiss electricity distribution businesses. Their results tend to confirm that robustness problems reported in relation to cross-sectional data might also apply to panel data.

The use of panel data may create its own problems. Value measures (e.g., for some inputs) need to be deflated to derive the equivalent constant-dollar measures. However, the availability of appropriate price deflators can be an issue. Moreover, data may be inconsistent or discontinued over time due to changes in definitions, accounting standards, or data providers. These may limit data comparability over time and across businesses. It is noted that the lack of quality panel data has prevented the Ofgem from using panel data for benchmarking analysis in its earlier price control reviews. It is not until the most recent price control review (2009-10 to 2014-15) that panel-data regression was applied to its benchmarking analysis. The Ofgem considered that one of the limitations of its panel-data analysis was the assumption of constant effect of cost drivers over time, which might not necessarily be the case (Ofgem, 2009, p. 74).

International benchmarking

Another way to increase the sample size is to include energy utilities operating in other countries in the dataset. By doing international benchmarking, the industry frontier or performance can be strongly influenced by international best-practice utilities rather than the domestic best-performers.

In the academic literature, some studies, including Jamasb and Pollitt (2003), Estache, Rossi and Ruzzier (2004) and Goncharuk (2008), have focussed on comparing utilities in one country to utilities in other comparable countries. The key issues expressed in relation to the application of international benchmarking relate to the availability of data, exchange rate issues and technical issues for addressing country differences in labour price, cost of capital, regulatory and environmental factors and so on. Some trade-off has to be made between increasing sample size and maintaining homogeneity (or adjusting for heterogeneity) of the sample utilities.

In recognition of the increasing complexity in conducting international benchmarking, Estache, Rossi and Ruzzier (2004) considered that there would be net benefits of good coordination across regulators in establishing an international database for benchmarking. Jamasb and Pollitt (2003, pp. 30-31) made some recommendations on the approaches to co-ordinating international benchmarking exercises, including:

- Agreement on long-term commitment and procedures for data collection, common templates, and submission deadlines for data standardisation;
- Identifying and defining a minimum set of input, output, and environmental variables for data collection;
- Other desirable variables including maximum demand, transformer capacity, service area, quality of service, and voltage-based physical and monetary breakdown of assets;
- Collecting data of a representative sample covering different size groups and types of utilities, starting from the most recent years and accumulating over future years;
- Discussion on benchmarking models, functional forms and weightings; and
- In-depth examination of the extent of similarities and differences between the inefficient firms and their peers to support the benchmarking results.

The development of an internationally consistent dataset that is useful to benchmarking would be beneficial to regulators across countries. For regulatory applications, international benchmarking has more often been used for benchmarking transmission service providers given their very limited number in a single country. For example, the Agrell and Bogetoft (2009) study on electricity and Jamasb, Newbery, Pollitt and Triebs (2008) study on gas, both commissioned by the Council of European Energy Regulators (CEER), provided a useful input into the German approaches to efficiency benchmarking and regulation of the transmission sub-sectors.

Caution

Caution should be exercised when colleting the panel data and/or international data to ensure that the dataset contains the most comprehensive information that is broadly consistent over time and comparable across energy utilities. In-depth examination of the data is required to ensure consistency, comparability and quality. For benchmarking analysis, data may need to be adjusted to ensure a valid comparison for energy utilities providing slightly different services and/or operating in different environments.

7.5.2 Addressing model specification problems

A good understanding of the nature of the production process implemented by the energy utilities in transforming labour, capital and other resources into utilities' services provided is fundamental to the development of sound benchmarking analysis. The economic theory and industry knowledge, together with comprehensive cost-driver analysis and engineering studies, can be useful for informing the development of model specifications and production functional forms.

For alternative model specifications, it is important to consider the assumptions underpinning the model and their implications for the measurements. If there is no strong theoretical foundation favouring a particular model specification, sensitivity analysis can be conducted to examine the robustness of the results.

A common theme among much of the reviewed literature has been the advocacy of the use of sensitivity analysis as part of any benchmarking technique. A number of authors have suggested that this approach is necessary to ensure that the benchmarking results (e.g., efficiency scores and rankings) are robust and accurate. These sources include the IPART (1999), Farsi and Filippini (2004), and Jamasb, Nillesen and Pollitt (2004). It also appears from the literature that the application of the DEA method can be particularly sensitive to model specification. DEA does not incorporate any error terms and thus can be very sensitive to measurement errors and selection of variables.

7.5.3 Choice of methods

Some interesting and relevant discussion on the choice of benchmarking method is presented by Coelli, Estache, Perelman and Trujillo (2003). Relevant factors affecting the potential use of benchmarking and the choice of the benchmarking method include:

- Industry characteristics: How many like businesses in the sample that can be used to benchmark? As previously noted, some methods require a sufficiently large number of observations and thus may not be particularly suitable for an industry with relatively few comparable utilities domestically.

- Data availability and quality: the use of panel data or international benchmarking to address the data-availability issue has a challenge in obtaining quality and consistency data for comparable utilities. The extent of data noises present will also affect the methods that can be chosen.

- The intended use of the benchmarking results under the regulatory regime: for example,
  - the benchmark industry-average productivity growth rate can be derived from the index-number-based TFP method; or
  - the comparative performance of a benchmark frontier, average or other businesses, whichever is considered appropriate, can be derived from one of the non-index-number-based methods (EM, DEA and SFA).

Each of the five benchmarking methods provides useful information for benchmarking the utilities regulated. However, depending on the legal and regulatory requirements, one or both of the two types of methods may be used. For regulatory applications, TFP is generally used for estimating the frontier-shift component while comparative performance from DEA or regression analysis has been used to assess the catch-up component of the X factor. Under the Building-block-model (BBM) adopted in Australia, there is no need to estimate the productivity-offsetting X factor directly. Under the BBM, the X factor in the CPI–X form of price or revenue path is simply a smoothing factor. The TFP results may be used as a cross-check for the future productivity change implied in the forecasts proposed by the utilities.

