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Keywords benchmarking; regulation; operating companies; electricity distribution

JEL Classification L98; M21

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USING REGULATORY BENCHMARKING TECHNIQUES TO SET COMPANY PERFORMANCE TARGETS: THE CASE OF US ELECTRICITY

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Abstract

Consolidation in many sectors has lead to the formation of “groups of companies”. Extracting all the potential cost savings from these independent or separate operating units is a challenge given asymmetric information. We develop a step-by-step approach that applies regulatory benchmarking techniques to set efficiency targets for operating units. Holding company management – like a regulator – will want to set targets to encourage efficient operation but in the absence of full information on effort, costs and environmental conditions. Our approach using the parallel with regulation incorporates issues such as measurement error and potential environmental factors that could influence the underlying efficiency score. We demonstrate the approach using data from the US electricity distribution sector and show that substantial savings can be extracted using this approach that was originally developed for regulatory purposes.

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Using Regulatory Benchmarking Techniques To Set Company Performance Targets: The Case Of US Electricity[1]

Paul Nillesen[*] *Michael Pollitt*

Section 1: Introduction

Rapid consolidation in many sectors has led to the creation of groups of daughter companies owned by a single Holding company (e.g. in the US energy sector National Grid or FirstEnergy). In the absence of direct competition the management of the Holding company is faced with the challenge of setting targets for the companies to extract and realise all potential (latent) value. In some sectors, such as electricity distribution and retail, there are often no direct competitive effects, as a result of strong scale effects and franchised monopolies. The lack of these competitive pressures can lead to inefficiencies. In some instances environmental factors, such as climatic conditions or wage costs may be used by managers to excuse poor relative performance. In this paper we use a regulatory benchmarking approach to assist Holding company management in estimating potential efficiency gains.

Our approach includes a number of steps designed to create "buy-in" and "lock-in" from managers within the benchmarked companies and focuses on dissecting the measured inefficiency into: (i) inefficiency as a result of "pollution" in the data, i.e. from data quality issues (ii) inefficiency due to environmental factors, and (iii) inefficiency attributed to management. The latter inefficiency can be used by Holding company management to set goals for the companies. We use data from the US electricity distribution sector to illustrate this approach. However, this approach could be applied in any sector where good national data is available.

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[*] Corresponding author. Authors would like to thank the ESRC Electricity Policy Research Group and Tim Tutton for their contributions. The views expressed here are those of the author and do not necessarily reflect the views of PricewaterhouseCoopers Advisory N.V. or any of the PricewaterhouseCoopers network of firms.

The parallel with regulation comes from the identical aim of Holding companies and regulators to realise efficiency gains in separately managed business units, whilst facing classic principal-agent problems. The Holding company's underlying aim for realising cost savings within the daughter companies will be driven by optimising shareholder value. The regulator will aim for cost savings in the utilities to reduce tariffs and increase social welfare. In both cases, the Holding company and the regulator will have an information disadvantage relative to the company over the actual potential savings available. There are a number of reasons why Holding company management can draw parallels with a regulator. More positively both approaches can be seen as ways of providing clear and reasonable targets against which performance can be assessed.

First, a regulator is often forced to set tariffs without a competitive environment or competitive benchmark. This is due to the natural monopolistic nature of many network industries and the main reason why there is a regulator in the first place. The regulator therefore has to "simulate" a competitive environment and give the company an incentive to operate efficiently. This "simulation" will induce the company to behave as if it were exposed to real competition. Shleifer (1985) uses the term 'yardstick competition' to describe this phenomenon.

Second, the regulator is faced with information asymmetry. The regulator often does not know the detailed costs, operating environment, and true efficiency potential of the specific company. A firm's cost opportunities can therefore be high or low based on inherent attributes of its technical production opportunities, exogenous input cost variations over time and space, or inherent 'environmental' differences in the costs of serving locations with different attributes (e.g. urban or rural). In addition, the cost savings potential is driven by managerial effort, which can neither be observed directly nor quantified in terms of impact or quality.

Third, the regulator is not interested in directly running or managing the business, but wants to set high-level targets based on some simple input and output data and monitor results. This will allow the company to run the business, whereas the regulator sets overall targets and leaves the management of the firm autonomous. This encourages initiative taking in how targets are to be achieved against a background of strong incentives to achieve them.

Within the regulatory context (but similarly in a Holding company – daughter company relationship), the information advantage gives the company a strategic advantage. The firm will attempt to convince the regulator that the efficient costs are actually higher – due to e.g. environmental factors or other structural factors – in the belief that the regulator will then set higher prices for the services it provides or require less stringent cost savings.

A classic regulatory approach to this has been to set prices for the next period equal to *ex post* audited costs (so called 'cost-plus' regulation). The main disadvantage with this approach is that there is little incentive to realise cost savings, as these filter directly through into lower prices. Incentive-based regulation or performance-based regulation attempts to introduce dynamic incentives that involve the sharing of efficiency savings over a defined period (see Laffont and Tirole, 1993, Joskow, 2005, Jamasb and Pollitt, 2007). That is to say, the regulator sets a target for a number of years. If the company manages to beat this target, the benefits (in terms of additional profits) can be kept by the company, rather than creamed-off by the regulator. In general, the regulatory approach will involve a form of profit sharing contract or a sliding scale regulatory mechanism where the price that the regulated firm can charge is partially responsive to changes in realized costs and partially fixed *ex ante* (see Joskow, 2005) thus limiting the rate of return of the regulated entity.