Taking into account these factors, judgements need to be made for the choice of appropriate benchmarking methods. It is also important to note that different benchmarking methods may differ in many aspects and some of the differences may affect the results differently. For example, using the same set of cost data, DEA and SFA methods estimate the cost frontier formed by the best-practice businesses, which can be substantially different from the estimated cost function formed by the average of the sample under the conventional EA method.

Therefore, while one method may be favoured, sensitivity analysis that examines the robustness of results with respect to more than one technique is desirable. Bauer, Berger, Ferrier and Humphrey (1998) and Rossi and Ruzzier (2000) proposed a set of 'consistency conditions' that should be met by efficiency estimates generated from different methods to ensure that they are mutually consistent. Specifically, the consistency conditions are:

- the efficiency scores generated by the different methods should have comparable means, standard deviations, and other distributional properties;
- the different methods should generate approximately the same ranking of the efficiency scores;
- the different methods should identify mostly the same group of observations as 'best practice' and as 'worst practice';
- all of the useful methods should demonstrate reasonable stability over time, i.e., tend to consistently identify the same institutions as relatively efficient or inefficient in different years, rather than varying markedly from one year to the next;
- the efficiency scores generated by the different methods should be reasonably consistent with competitive conditions in the market; and
- the measured efficiencies from all of the useful methods should be reasonably consistent with standard non-frontier performance measures, such as return on assets or the cost/revenue ratio.

The set of consistency conditions requires both internal consistency (i.e., consistent efficiency levels, rankings, and identification of best and worst performers) and external consistency (i.e., consistent over time and with competitive conditions in the market, and with standard non-frontier measures of performance) across alternative methods and model specifications. Estache, Rossi and Ruzzier (2004) explored the implications for price cap regulation if consistency in efficiency levels and rankings is not met. They considered consistency in identifying best and worst performers most important as it would facilitate public naming and shaming those that were not performing well.

Consistency analysis can be performed to improve robustness of benchmarking results with respect to alternative methods and model specifications. Wherever the results from alternative methods and model specifications differ materially, justifications for the use of the results need to be provided.

7.6 Conclusions

The review into benchmarking of energy networks shows that benchmarking can be used to measure industry average performance and/or comparative performance of individual energy network service providers. Overall, benchmarking has been used widely in the literature and in the regulatory work. It provides information about the performance of comparable energy networks and is of potential use to the regulators.

The outcome of benchmarking may depend on the availability, comparability and quality of data, choice of method, and selection of model specification. As discussed previously, the appropriate input-output specification and functional form used in benchmarking should be informed by a combination of sound economic theories, good industry knowledge and rigorous 'cost driver' analysis. To the extent that data are available, some aggregation and/or approximations are required to facilitate the high-level benchmarking at the potential cost of generating errors in measurement. Where the issue of choosing the most appropriate benchmarking methods and model specifications cannot be settled on theoretical grounds, sensitivity analysis is needed to test the robustness of the benchmarking results.

Robust benchmarking analysis is highly desirable and as such, benchmarking results should be examined against the set of the Bauer consistency conditions proposed in the literature. In some cases inabilities to produce similar results with alternative model specifications and methods require further investigation so that benchmarking outcomes can be supported by more rigorous analysis; otherwise caveats for the conclusions should be provided.

Other insights into benchmarking energy networks are also provided, suggesting the potential use of panel-data analysis and international benchmarking. However, caution should be exercised when collecting and analysing the data to ensure that the information contained in the larger dataset is consistent over time and comparable across businesses.

Chapter 8 Implementation issues in achieving effective benchmarking

8.1 Introduction

The preceding chapter reviews the various issues when applying benchmarking methods to energy networks. In particular, it has considered potential data availability and quality issues and model specification problems. This chapter follows by considering the broader challenges that the regulators may face when applying benchmarking of operating expenditure (opex) and capital expenditure (capex) in the electricity and/or gas sub-sectors (distribution and/or transmission).

The chapter is divided into six sections. Section 8.2 provides a definition of opex and capex and explores the potential challenges arising from the measurement and comparability of the two categories of expenditure across regulated utilities. Section 8.3 is a consideration of service quality and reliability in regulatory benchmarking – how is quality-of-service performance defined, can it be quantified, are there tradeoffs between quality and efficiency, and can service quality be benchmarked? Section 8.4 examines the role of benchmarking as an informative tool and as a deterministic tool. For benchmarking tools, informativeness and determinism are not substitutes; rather it is argued that they may be sequential complements in the adoption of a regulatory benchmarking program. Section 8.5 maps the implementation process when a regulatory benchmarking program is introduced. Finally, section 8.6 explores the opportunities and possibilities that may enhance the use of benchmarking in the regulatory context, considered in the light of the available techniques and data reviewed in previous chapters of this paper.

8.2 Operating expenditure, capital expenditure and total expenditure and their tradeoffs

Benchmarking a regulated utility's performance normally involves a standardisation and comparison of opex, capex and/or total expenditure (totex), where the latter is the sum of the former two expenditures.

Operating expenditures and capital expenditures are accounting categories that itemise the incurrence of capital and operating costs. If a regulator adopts benchmarking, it is important that the categorisation and incurrence of such cost is transparent, accurate and comparable across utilities.

However, accounting classifications in many respects are subjective – for example, accounting standards between Australia and the United States differ on what items should be immediately expensed and what items should be capitalised. Under the International Financial Reporting Standards – that represent the standards followed by the European Union, Australia and many emerging economies – Research and Development (R&D) expense is capitalised and amortised. However, in the United States, the Generally Accepted Accounting Principles require an immediate expensing of R&D (see Cohen, 2005, pp. 58-59).

In a regulatory setting, how opex and capex are categorised may directly affect the regulated utility's path of allowed revenues. Therefore, transparency, accuracy and comparability of cost categorisation and cost incurrence are crucial for effective regulation of utilities, whether benchmarking is undertaken or not.

Operating expenditure

Opex pertains to operating and maintenance expenditure items that are expensed for the utility's income year. It includes both variable and fixed costs with respect to variations in the production level. Some types of opex are costs which are normally direct costs expensed for a utility's income year that also vary with output. For example, intermediate inputs/materials, fuel or electricity, and some types of labour and labour-related expenses (e.g., overtime payments for labour).

A large proportion of opex, including some labour-related expenditure, is fixed over certain ranges of output(s). They are quasi-fixed inputs; for example, direct cost related to the activities undertaken, such as maintenance expenditure and transportation cost; and indirect costs or operating overheads, such as, leases, insurance, administration, marketing, human resources and IT support. As these costs are generally shared among services and are not responsive to units of outputs, additional cost drivers are applied to allocate the costs to individual services or activities.

While depreciation of capital stock is normally considered to be an operating cost (and there are direct and indirect cost components to depreciation), this annually expensed item is normally outside the measured opex and is treated separately as the 'return-of-capital' component in a building-block model.

Capital expenditure

Capex pertains to an outlay that will generate a flow of future income over time (i.e., beyond the income year). Capex is commonly recorded on the cash-flow statement as 'payment for property, plant and equipment' or similar items. The resulting addition to fixed assets will be reflected on the balance sheet and then depreciated or amortised over time. Relevant expenditure items include: the purchase of fixed assets; upgrading a fixed asset or repairing a fixed asset that will extend its useful life; and developing intangible assets through R&D, or acquiring intangible assets such as copyrights, trademarks, trade secrets and patents.

If opex is capitalised, such as wage and installation costs, then the assessment of capex becomes problematic because that capitalisation of opex may be idiosyncratic across utilities. Regulated utilities may have an incentive to capitalise opex in order to inflate the regulatory asset base if allowance for capital cost is subject to rate-of-return regulation, rather than external benchmarking. In a review of incentive regulation of electricity distribution and transmission networks, Joskow (2006, p. 2) pointed out that:

> In the UK, for example, the initial failure of regulators to fully understand the need for a uniform system of capital and operating cost accounts as part of the foundation for implementing incentive regulation mechanisms has placed limitations on their effectiveness and led to gaming by regulated firms (e.g. capitalizing operating costs to take advantage of asymmetries in the treatment of operating and capital costs).

Since benchmarking requires standardised definitions and classifications of opex and capex, an effective benchmarking program will detect such gaming – unlike the building-block model, which permits idiosyncratic incurrence of costs.

Benchmarking operating expenditure

Benchmarking opex is subject to particularly challenging data-quality and data-comparability problems. This is particularly the case when benchmarking is performed at an activity and/or business segment level. However, when opex as an aggregate is compared across utilities, the idiosyncratic processes employed by individual utilities in asset and cost allocation are diluted, and measures of aggregate per unit (i.e., a standard unit of single output or a standard combination of multi-product output) become more important.

As noted above, effective opex benchmarking requires clear and sound rules for cost classifications and allocation that are uniformly and consistently applied across utilities. These cover, for example, allocations of shared costs across services and classifications of capex as opposed to operating and maintenance expenditure.

Benchmarking capital expenditure

Regulators have often adopted a bottom-up approach to reviewing the reasonableness of certain categories of expenditure (e.g., asset replacement expenditure) or total capex proposed by an individual utility. Simple capex benchmarking, such as trend or ratio analysis, has also been employed to assess the efficiency of capex. Benchmarking capex against other utilities has not been consistently relied upon, possibly due to significant differences across businesses in terms of asset ages, investment pattern, network capacity utilisation and other requirements.

Regulatory treatment of capex could potentially be different from opex. The building-block model approach includes an allowance for cost of capital, which is the product of the weighted average cost of capital (WACC) and the value of the regulatory asset base that reflects changes to assets due to depreciation and addition.

Benchmarking total expenditure

Benchmarking totex involves a comparison of total expenditure (i.e., the sum of opex and capex) across utilities once controlling for the following, among other factors that may affect the comparability of cost incurrence:

- scale, scope, sequence and density economies; [138]
- geography and topography of the network of operations (partly relating to density);
- composition of consumers; and
- timeframe.

[138] Since Adam Smith’s observation of the division of labour in a pin factory, economists have recognised that production involves a sequence of steps. And these steps are often integrated within a single entity – such as, processing raw materials, assembling inputs, and the sequences of design, production and marketing. And the sequence of steps within a single entity defines its boundary. Economies of sequence arise when it is less costly to integrate a sequence of production steps within one producer rather than having that sequence of steps undertaken separately and independently by multiple producers. Producers will continue to vertically integrate until the economies of sequence of integrating production processes/steps are exhausted. See Spulber (1989).

Totex benchmarking requires identification and comparability of opex and capex without the potential requirement that utilities possess the same input shares/production technology; and the same degree of uniformity, standardisation and comparability of opex and capex. In other words, this is perhaps a less intrusive approach to benchmarking economic performance across utilities.

Benchmarking totex has further advantages compared to benchmarking opex or capex alone.

Firstly, using totex avoids the potential gaming problem when the two categories of expenditure (i.e., opex and capex) are subject to asymmetric regulatory treatment. Benchmarking of one but not the other category of expenditure may provide an incentive to change the composition of inputs in both the short run and long run. The short-run change may involve an accounting re-classification of opex and capex items so that the expenditure item that is subject to the more stringent assessment of benchmarking may be under-reported. Further, the regulated utility may have an incentive to change its input technology – inducing a long-run substitution away from the benchmarked expenditure toward the expenditure category that is not subject to benchmarking. This will not promote cost efficiency.

Secondly, totex benchmarking avoids another 'gaming' problem that may arise from benchmarking opex alone. Under opex benchmarking, the regulated utility may have an incentive to split into a number of micro-entities that engage in related-party trade of inputs, as opposed to an internal allocation of inputs within the single utility. The complex operational structure and large number of related parties and interposed entities associated with some energy utilities is consistent with the disincentive to realise economies of scale, scope, sequence and density within a single entity, and gives rise to regulatory concern of the efficiency of the structure. Totex benchmarking may capture a wider view of the overall efficiency of the regulated entity compared to its peers and assist in identifying whether such operational structures are, in fact, inefficient.