The challenge faced by regulators when setting targets for the regulated companies is similar then to the challenge faced by Holding companies when setting targets for daughter companies: *What are reasonable costs and what is a reasonable target level of cost?* The regulatory approach we discuss in this paper draws on the incentive-based mechanisms that have been developed by regulators and looks specifically at regulatory benchmarking as a method to assess efficiency potential. This method includes explicit corrections for common "management excuses" such as environmental conditions or data quality.

Using the regulatory approach will allow the Holding company to "regulate" their daughter-companies and use it as an incentive revelation device and as an incentive tool for the management of these businesses. Ultimately, the targets for the companies can and indeed should be directly linked to the remuneration of company management.

In order to apply this regulatory benchmarking approach successfully within a company we have defined a number of steps that need to be taken. This approach is based on our experience with advising the holding company management of a firm owning and operating a number of utilities in the US and is a form of *interactive preference target setting* (Post and Spronk, 1999 and Thanassoulis, Portela and Despic, 2008). The focus here is on translating the analytical results into information that can be used for target setting. An essential ingredient in this process is engaging the management at the subsidiary companies that are included in the benchmarking analysis. This means creating "buy-in" into the data and methodology and allowing a number of interactive steps where the companies can challenge the results.

[here figure 1]

In Figure 1 we outline the steps a holding company or investor needs to take when applying a regulatory benchmarking approach internally for target setting. In this paper we will discuss each step and use a dataset from the US electricity sector to demonstrate our approach and the results it can generate. We use FirstEnergy as a specific example to highlight the specific application to a holding company owning several utilities.[2]

The outline of this paper is as follows: In Section 2 we discuss the structure and regulatory framework of the US electricity sector. In section 3 we briefly discuss the regulatory benchmarking approach. In Sections 4 to 8 we discuss the steps in our benchmarking approach. Finally, in Section 9 we present our conclusions.

Section 2: The US electricity sector

The US electric power sector has been dominated by regulated monopoly utilities. With the gradual introduction of more competition in the 1970s, the composition of the electricity sector has changed to include both utility and non-utility entities.[3] There are now five broad types of utilities: (i) publicly-owned utilities, (ii) investor-owned utilities, (iii) cooperatives, (iv) Federal power agencies, and (v) non-utilities.

However, the investor-owned utilities (IOUs) remain the major players in the sector accounting for 67 percent of the market measured in number of customers (this is equivalent to 94mln. customers). Retail electricity sales totalled almost \$270 billion in 2004, whereas total operating revenues of the IOUs were approximately \$387 billion. Total capitalisation of the IOUs was approximately \$963.6 billion in 2004.

After the introduction of competition in generation in the 1970s, several US states began to explore opening retail electric service to competition in the 1990s. With retail competition, customers could

[2] The example of FirstEnergy was selected due to data availability and applicability as example for our approach. The authors do not have any formal or informal relations with this company.
[3] The introduction of the Public Utility Regulatory Policies Act (PURPA) in 1978 was largely responsible for creating an independent competitive generation sector. The critics of the cost-based regulation argued that the industry structure provided limited opportunities for more efficient suppliers to expand and placed insufficient pressure on less efficient suppliers to improve their performance.

choose their electric supplier, but the delivery of electricity would still be done by the local distribution utility. The disparity in rates between different States provided an impetus to initiate their restructuring efforts.

As Joskow (1997) notes not all state commissions adopted retail competition plans. States such as California and those in New England and the mid-Atlantic region, with high electricity rates, were among the most aggressive in adopting retail competition in the hope of making lower rates available to their retail customers. According to EEI (2006) statistics, 18 States have adopted electricity restructuring, 2 States have large customer competition only, 2 States have delayed start dates, 2 States have repealed their restructuring, 1 State has suspended restructuring, and 26 States have not adopted restructuring and follow a vertically integrated utility model.

As FERC (2006) notes, the future for retail competition nationwide is unclear, especially in light of California's experience with utility restructuring and competition. State policy makers and regulators are adopting a more pragmatic approach to achieving and protecting customer benefits, which were once expected to flow almost automatically from competition.

The increased competition in generation and retail has led to massive sector restructuring. The consolidation has further been accelerated by the Energy Policy Act of 2005, which repealed the Public Utilities Holding Company Act of 1935 (PUHCA). PUHCA restricted, *inter alia*, holding companies to only acquire or merge with utilities from the same integrated system. Figure 2 demonstrates the large deal flow in the sector. A number of trends can be identified within the consolidation activity.

[here figure 2]

First, many deals have focused on the divestiture of generation assets. This divestiture was sometimes market-driven, but in some cases required by State legislation as a pre-requisite for retail competition. For example, California, Connecticut, Maine, New Hampshire, and Rhode Island enacted laws requiring utilities to divest their power plants. Between 1998 and 2001 alone over 20 percent of total installed generation capacity changed hands.[4]

Second, there has been a trend to mergers between electricity and gas companies (convergence mergers). Between 1997 and early 2000, 23 convergence mergers involving companies with assets valued at $0.5 billion or higher have been completed or are pending completion. One of the most frequently cited reasons for a convergence merger is the transferring of a gas company's experience in marketing and trading to an electric company that is relatively new in competitive markets and commodity trading. The gas industry has been deregulated since the 1980s, and over that time surviving gas companies have developed skills and experience in working in competitive energy markets. A good example of the convergence between gas and electricity was the acquisition of KeySpan (gas) by National Grid (mostly electricity in the US) at the beginning of 2006.