Moreover, under the related-party trade arrangement, the purchase of inputs is more likely to be capitalised. For example, suppose an electricity distribution pole had to be replaced, in which case the associated opex and capex may be clearly itemised. However, if the utility purchased the service from a related party, the entire outlay may be more likely to be capitalised, so that the opex component will be under-reported or not reported at all. This is because the installation service is purchased from another 'entity' that is contracted to supply the fixed assets and is therefore classified as a capex item. Financial Statement practitioners warn about excessive capitalisation. Examples include the capitalisation of wages and associated costs, installation costs and development costs (See, Hey-Cunningham, 2006, p. 321).

The resulting under-reporting of opex will provide the regulator with an impression that the efficient level of opex is being incurred, when, in fact, the focus on opex only has elicited a 'waterbed effect' of reclassifying and moving costs toward expenditure items that are not benchmarked.[139] In this case, the regulated utility has morphed into micro-entities so that opex can be redefined as capex.

Notwithstanding, totex benchmarking can be challenging, given the inherent data quality and comparability issues. There is also a specific aggregation problem associated with totex being an aggregate measure; that is, there are potentially more sources of annual fluctuations in totex as opposed to opex or capex respectively. More importantly, totex is subject to the lumpy, indivisible and cyclical nature of investment, which may result in yearly fluctuations of expenditures, and the expenditure patterns differ substantially across utilities. It can be problematic to compare totex across utilities using yearly data that sum up infrequent capex incurrence and yearly opex expenditure incurrence.

Therefore benchmarking totex in short timeframes is not feasible for energy utilities that invest in transmission or distribution assets of very long service life. It may require a longer timeframe (than a typical five-year regulatory period) to establish representative capex profiles at the utility level unless there are also independent assessments of capex, and to a lesser extent, of opex, to control for any fluctuations in these expenditures from year to year.

Benchmarking total cost

Another integration approach is to benchmark yearly opex and flow of capital services – that is, total cost measured as the sum of opex, the return on capital and the return of capital each year – so that there is increased consistency of expenditures over time. If net present value is zero for all projects undertaken, then comparing capital expenditure across utilities is equivalent to comparing the cash flows (return on and return of capital) across utilities over time.

However, such benchmarking may present its own data availability and comparability challenges. The approach can be more information-intensive as it requires not only historical series of capital investment, but also an asset valuation to start with. Furthermore, the capital prices and depreciation profiles (asset valuation, asset life and depreciation pattern) can be substantially different across utilities. There are differences in utilities' accounting policy on net residual or scrap value of the assets.

Issues may, therefore, arise with the measurement of the volume of capital services consumed periodically. When a business makes a sunk, long-lived investment, the allocation of the cost of that investment to any year of the life of the asset will affect estimates of efficiency of the business. This is because efficiency estimates are usually made over a relatively short period, such as one year. It is therefore necessary to benchmark expenditure of several or more years, and that depreciation profiles are assumed to be the same across utilities.

Moreover, if the asset is depreciated based on estimated levels of productivity, incorporating these estimates into the relative efficiency performance of businesses may involve circular reasoning. Turvey (2006) suggests that circular reasoning can

[139] The 'waterbed effect' in this context occurs when the regulatory scrutiny and subsequent cost reductions in one expenditure category shift the effort of the producer toward an equi-proportionate uplift in expenses in other expenditure categories so that allowed revenue remains unchanged.

be avoided by measuring the volume of capital services that is independent of what it actually produces. This can be achieved by measuring capital services *ex ante*, from the time of asset commissioning, while measuring output *ex post*, at the time of production, both at constant prices.

8.3 The consideration of service quality and reliability

As outlined in chapter 7, quality of service can be an important issue for the regulator when undertaking benchmarking. The requirement that utilities achieve cost savings on the basis of benchmarking studies should not be at the expense of service quality. The regulatory benchmarking of service standards across network operators is a challenging task which requires, first, a standardised and quantifiable definition of reliability and service quality.

Reliability can be thought of and measured differently in various industries and within industries. For example, in telecommunications one may measure reliability by the number of call drop outs, network downtime, or number of line faults. The measures will vary depending on whether a mobile or fixed line network is considered. On the other hand, for an airline industry, measuring reliability may involve consideration of flight cancellations, on-time performance, or accident rate.

Often it will be possible to agree on a common set of indicators. For example, in energy, there are a number of distribution reliability indicators produced by the Institute for Electrical and Electronics Engineers (IEEE), which is an international body that sets service standards for network industries. The IEEE Standard 1366-2003 focuses on the following measures of network reliability which quantify service interruptions across electricity network providers:[140]

- SAIFI – System Average Interruption Frequency Index;
- SAIDI – System Average Interruption Duration Index; and
- CAIDI – Customer Average Interruption Duration Index.

In addition to the above, a number of other reliability measures are sometimes considered. In particular, the Australian Energy Regulator (AER)'s Service Target Performance Incentive Scheme focuses on three parameters; namely unplanned SAIFI, unplanned SAIDI and a third parameter which measures very short term interruptions, MAIFI – Momentary Average Interruption Frequency Index.[141]

Service quality in other dimensions can also be considered using a number of different measures. Usually these measures relate to customer satisfaction, and can vary between industries and customer groups. For example, large energy customers may only be concerned with network reliability to ensure service quality, whereas

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[140] See the Institute for Electrical and Electronics Engineers website, http://www.ieee.org/index.html and IEEE (2006).

[141] MAIFI is only used for some jurisdictions. AER (2009c, p. 9) prescribed that 'Where the DNSP demonstrates to the AER it is unable to measure MAIFI, a DNSP may propose a variation to exclude MAIFI in accordance with clause 2.2, for a regulatory control period or a portion of a regulatory control period'.

residential telecommunications customers may require prompt installation of lines and rectification of line problems, help-desk availability, simple billing process, etc.

Although common measures can be established, it is important to note that benchmarking should take into account any specific differences across utilities. For example, in measuring reliability of energy networks, it is important to consider reliability measures under normal operating conditions, and account for major events separately. As noted above, most of energy reliability measures are related to service interruption. However, these measures can be dominated by a single major event, such as a storm or a flood. While the response to the major event can be accounted for as a measure of reliability, any benchmarking method would need to isolate these events from benchmarking under normal operating conditions.

Further, when benchmarking, it may be necessary to recognise factors that affect reliability levels, which may not be controllable by the benchmarked utilities. In case of energy networks, these may include:

- Definition and data classification – e.g., What is a major event? What is classified as an interruption?
- Data-collection process – how and when are outages reported?
- Service territory – geography, weather and vegetation patterns; and
- System design – urban, rural, and remote overhead/underground wiring.

Of course, different service quality and reliability levels may be associated with varying levels of expenditure. Cost benchmarking would therefore need to consider service quality and reliability levels in the context of cost incurred in attaining these levels. Both service quality and reliability, and cost would need to be controlled for factors outside management control. For example, service quality and reliability performance could be compared to the average cost per user separately for central business district, urban and rural areas.

Further challenges arise with the aggregation of service capacity, which can determine service quality. It is possible to express the service capacity of an individual piece of equipment. But questions arise as to how to express the capacity of an entire network which has the potential to deliver different volumes of electricity at different voltage levels at different geographic locations. According to Turvey (2006), benchmarking studies have sought to compare the performance of electricity networks using measures of throughput (MWh) and line length as a proxy for measures of capacity at different locations. Turvey (2006) suggested that these measures were appropriate only when certain conditions were satisfied.

While few studies explicitly have considered service quality as an output variable (see Coelli, Crespo, Paszukiewicz, Perelman, Plagnet, and Romano, 2008), service quality is a crucial consideration in benchmarking – the downside risk of ignoring service quality is that utilities that seek or are required to achieve cost efficiencies may do so at the expense of service quality.

The main difficulty, however, is likely to lie in the comparison between benchmarked utilities. While some may choose greater levels of reliability and service quality at higher cost, others may opt for lower levels. Ideally, levels would be set such that the marginal benefit to the average consumer from greater service quality or network reliability equals the marginal disbenefit from the higher service cost. These are difficult to measure empirically, and internationally individual utilities are usually allowed to set their own targets. Further, as customer groups may be characterised by different attitudes toward service quality and reliability – indeed it is likely that different customer groups of each individual utility may exhibit varying attitudes – it is difficult to determine whether any utility is making a sub-optimal cost-service level choice.

In Australia, the AER has already set reliability targets (SAIDI, SAIFI and, in some jurisdictions, MAIFI) for electricity distribution utilities, but the other service quality standards are set by the jurisdictions. The service quality targets are part of the AER's national service target performance incentive scheme focusing on supply reliability and customer service (AER, 2011, p. 69):

> The national scheme generally provides financial bonuses and penalties of up to 5 per cent of revenue to network businesses that meet (or fail to meet) performance targets. The results are standardised for each network to derive an s factor that reflects deviations from target performance levels. While the scheme aims to be nationally consistent, it has flexibility to deal with the differing circumstances and operating environments of each network.

With an established institutional and legal structure of standards of service quality already specified and in place, the above challenges in controlling for service quality standards when undertaking cost benchmarking may be less numerous and/or less onerous.

8.4 Benchmarking: an informative tool and a deterministic tool

Benchmarking performance can be used to inform the regulatory approach and also determine regulatory decisions. The informative and deterministic dichotomy is drawn from papers that identify issues with the efficacy of benchmarking, such as Shuttleworth (2005) and Lowry and Getachew (2009b), and thus the dichotomy connotes substitutability between the two tools. However, benchmarking as an informative tool is not a substitute for benchmarking as a deterministic tool – rather, the two tools are sequential complements in the development of a program of regulatory benchmarking. The complementarities that exist between informativeness and determinism are highlighted through an exposition of these two stages in a regulatory benchmarking program.

Informativeness

Informativeness characterises the first stage of regulatory benchmarking which consists of defining an inter-utility set of expenditure parameters in consultation with stakeholders, collecting the data, and refining the data to achieve the required quality and comparability.

The aim of benchmarking is to improve the efficiency and competitiveness of regulated utilities. Utilities may only be deemed to be profitable, efficient and competitive when compared to competitors in the same industry or comparable businesses. For example, whether or not a utility is profitable can only be ascertained if it is known what constitutes an opportunity cost or normal rate of return for the market/industry. The relativities determine the regulatory information requirements – the regulator is not required intrusively to collate granular data from utilities with the object of constructing a surreal and 'optimal' benchmark. Benchmarking against a theoretical optimum would be analogous to the futility of central planning where a static and synthetic construct of an 'economy operating optimally' was applied when computable general equilibrium (CGE) became possible in the 1960s (Wheatcroft, Davies and Stone, 2005). It is also similar to the 'Nirvana fallacy' identified by Harold Demsetz (1969) where an idealised outcome from government intervention is posited against an actual free-market outcome. Demsetz contends that the nirvana approach encapsulates the fallacies such as 'grass is always greener', 'people could be different', and the 'fallacy of the free lunch'.

Benchmarking as an informative tool characterises the first stage of regulatory benchmarking that involves:

- a review of each regulated utility's past and future expenditure;
- determining a common set of expenditure items, output parameters, and other cost drivers in collaboration with the regulated utilities;
- collecting and collating the data; and
- estimating and assessing the benchmarking results – for example, whether the estimated residual from an econometric method may pertain to the potential efficiency and productivity differences between regulated utilities.