Third, new investors have shown an interest in the utility market. In the last few years more financial investors – in the form of infrastructure funds – have shown an interest in investing in utilities (notably the networks). In 2006 for example, Babcock & Brown Infrastructure attempted to acquire NorthWestern Energy[5], and a consortium led by Macquarie Infrastructure Partners acquired Duquesne Light Holdings. This has created a market for predominantly network companies.

Fourth, capturing scale and scope economies remains a dominant driver behind the consolidation. The introduction of more competition and increased risks associated with wholesale power markets has led companies to increase scale. The combination of resources and the elimination of redundant

[4] FERC (2006). Between 1998 and 2001 over 300 plants changed hands.
[5] This deal was not consummated due to regulatory concerns by the Montana Public Service Commission.

or overlapping activities can increase efficiency and thereby enhance the competitive position of the utility. The number of Holding companies under the IOUs has decreased dramatically due to merger activity. According to statistics from the Securities and Exchange Commission (SEC) there were 70 Holding companies in 1992, approximately 53 in 2000, and 31 in 2004.[6] FirstEnergy – the example used later in this paper - is a good example of Holding companies owning several utilities.

Section 3: The regulatory benchmarking approach

Our performance target-setting approach is derived from the incentive-based regulatory framework (Laffont and Tirole, 1993). In incentive-based regulation the company is given a pre-determined efficiency target for a set regulatory period – with associated lowered tariffs. The company has a strong incentive to reduce costs beyond the pre-determined efficiency target or to achieve the efficiency target faster than required by the regulator. The total efficiency savings are therefore shared between customers – receiving a pre-determined and guaranteed tariff reduction – and the shareholders of the company – generating additional profits by realising efficiency gains over and above the pre-determined targets. Many countries have introduced incentive-based regulation.[7] The main advantage over more traditional cost-of-service or rate-of-return regulation is the strong incentives to achieve efficiency improvements by the company.

From a technical perspective the regulatory approach we are proposing relies on sophisticated benchmarking techniques that attempt to capture the production process and can account for environmental factors that could influence underlying efficiency. From a process perspective the regulatory approach engages the benchmarked companies and provides them with a strong incentive to participate – thus increasing the acceptability and credibility of results. However the

[6] U.S. Securities and Exchange Commission Financial and Corporate Reports.
[7] See Jamasb & Pollitt (2001) for a good review.

choice of technique must also offer transparency, in terms of how results are arrived at, and consistency with the results suggested by other methods (Bauer *et al*., 1998).

In this paper we present the process by which efficiency targets for individual businesses within a given electricity holding company might be set. Our approach follows the steps defined in Figure 1 We demonstrate the effects by using a dataset of 109 investor-owned utilities (IOUs) in the US from 2003. In order to examine the efficiency we apply Data Envelopment Analysis (DEA). This technique is widely used by regulators and has particular advantages in a management context. Thanassoulis, Portela and Despic (2008) discuss the advantages of DEA for performance target setting and its use within an interactive approach. According to the authors there is a "*stong argument for the simplified interactive procedures since it increases the understanding of the efficiency evaluation procedure by non technical users and therefore facilitates organizational learning*".[8]

The results from the DEA analysis are then corrected to account for possible measurement error in the data. This is done by "stripping" the best-practice companies out of the DEA analysis and re-running the model. This will give a sense of the stability of the results. We discuss the advantages of this approach later in the paper.

Finally, the efficiency scores are corrected for environmental factors that could influence the underlying efficiency of the company, but are beyond the direct control of management. An example of such a factor is the customer mix of the utility or the connection density in the franchise area. Once these corrections have been made it is possible to assess the true efficiency potential of the companies (i.e. the endogenous controllable inefficiency). Controlling for environmental variables is important from a management perspective for a number of reasons. First, when setting targets the efficiency gains should be realistic and achievable. If there are environmental factors

[8] Thanassoulis, Portela and Despic (2008), page 376.

that are beyond the control of management, the subsidiary company could be unfairly penalised. Second, including environmental factors will allow the subsidiary company management "to defend" itself by proposing environmental factors that could negatively influence the underlying efficiency.

Inefficiency can therefore be divided into three components: (i) inefficiency due to measurement error or data quality, (ii) inefficiency attributable to environmental factors beyond management control, and (iii) endogenous inefficiency under the control of management.

As part of the analysis we also examine whether correcting for environmental factors is justified by looking at the top performing companies and their operating environment. This analysis can provide insights into whether companies manage to become best-practice even in difficult or adverse conditions.

Section 4: The dataset

The research sample covers 109 US private operating utilities (an operating unit can be part of a holding company) during 2003. The benchmarking data is public data and part of the annual data filings that are required by FERC covering both operational and capital costs, and data on number of customers, kWh's sold, and network length.[9] Additional data on environmental factors were collected from various public sources.

In order to apply the regulatory benchmarking approach we are interested in examining the efficiency of the distribution activities of the IOUs (that is to say, the non-competitive but easily comparable network part of the business). In the US this includes distribution network services and

[9] In the sector known as FERC Form-1 files.

retailing costs of the distribution company.[10] The key data we data we use is not directly collected by FERC, as most companies are integrated utilities producing, transmitting and retailing electricity. We have therefore constructed the operational and capital cost for the distribution activities using allocation keys. A full description of the data adjustments can be found in Appendix 1.

Table 1 presents descriptive statistics of the benchmarking data from FERC.