Within the informative-tool framework, utilities that appear to be relatively inefficient (that is, operating within the frontier) are engaged by the regulator on a consultative basis to discover the likely causes of higher costs. The difference between the informativeness tool and the deterministic tool is that the regulator does not necessarily assume that the residual, either proportionally or in its entirety, can be conclusively attributed to relative inefficiency.

As chapter 7 discusses, the greatest challenge to benchmarking is data quality and comparability. The outputs of many regulated entities are potentially more homogeneous than outputs produced by the non-regulated sector – even if they may argue to the contrary – water, gas and electricity may be more homogeneous than, for example, highly differentiated products such as vehicles, books and groceries. Since product/service categorisation may be relatively straightforward (with the possible exception of the reliability/quality of service), output data are less problematic than the input data.

Quality and comparability of input data corresponds to accurately quantifying the differences arising from factors including:

- economies of scale, scope, sequence and density;
- regulatory structures;
- geographic region of operation;
- customer composition; and

- existing tariffs.

It also requires achieving a reasonable standardised definition and comparability of the cost-allocation method, the incurrence of opex, and the incurrence of capex (including the lifecycle of investment programs).

The quality and comparability of the data, or the regulator's assessment of the quality and comparability of the data, may influence how the regulator interprets and uses the benchmarking results. For example, the regulator may consider, to what extent, the estimated residual from an econometric cost function analysis quantifies the efficiency differences between utilities on and within the frontier. On the one hand, if the data available cannot reach an acceptable degree of quality and comparability, the estimated residual may only prompt an inquiry into the efficiency of the operations for the utilities under examination. On the other hand, if the data are of a high level of quality and comparability, the entire estimated residual may be used as relative cost inefficiency to determine the path of prices and revenues for regulated entities. The two uses of the residual are not necessarily two discrete and substitutable outcomes – the benchmarking program is an evolution. While the benchmarking results may be used to inform in the early stages of regulatory benchmarking, improvements in data quality and comparability will enable the regulator to ultimately use the results in a deterministic manner.

Poor data quality and comparability may be the main reason why a regulator may not proceed beyond benchmarking as an informative tool in the early stages of regulatory benchmarking. While the benchmarking results may elicit further inquiries into the operations of utilities within the efficiency frontier, the regulator may not use the benchmarking results directly to inform the determination of revenues and tariffs for regulated utilities. However, the situation may change when data availability, quality and comparability reach a sufficient standard at a later stage.

Determinism

Determinism is the use of the benchmarking results to directly determine the path of prices or revenues for utilities on and within the frontier. There are varying degrees of determinism. For example, the regulator may use only part of the estimated cost inefficiency to set the path of revenues or prices – so that if it was established that if the least-efficient utility incurred five per cent higher costs than a comparable business on the frontier, perhaps only half of the five per cent will be used to set a lower path of prices or revenues over the next regulatory period for the less efficient utility.

However, once the regulator has refined the process and nature of data collection so that quality and comparability of the data may meet a standard, the regulator may decide to use the benchmarking results more deterministically. For example, the entire estimated business-specific inefficiency, together with the estimated scope for industry frontier shift, may be used to jointly determine the path of prices and revenues for a regulated utility.

8.5 Implementation process

The assessment of the reasonableness of costs of a particular utility against those of other network service providers or even against costs estimated in economic-engineering models has a long history both in Australia and internationally.

Cost benchmarking has been applied in a large number of leading countries across the Organisation for Economic Cooperation and Development (OECD); for the regulation of energy networks, particularly electricity and gas distribution businesses (WIK-Consult, 2011, pp. 1-2). Countries applying these techniques have been reviewed in this paper and the supporting research.

In Australia, there has been an interest in benchmarking, dating back at the state level to the late 1990s. The AER has cost efficiency as a key objective under both the National Electricity Law and the National Gas Law. It must have reference to the costs of an 'efficient operator' in a revenue or price determination. As noted elsewhere in this paper, the AER considers a number of benchmarks in its investigations of forecast efficient and prudent opex and capex of regulated entities and is actively pursuing enhancement of its benchmarking activities.

Implementation issues must be considered in the light of these long international and Australian experiences with benchmarking applications – simply, it is not experimental or speculative; rather it is a real-world phenomenon where any enhanced application will build on a basis familiar to all participants in the regulatory process. Further, the challenges of implementation have presented opportunities for refinement of the data and benchmarking methods, and further enhancements can be expected with continued implementation.

8.6 Benchmarking: opportunities and possibilities

Since an economic assessment of any topic is always framed in terms of opportunity cost, the challenges of benchmarking should also be framed in terms of the resource cost involved *vis-à-vis* that of alternative regulatory regimes, such as building-block model.

Shuttleworth (2005) summarised the challenges of applying benchmarking. It is worthwhile exploring each of these challenges to determine the feasibility of benchmarking, particularly when comparing the resource cost of benchmarking to that of a cost-of-service regulatory regime.

The choice of technique: There are subjective choices as to the technique used – for example, parametric versus non-parametric methods, as well as the different ways of defining the frontier, can all affect the results differently. Therefore, while one method may be favoured, robustness of the results may require the application of more than one technique to corroborate results arising from the favoured technique or to determine which technique is best suited to the benchmarking of businesses in that particular sub-sector. For example, WIK-Consult (2011, p. 25) reported that the Energy Market Authority in Finland used both the DEA and SFA methods to benchmark electricity distribution networks so that estimations from one technique are corroborated by the estimates generated by the application of another technique. Using multiple methods reduces the uncertainties and weaknesses attributed to the use of a single method. This challenge presents an opportunity for refining and using techniques to more robustly and effectively gauge economic performance of comparable utilities.

However, the different methods are just different ways of measuring the same thing (i.e., the relationship between inputs and outputs), and in many circumstances can be expected to yield similar results (Cooper, Seiford and Zhu, 2011). For example, several healthcare papers have compared SFA and DEA methods, and it was observed that both are useful in answering slightly different questions. That is, SFA may be more helpful to understand the future behaviour of the population of hospitals whereas DEA might be used when the policy problem centres on how hospitals may improve on specific inefficiencies. That said, Cooper, Seiford and Zhu (2011, pp. 452-453) found that, if DEA was required to model the same dependent variable as SFA, it would lead to the conclusion of similar, but not exactly the same, results. Where results from different methods differ materially, it is important to investigate the sources of the differences and to provide sufficient justifications for the intended regulatory use of the results.