[Table 1 here]

Table 1 demonstrates that our sample contains companies with substantial differences in scale. The smallest company has just of over 8,000 customers, whereas the largest has more than 4.8 million customers. To demonstrate the approach we examine the efficiency of a group of companies owned by the FirstEnergy Corporation (FirstEnergy) in more detail.

FirstEnergy is a diversified energy company headquartered in Ohio. It owns seven electric utility operating companies that together comprise the fifth largest investor-owned electric system in the US, serving almost 5 million customers within 36,100 square miles of Ohio, Pennsylvania and New Jersey. FirstEnergy has approximately US$ 12.4 billion in annual revenues and more than US$32 billion in assets.[11] The subsidiaries FirstEnergy owns are:

- Jersey Central Power and Light (JCPL)
- Metropolitan Edison (MedEd)
- Ohio Edison (Ohio)
- Pennsylvania Electric Company (PennElec)

[10] This is in contrast to Europe, where 'distribution' refers to the network services only and incumbent companies are legally and functionally separated from retailing.
[11] See FirstEnergy's website for further details: www.firstenergycorp.com.

- Pennsylvania Power Company (PennPower)
- Cleveland Electric Illuminating Company (CEIC)
- Toledo Edison (Toledo)

In Table 2 below we give an overview of the FirstEnergy companies. Unfortunately, we do not have data for Toledo Edison. Toledo Edison is however relatively small with approximately 300,000 customers (6 percent of all FirstEnergy customers).

[here table 2]

From Table 2 it can be seen that three of the FirstEnergy companies have more than one million customers. PennPower is the smallest in the group with approximately 155,000 customers.

Section 5: Preliminary analysis and Buy-in

Once the data has been collected it is necessary to undertake some preliminary analysis. This analysis provides an initial feel of the potential results and whether the data has any outliers (in particular among the firms of interest to the holding company). In the DEA model we use later in this paper we have two cost inputs: operational costs (Opex) and total costs (Totex); and three outputs: customers, units transmitted, and network length. The DEA model combines the inputs and outputs to construct a single efficiency score. In the preliminary analysis we examine the one-dimensional efficiency by examining the following ratios:

- Opex per customer, per unit transmitted, and per network length; and
- Totex per customer, per unit transmitted, and per network length.

The company with the lowest ratio is considered best-practice and assigned an efficiency score of 100 percent. Other firms are scaled relative to this. Subsequently the other companies can be assigned an efficiency score scaled to this best-practice company. In Table 3 we provide an overview of the relative efficiency scores based on the one-dimensional ratios for FirstEnergy.

[here table 3]

The FirstEnergy companies achieve a combined customer-weighted efficiency score of 61.2 percent when examining operational costs per customer compared with 76.5 percent when examining total costs per customer. This suggests savings between 25 to 40 percent are possible for operational and total costs respectively on a per customer basis. On the per customer basis both CEIC and Ohio score very well. The scores for network length are very low and could be explained by the higher degree of urbanisation in FirstEnergy's service area. Network length is a measure of the spread of the coverage of the network.

Single ratios are a good screening device to identify any odd data. As DEA is an extended form of ratio analysis, the single factor ratios provide a sneak preview of the final DEA scores.

Once all the data has been collected and the preliminary analysis has been done it is important to create "buy-in". By buy-in we mean that the subsidiary companies being benchmarked (like the FirstEnergy companies in our example) should be involved in the analysis and become a stakeholder in the results. At this stage it is useful to organise a seminar discussing the objectives, the methodologies and the data available. The preliminary results should be shared so that any outliers or data errors can be identified.

At this point in the process the companies being benchmarked will start to think about relevant environmental factors that could explain (a part of) the inefficiency if provisionally identified in the ratio analyses.

Section 6: Analysis

The next step in the process is to extend the ratio analysis to more sophisticated benchmarking techniques that allow the combination of multiple inputs and outputs. The purpose of this type of benchmarking is to assess the performance of a decision-making unit relative to a best-practice decision-making unit. The gap can then inform the decision-making unit of the efficiency potential available and – subject to the technique used – can indicate where the inefficiencies might be located. There are two main approaches that regulatory authorities use for benchmarking: parametric and non-parametric techniques. In our analysis we have chosen to use the non-parametric approach Data Envelopment Analysis (DEA) (following Farrell, 1957, Charnes, Cooper and Rhodes, 1978, and Fare et al., 1985) as this is popular with electricity regulators (see Jamasb and Pollitt, 2001)[12] and has the advantage of being well suited to use in a corporate context.

DEA identifies an efficient frontier made up of the best-practice firms and uses this to measure the relative efficiency scores of the less efficient firms. An advantage of the method is that it does not require specification of a production or cost function.

DEA uses piecewise linear programming to calculate the efficient or best-practice frontier of a sample. The decision-making units (DMUs) or firms that make up the frontier envelop the less efficient firms. The efficiency of the firms is calculated in terms of scores on a scale of 0 to 1, with the frontier firms receiving a score of 1 (or 100 percent).

[12] For example, Norway uses the DEA in setting revenue caps for regional electricity transmission and distribution utilities.

DEA models can be output or input oriented and can be specified as constant returns to scale (CRS) or variable returns to scale (VRS). Output-oriented models maximise output for a given amount of input. Conversely, input-oriented models minimise input factors required for a given level of output. An input-oriented specification is generally regarded as the appropriate form for electricity distribution utilities as demand for their services is a derived demand that is beyond the control of utilities and that has to be met.

The linear program calculating the efficiency score of the i-th firm in a sample of N firms in CRS models takes the form specified in Equation (1) where θ is a scalar (equal to the efficiency score) and λ represents an $N \times 1$ vector of constants. Assuming that the firms use K inputs and M outputs, X and Y represent $K \times N$ input and $M \times N$ output matrices respectively. The input and output column vectors for the i-th firm are represented by x_i and y_i respectively. The equation is solved once for each firm. In VRS models a convexity constraint $\Sigma\lambda=1$ is added. This additional constraint ensures that the firm is compared against other firms with similar size.

$$
\begin{aligned}
&\min_{\theta,\lambda} \theta, \\
&s.t. \\
&-y_i + Y\lambda \geq 0, \qquad\qquad (1) \\
&\theta x_i - X\lambda \geq 0, \\
&\lambda \geq 0
\end{aligned}
$$

In equation (1) firm i is compared to a linear combination of sample firms which produce at least as much of each output as it does with the minimum possible amount of inputs. Figure 3 illustrates the main features of an input-oriented model with constant returns to scale. The figure shows three firms (G, H, R) that use two inputs (capital K, labour L) for a given output Y. The vertical and horizontal axes represent the capital and labour costs per unit of output respectively.

[Figure 3 here]

Firms G and H produce the given output with lower inputs and form the efficient frontier that envelops the less efficient firm R. The technical efficiency of firm R relative to the frontier can be calculated from OJ/OR ratio. Technical efficiency measures the ability of a firm to minimise inputs to produce a given level of output.

An important step in DEA is the choice of appropriate input and output variables. The variables should, to the extent possible, reflect the main aspects of resource-use in the activity concerned. The basic DEA model illustrated above does not impose weights on model input and output variables. However, the model can be extended to incorporate value judgements in the form of relative weight restrictions imposed on model inputs or outputs. This can be achieved by including additional constraints to the model. The aim is to control for the influence of values of individual input and outputs on the efficiency scores (see Thanassoulis, 2001).

An advantage of DEA is that inefficient firms are compared to actual firms rather than to a statistical measure. In addition, DEA does not require specification of a cost or production function. However, efficiency scores tend to be sensitive to the choice of input and output variables, and to measurement errors in the frontier firms as these comprise the best-practice frontier. The method does not allow for stochastic factors and measurement errors. Further, as more variables are included in the models, the number of firms on the frontier increases, therefore it is important to examine the sensitivity of the efficiency scores and rank order of the firms to model specification.

Using the US data we apply a standard DEA model. We use both Opex or Totex as inputs. The advantage of using Opex is that it covers those costs that are under direct control of management. In comparison Totex includes capital costs, such as depreciation and a rate of return on invested capital. We assume a standard rate of return for all assets of 6 percent. The return is calculated over the total assets in distribution. The depreciation charge is taken directly from the FERC dataset.

The main advantage of using Totex is that it captures potential trade-offs between capital and labour. For example, a network company can seem efficient when examining Opex. However, this efficiency in Opex can be offset by large capital expenses allowing for a substitution of costs.

For the outputs we use customer numbers, number of kWh transmitted, and network length. The task of a network operator is to deliver a certain amount of power to a number of customers making use of a network. Network length can be used both as an input, when it functions as a proxy for the value of the capital in the business, or as an output, when it is a proxy for the complexity of the network. In our analysis we focus on the Opex cost savings as these can be interpreted more easily than the Totex savings. Totex inefficiency could be the result of accumulated inefficiency in capital that cannot be reduced in the short-term. The Totex efficiency scores should therefore be treated with caution.

We assume constant returns to scale (CRS). The choice between variable returns to scale (VRS) and CRS depends on the degree of control a company has regarding its scale. If we assume that network companies cannot control the scale of their operations, by for example merging, then we should apply VRS. Under VRS companies are neither penalised nor rewarded for scale (dis)economies. If on the other hand, we assume that companies can control the scale of their operations, we should compare all companies on an equal scale, thus penalising those companies that are either too small or too large relative to the optimal scale. In our analysis we assume that network companies can control the scale of their operation through mergers and spreading fixed costs. We therefore use CRS.

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 (SFA).

In Table 4 we report the DEA efficiency scores for the FirstEnergy companies.

[here table 4]

The customer-weighted average Opex efficiency score is 63.7 percent for the FirstEnergy companies. The customer-weighted average Totex efficiency is score is 77.6 percent. CEIC and Ohio are best-practice companies when examining Totex efficiency. Both companies – although not best-practice – perform relatively better than the other companies when examining Opex efficiency.

Table 5 reports the Opex savings potential per FirstEnergy company.

[here table 5]

The average Opex per customer for the FirstEnergy group is US$207. Applying the raw Opex efficiency scores to the individual costs bases, we find total potential savings of US$87 per customer. The total one-off savings for FirstEnergy are US$418mln. In absolute terms JCPL has the largest potential one-off saving of US$188mln.

At this stage in the analysis, after the presentation of the raw DEA scores, it is very likely that a number of the companies in the FirstEnergy group would wish to challenge the results. Certainly the efficiency scores for JCPL and PennPower are very low and do not seem realistic and not feasible to implement. The two main challenges focus on (i) measurement error or sample selection issues, and (ii) environmental factors, that could influence underlying efficiency scores. The companies may complain that the best-practice companies are not normally best-practice or have specific or unique operating characteristics that make a direct comparison impossible. In our approach we deal with both challenges. In the next section we discuss the way to correct for environmental conditions. In this section we further discuss the issue of sample selection and measurement error.