Choice of variables and model: Shuttleworth challenged that different models using different variables could generate quite different results and could impose quite different targets for cost reduction. Shuttleworth's challenge is supported by Bauer, Berger, Ferrier and Humphrey (1998). They proposed a series of criteria that can be used to evaluate whether the efficiency levels obtained from different methods and models are mutually 'consistent'; that is, leading to comparable efficiency scores and ranks. However, in many cases because of a considerable discrepancy, these criteria are not satisfied. This challenge presents a stringent requirement for any regulatory benchmarking – a requirement for extensive stakeholder consultation and agreement on the common set of variables and the models employed.

Interpretation of the residual: The residual in an econometric cost model is the difference between observed costs and benchmarked costs. As this cost difference is what the model has failed to explain, the regulator cannot automatically conclude that the entire estimated residual is due to relative inefficiency. This challenge is not insurmountable – during the informativeness stage of the benchmarking program, and in consultation with regulated utilities, the estimated efficiency differences across utilities may direct the inquiry of the regulator into what inferences can be drawn from the value of the efficiency estimates. The results of such an inquiry should inform the regulator of the extent to which the residual can be attributed to relative inefficiency. That is, the inquiry may first identify the operating environment factors that may affect the costs of regulated utilities. Once such variables have been reasonably measured and their proportional influence on a utility's costs can be quantified, papers such as Yu (1998) provide a guide to identifying and isolating the cost efficiency from the environmental factors. Yu (1998) outlines both a one-step and a two-step procedure to separate out the environmental influences from the 'gross efficiency' estimates so that the efficiency effects can be isolated and identified.

Burden of proof: Shuttleworth contended that the regulated businesses should be required to explain the reasons behind the estimated residual, other than relative inefficiency. Shuttleworth purported that this might require detailed knowledge, not only of that business but also of all other businesses in the dataset. However, the burden should be examined in light of the possibility that, first, the burden of proof is likely to be quarantined to a segment of its operations; and second, the burden of proof primarily rests with the subset of underperformers, and therefore the costs of compliance are limited. Unlike cost-of-service or rate-of-return regulation, where intrusive regulatory inquiries may encompass cost data on a granular level, and which penalise both efficient and relatively inefficient utilities equally with regulatory compliance costs, the burden of proof under a benchmarking regime may only apply to a subset of costs for a subset of utilities. Further, to the extent that the residual explains relative inefficiency, the burden-of-proof requirements act as an additional impetus for least-efficient utilities to achieve efficiencies in their operations over time.

Duration of adjustment period: Shuttleworth contended that the time period in which a utility is required to achieve the target level of costs may be a source of 'regulatory risk'. While there is a risk that underperformers may fail if given an inadequate adjustment period to achieve target efficiencies, the adjustment path for the attainment of efficiencies provides temporal scope for regulated utilities to adjust; and it is already proven to be feasible since one or more comparable businesses are already on the efficiency frontier. For example, Giannakis, Jamasb and Pollitt (2005) found that the convergence to industry best practice partly explained the substantial improvement in average productivity of up to 38 per cent for electricity utilities in the United Kingdom between 1991-92 and 1998-99.

Note also that these benchmarking techniques have been used in various jurisdictions for up to twenty years, and their regulatory applications are therefore variations of previous ones.

Inevitably there are questions over the extent to which benchmarking can be used as a deterministic tool *vis-à-vis* a tool used to inform and inquire into the operations of regulated entities. In economic welfare terms, some forms of determinism derived from the benchmarking analysis, being mild or moderate, may be a superior alternative to cost-of-service and rate-of-return regulation.

Cost-of-service regulation, rate-of-return regulation and their combination – the current building-block model – are rigorously and extensively critiqued by economists for creating perverse incentives to cost pad and overcapitalise essential services. Indeed, many standard textbooks on regulatory economics highlight such problems. See, for example, Church and Ware (2000), Spulber (1989), Berg and Tschirhart (1988), and Bonbright, Danielsen and Kamerschen (1988).

Cost-of-service regulation is where the utility is reimbursed for the costs it incurs plus a reasonable rate of return. The current building-block model is cost-of-service regulation with rate-of-return regulation embedded within it.[142] Under the current building-block model, the utility submits its operating expenditure, asset base, capital expenditure, depreciation and cost of capital so that 'made-to-measure' revenue for the utility can be determined.

[142] Church and Ware (2000, pp. 847-852) observed that rate of return regulation is embedded in the cost of service regulation.

Such regulatory approaches accentuate the gaming and strategic behaviours arising from the principal-agent problem, which elicits allocative, dynamic and cost inefficiencies. The principal-agent problem arises because the principal (regulator) has imperfect knowledge of an agent's (utility's) actual costs. The agent exploits this information asymmetry by:

- submitting costs to the regulator that may be above efficient costs – potentially resulting in cost and allocative inefficiencies (such bloated costs may be due to overstaffing, failing to negotiate with input suppliers, managerial slack and consumption of perquisites);

- submitting expected opex and capex without the requirement or incentive to improve the productivity of these inputs – potentially resulting in dynamic inefficiencies; and

- failing to develop and introduce new services that may not only lower cost, but may improve convenience for customers.

Under cost-of-service regulation, rate-of-return regulation and the current building-block model, the regulator often has to attempt to replicate or even exceed managerial knowledge. The necessity for the regulator to replicate and exceed managerial knowledge seeks to resolve the problem of the agent deviating from the behaviour desired by the principal – an impossible task given that informational symmetry is never achieved.

Further problems of resource misallocation and waste arise because the regulator/principal has to incur substantial resource costs in monitoring and examining the utility's books under the current building-block regime.