In order to take measurement error into account we re-run the DEA analysis after removing the first layer of best-practice firms.[13] By doing this we get a sense of the sensitivity of the results. We would expect that removing the best-practice layer only marginally influences (improves) the efficiency scores of the remaining companies. If the scores change substantially then this would indicate that the initial frontier was being defined by extreme outliers. This method to assess the sensitivity of results is not as sophisticated as those approaches that rely on statistical techniques to determine the measurement error, such as SFA. In our view however, we find that our approach is to be preferred in a management setting. There are a number of reasons for this. First, it is easy to implement and does not require any statistical modelling. Second, from a process perspective the companies being benchmarked can actually see the effect of removing the first layer of best-practice companies. Being measured against "second-best" should make the results more acceptable. The main disadvantage with this approach is that it is arbitrary and could result in higher efficiency scores than the underlying data suggests. In Tables 6 we focus on the results from the peer stripping for the FirstEnergy companies.

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[13] Measurement error is assumed to be in the frontier firms not in the firms of interest, this is because the company should be able to ensure that its own data is accurate or adjusts for exceptional circumstances.

[here table 6]

On average the efficiency scores for the FirstEnergy companies do not increase substantially. The increase is on average 3.2 percentage points and 3.3 percentage points for Opex and Totex respectively. Although these changes do not seem substantial, they nevertheless have a large absolute impact on the potential one-off cost savings. If we apply the new stripped Opex scores in the calculations from Table 5 the annual Opex savings would be US$388mln. instead of US$418mln.

The "peer stripping" results show that the overall efficiency scores in our two samples do not change dramatically. This suggests that the companies in our dataset are relevant for benchmarking purposes. In the following section we include a further step in our analysis. This step involves correcting the efficiency scores for environmental factors that are beyond the direct control of management. The analysis is performed on the full dataset without applying the peer stripping. In the final results we also include an upward correction for the peer stripping.

Section 7: Environmental factors

DEA can also control for the effect of environmental variables that are beyond the control of the management of firms but affect their performance. There are five main approaches to include and correct for environmental factors (see Yang and Pollitt, 2008). These five approaches are: (i) a separation approach, (ii) one stage (or direct inclusion) approach, (iii) two-stage, (iv) three-stage, and (v) four-stage regression based methods.

The separation approach divides the dataset into comparable sub-samples with similar environmental conditions. This approach does not handle continuous environmental variables well and reduces the size of the sub-samples to unacceptable low levels in most circumstances.

Banker and Morey (1986a, b) consider all inputs, outputs and environmental factors together, but optimise only on the basis of inputs and outputs (one-stage) – this is the direct inclusion approach.[14] The aim is to limit the field of comparison to only those DMUs subject to equal or worse environmental conditions. Although this approach is relatively easy to use, it has a number of drawbacks. First, the influence of each environmental factor must be known *a priori* in order to determine its orientation on the optimisation. Second, DMUs in worse conditions are by definition assumed to be efficient. Third, as the number of environmental factors increase, so will the number of DMUs considered efficient.

The two-stage approach was pioneered by Timmer (1971). In this approach the efficiency scores from the DEA are regressed against a set of environmental factors to test whether there is a statistically significant relationship between an environmental factor and the relative efficiency score. As the relative efficiency scores are truncated – they cannot be greater than 1 – a Tobit regression is required. The main advantage of this approach is that it allows for a sequential correction in the relative efficiency scores – thus giving the management of a benchmarked company the opportunity to respond to their specific score by highlighting particular environmental factors. The main drawback with this approach is that although the efficiency scores are corrected for environmental factors, there remain possible stochastic elements which could influence the relative position of a DMU.

In a recent paper by Simar and Wilson (2007) the authors demonstrate that a number of statistical problems arise when using a two-stage approach with Tobit regressions in the second stage. They note that none of the published studies examined have defined a Data Generating Process (DGP) that might be estimated. Using Monte Carlo experiments Simar and Wilson demonstrate that coverage of estimated confidence intervals is poor. They propose a double bootstrap procedure to overcome these problems.

[14] For a discussion of the single-stage approach see Adolphsen (1991).

In the three-stage approach the DEA results are corrected for environmental influences and stochastic elements.[15] In the first step a DEA analysis is performed. The total slacks from the DEA (radial plus non-radial) contain (i) environmental influences, (ii) managerial inefficiency, and (iii) statistical noise arising from measurement errors in the data. In the second step these slacks are decomposed into the three components using Stochastic Frontier Analysis (SFA).[16] The advantage of using SFA rather than the Tobit approach is that the error term is asymmetric, allowing for the decomposition of the inefficiency. The results from the SFA are then used to adjust the input or output data purging the effect of environmental factors and measurement error. In the third step the DEA analysis is re-applied using this corrected data.

A four-stage model was introduced by Fried *et al*. (1999) to measure the impact of uncontrollable variables on DMU efficiency. In the first step, a standard DEA is constructed using traditional inputs and outputs. In the second step, total input slacks (radial plus non-radial) are regressed using Tobit against selected uncontrollable variables. In the third step, parameters estimated in the second stage are used to estimate allowable input slacks. Then the values of primary inputs are adjusted accordingly. In the fourth step, the DEA is repeated using the adjusted input values. This model is similar to the three stage model, but less sophisticated because it does not adjust for statistical noise (see Yang and Pollitt, 2008, for details of these potential approaches to environmental variables).

In this paper we apply the two-stage Tobit approach and have collected a number of environmental factors that could influence the relative performance of an IOU. Although this method has been criticised as noted above, Yang and Pollitt (2008) find a high correlation between the scores arising from the two stage method and the preferred three stage method for their sample, suggesting that the choice of method may not be that important. The main advantages of this approach are that is a

[15] See Fried *et al.* (2002) for a discussion of this approach.
[16] See Aigner *et al.* (1977) and Meeusen & Van Den Broeck (1977).

proven method to examine the impact of environmental factors and that it is relatively easy to visualise and describe to company management. Table 7 presents descriptive statistics for the environmental data.

[Table 7 here]

Wage

We have collected average wage levels per State in the power sector. *A priori* there is no clear causal relationship between wage levels and efficiency. A company can be a price-taker and thus not directly control wages. This might reduce its efficiency levels if wage levels are substantially higher than average. However, it could extract more production from its labour force or switch to more capital intensive production. Higher wages may be reflecting higher quality labour or encourage capital-labour substitution.

Climate

We have collected data on the number of heating degree days (HDD) by State.[17] We have collected two types of HDD information. We have collected the HDD in 2003 weighted by population. This gives weight to those HDD's that are in populous areas. In addition, we have collected the 30 year simple State average. We have also collected data on average 3-day maximum snowfall. We have not collected cooling degree days, which similar to HDD, measures the occasions when cooling (via air-conditioning) may be required.

[17] Degree day is a quantitative index demonstrated to reflect demand for energy to heat or cool houses and businesses. This index is derived from daily temperature observations at nearly 200 major weather stations in the contiguous United States. The "heating year" during which heating degree days are accumulated extends from July 1st to June 30th and the "cooling year" during which cooling degree data are accumulated extends from January 1st to December 31st. A mean daily temperature (average of the daily maximum and minimum temperatures) of 65°F is the base for both heating and cooling degree day computations. Heating degree days are summations of negative differences between the mean daily temperature and the 65°F base; cooling degree days are summations of positive differences from the same base. For example, cooling degree days for a station with daily mean temperatures during a seven-day period of 67,65,70,74,78,65 and 68, are 2,0,5,9,13,0,and 3, for a total for the week of 32 cooling degree days.

Climatic conditions are often cited to explain differences in distribution performance. Differences in average temperatures can influence the demand on the network. For example, in cold periods demand for electricity may be greater due to e.g. heating. This increases network throughput and results in higher average consumption per connection – although the direct costs associated with the network will not necessarily increase. Alternatively, in hotter regions demand for electricity may be greater due to e.g. air conditioning. This would also increase network throughput and result in higher average consumption per connection.

Climatic conditions can also directly impact operational and capital costs. From a maintenance perspective it is likely to be more difficult to manage the network in an area with a lot of snowfall. Snowfall may also require greater capital expenditures, in the form of using more underground cables than overhead wires. The equivalent underground cable is approximately seven times more expensive than an overhead wire. This additional capital outlay reduces subsequent operational costs as underground cables require less maintenance and are not subject to outages as frequently.

Ideally, we would like to measure the variation in weather conditions rather than the absolute number of warm days or inches of snowfall. It seems plausible that companies facing extreme variations in climate, such as storms, may require greater operational and capital costs than those companies operating in warm or cold conditions that are in a sense predictable. Unfortunately, we have not been able to identify a variable that captures this variation in a single measure.

Customer mix

We have constructed a customer mix variable. This variable expresses the percentage of volume transported to industrial customers relative to total distribution.

A priori we expect that companies with more industrial consumers will be more efficient than those companies delivering power to predominantly residential consumers. This is due to the economies of volume density in distribution as a result of low marginal costs relative to fixed costs. In addition, the demand profile of an industrial customer is likely to be more stable over time than a household, thus ensuring that the network is more optimally used when there are more industrial customers.

Age

We have constructed a variable to capture the approximate age of the network. This variable is calculated by dividing the cumulative depreciation by the annual depreciation charge. This gives an indication of the number of years the network has been in use.

A priori the causality between age of assets and efficiency is not clear. Older assets result in lower capital costs. At the same time there is a potential trade-off with operating costs that may be higher for older assets.

Vertical integration

Energy companies have traditionally been involved in all or parts of the value chain (production, transmission, distribution, and retail). Reasons for vertical integration may be, *inter alia*, historic, strategic, or economic. A company may choose for vertical integration to offset or mitigate regulatory uncertainty or to use vertical integration to reduce transaction costs and realise economies of scope.

Delmas and Tokat (2003) find evidence that vertical integration affects the performance of IOUs. They find a U-shaped relationship where firms that are either 0 percent or 100 percent vertically integrated perform better than hybrid firms.

We expect that vertical integration could be an explanatory factor when comparing operational cost or total cost efficiency of the distribution activities. As production and distribution of electricity are not directly related businesses we expect *a priori* that the degree of vertical integration will have a neutral or negative effect on the relative performance of IOUs.

We define the degree of vertical integration as the percentage of power generated by the company relative to the total purchased power plus own generation of power. Companies with a low percentage acquire most of their power from the wholesale market.

Connection density

As the number of connections per square kilometer or network length increases it is likely that average costs will fall. This is due to positive economies of density. The network investment is relatively fixed and more connections will thus increase the load factor (similar to seats being filled on an airplane). The fixed capital outlay is spread over a number of connections. However, at a certain degree of connection density there may be increasing costs. For example, network companies operating in highly dense cities may experience increased costs due to increasingly difficult circumstances to work in (digging up busy streets for example), may experience higher costs (for example higher wage costs), or may need to increase system reinforcements beyond what might be considered normal, to ensure reliability as the economic damage of an outage is larger in densely populated area.