Hayek's (1945) seminal paper on the use of knowledge in society lucidly demonstrates the impossibility of government planning boards knowing more than the decentralised decision-makers that manage production units. Unlike the current building-block approach, benchmarking does not unrealistically, burdensomely and intrusively aspire to duplicate or exceed the knowledge of business operation possessed by decentralised decision-makers in regulated entities. Rather, the informational and regulatory burden of a benchmarking program is limited to *relative* knowledge – a knowledge that only need pertain to relative performance.

Benchmarking is underpinned by the economic precepts of another seminal paper – Hotelling's (1929) 'Stability in Competition'. Hotelling observed and explained that businesses have a strong tendency to converge to one another in process, product specifications and pricing in order to capture the market. Benchmarking exploits this inherent market tendency to 'standardisation and sameness' by:

- first, capturing and quantifying the degree of sameness and standardisation across regulated utilities within an industry; and

- second, instilling an incentive for businesses to converge to the most efficient utility that would normally occur in a competitive market ('sameness' in efficiency).[143]

The second objective does not require the synthetic creation of a surreal 'efficient' production unit, nor does it require the regulator to duplicate managerial knowledge and granularly scrutinise a utility's expenditures. Unlike building block, the microscopic cost-benefit question of whether the utility should purchase one more maintenance vehicle does not need to be posed nor answered by the regulator. Benchmarking has less of an informational requirement because it leverages off the natural tendency for sameness across utilities – the regulator is simply doing what occurs in a competitive market, comparing one utility's performance to that of its competitors using a common set of parameters (Hotelling, 1929).[144]

Indeed, the review of the Australian Energy Market Commission (2011, p. ii) into the use of Total Factor Productivity (TFP)-based regulation has found that its implementation as an alternative to the current building-block approach could, in principle, contribute to the national energy objectives – i.e., leading to increased productivity and lower prices for consumers in the long term.

[143] This paper does not cover potential problems with a high-power incentive regulation regime. The issue can be addressed under a carefully designed and evolutionary regulatory benchmarking program.
[144] Indeed, the Data Envelopment Analysis benchmarking method is marketed to competitive producers who wish to measure their performance against that of their rivals.

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Abbreviations

Abbreviation	Definition
ACCC	Australian Competition and Consumer Commission
ACT	Australian Capital Territory, Australia
AEMC	Australian Energy Market Commission
AER	Australian Energy Regulator
BBM	building block model
BNetzA	Federal Network Agency, Germany
BSI	British Standards Institution, the UK
CAIDI	customer average interruption duration index
Capex	capital expenditure
CEER	Council of European Energy Regulators
CEPA	Cambridge Economics Policy Associates
CER	Commission for Energy Regulation, Ireland
CGE	computable general equilibrium
COLS	Corrected Ordinary Least Squares
CPUC	California Public Utilities Commission, the US
CRS	constant returns-to-scale
CSV	composite size variable
DEA	Data Envelopment Analysis
DNSP	distribution network service provider
DPCR	distribution price control review
DRA	Division of Ratepayer Advocates
DRS	decreasing returns-to-scale
DTe	Office of Energy Regulation, the Netherlands
EI	Energy Market Inspectorate, Sweden
EM	econometric method
EMA	Energy Market Authority, Finland

Abbreviation	Definition
ERA	Economic Regulation Authority, Western Australia
ESAA	Energy Supply Association of Australia
ESBN	ESB Network
ESCOSA	Essential Services Commission of South Australia
ESCV	Essential Services Commission in Victoria, Australia
EUAA	Energy Users Association of Australia
FCM	financial capital maintenance
FERC	Federal Energy Regulatory Commission, the US
FTE	full-time equivalent
GJ	gigajoules
GRC	General Rate Case
GWh	gigawatt hour
ICRC	Independent Competition and Regulatory Commission, the Australian Capital Territory
IEEE	Institute for Electrical and Electronics Engineers
IPART	Independent Pricing and Regulatory Tribunal, New South Wales, Australia
IRS	Increasing returns-to-scale
kV	kilovolt
kVa	kilovolt amperes
kW	kilowatt
kWh	kilowatt hour
LECG	Law and Economics Consulting Group (formerly)
MAIFI	momentary average interruption frequency index
MOLS	Modified Ordinary Least Squares
MVa	megavolt amperes
MW	Megawatt
MWh	megawatt hour

Abbreviation	Definition
NDRS	non-decreasing returns-to-scale
NEL	National Electricity Law
NEM	National Electricity Market
NEO	National Electricity Objective
NGL	National Gas Law
NPAM	Network Performance Assessment Model
NSW	New South Wales, Australia
NTUC	Northern Territory Utilities Commission, Australia
NVE	Norwegian Water Resources and Energy Directorate
NZ	New Zealand
NZCC	New Zealand Commerce Commission
O & M	operating and maintenance
OEB	Ontario Energy Board, Canada
OECD	Organisation for Economic Cooperation and Development
OLS	ordinary least squares
Opex	operating expenditure
OTTER	Office of the Tasmanian Economic Regulator, Tasmania
PAS	Publicly Available Specification
PB	Parsons Brinckerhoff
PC	Productivity Commission
PEG	Pacific Economics Group
PFP	Partial Factor Productivity
PJ	Petajoule
PPI	Partial Performance Indicator
PPP	Purchasing Power Parities
PTRM	Post-tax Revenue Model
PWPN	Power and Water Power Networks, the Northern Territory

Abbreviation	Definition
QCA	Queensland Competition Authority, Queensland
R&D	research and development
RAB	regulatory asset base
RINs	AER's information collection templates
SAIDI	system average interruption duration index
SAIFI	system average interruption frequency index
SCER	Standing Council on Energy and Resources
SDG&E	San Diego Gas and Electric Company, US
SFA	Stochastic Frontier Analysis
TFP	Total Factor Productivity
totex	total expenditure
UK	United Kingdom
US	United States
VRS	variable returns-to-scale
WACC	weighted average cost of capital