Most of the empirical literature on this environmental factor finds a negative relationship between connection density and efficiency[18]. In addition studies by Gulli (2000), Filippini and Wild (2001), and Filippini *et al*. (2001) find some evidence of a non-linear relationship between connection density and cost efficiency.

[18] See for example, Roberts (1986), Nelson, & Primeaux (1998), Kwoka (2005), Salvanes & Tjoota (1994), Scarsi, (1999), Gulli (2000), Folloni & Caldera (2001), Filippini & Hrovatin (2002), Filippini & Wild (2001), Filippini, Wild & Kuenzle (2001), Estache, Rossi & Ruzzier (2002), Hirschhausen & Kappeler (2004), and Growitsch, Jamasb & Pollitt (2005).

In our benchmarking model we have included network length as an output. This means that those companies with relatively large networks (i.e. companies with low connection density) will perform relatively better. In this way, we account for connection density.[19]

Overhead cable percentage

In the US a large part of the distribution network is overhead. Overhead cables are likely to require more operational maintenance than underground cables. This is due to storm damage for example. Therefore, we expect that a higher percentage of overhead cables could negatively influence the operational cost efficiency of a network company. However, underground cables are generally more expensive than overhead cables. A high percentage of underground cables could therefore positively influence operational cost efficiency, but nevertheless negatively influence the total cost efficiency (where we include capital costs). *A priori* it is difficult to identify which effect is stronger.

Visual inspection of scatterplots between the relative efficiency scores and the environmental factors can provide a useful indication whether the variable is likely to be significant. In Figure 4 we demonstrate the scatterplots for the Opex efficiency score against the eight environmental factors.

[here Figure 4]

From Figure 4 a number of observations can be made. There seems to be a strong negative relationship between the wage level and relative efficiency. In other words, utilities with high wage costs are less efficient than those companies with lower wage costs. There is no clear relationship between HDD and the efficiency scores. However, the snowfall variable looks negatively

[19] An alternative approach is to exclude network length from the benchmarking and include a connection density variable in the environmental analysis.

correlated with the efficiency scores. More snowfall seems to reduce relative efficiency. As expected there is a positive relationship between customer mix and efficiency scores.

The average age of assets and the percentage of network overhead do not seem correlated with the efficiency scores. The degree of vertical integration and the percentage of total costs that are operational costs both seem strongly related to the efficiency scores. There is a positive relationship between the degree of vertical integration and efficiency scores.

Our Tobit model is specified as follows:

$$Tobit(efficiencyscore_i) = \alpha + \beta_1(wage_i) + \beta_2(HDD_i) + \beta_3(HHDpop_i) + \beta_4(snow_i) + \beta_5(custmix_i) + \beta_6(age_i) + \beta_7(vert\,\mathrm{int}_i) + \beta_8(overhead\%_i)$$

In the analysis we remove any statistically insignificant variables (at a 10 percent confidence interval). This reduces the number of regressors and increases their statistical significance. This approach may overstate the relationship, but this works in favour of apparently underperforming companies in the benchmarking dataset. In Tables 8, 9 we report the results from the Tobit regressions.

[here tables 8, 9]

Wage has a significant negative impact on the Opex efficiency score. In the Totex benchmark, wage is not statistically significant. It is likely that the impact of wage differences is dampened when examining the relative efficiency of total costs.

Customer mix has a significant positive impact on both the Opex and Totex relative efficiency scores. This implies that companies with a larger percentage of industrial customers are relatively more efficient than those companies with more retail customers. The coefficients are of similar magnitude.

Vertical integration has a significant positive impact on both the Opex and Totex relative efficiency scores. Therefore, companies that are part of an integrated utility with generation facilities are relatively more efficient that those companies that rely on purchasing power on the market.

A priori we expected more variables to be significant drivers of efficiency. Notably climatic conditions are often cited as causes for efficiency differences. In our analysis the factors for climatic conditions, however do not seem to be explanatory factors for differences in relative efficiency when combined with the other effects.

In order to correct the relative efficiency scores we want to compare all the companies under the same environmental circumstances. We therefore correct the score to take into account the impact of, for instance, higher or lower wages on the performance of the company. The correction we make is comparing the companies under sample average environmental conditions. In figure 5 we demonstrate this process. This process of adjusting for environmental factors is potentially favourable to operating units because the estimated relationship may be spurious.

[here figure 5]

In Figure 5 there is a negative relationship between the environmental factor and the relative efficiency score. The environmental factor in this example has a negative impact on efficiency. Therefore, those companies with higher than average exposure to this environmental factor look more inefficient than companies with lower than average exposure. In order to compare the companies under the same environmental conditions we correct the relative efficiency scores by scaling them back to the average. This scaling is done by multiplying the coefficient of the relationship with the distance from the average for the particular environmental factor. In the case of company A, the higher than average environmental factor partly explains the relative inefficiency. Correcting company A back to the average therefore increases the relative efficiency score upwards. In other words, were company A to operate under average environmental conditions, the relative efficiency score would be higher. The opposite is the case for company B. The more favourable conditions in part explain the relatively higher efficiency score. In order to compare the companies on an equal basis, the relative efficiency score is lowered for company B.

In Table 10 we examine the results for the FirstEnergy companies in more detail.

[here table 10]

The customer-weighted average efficiency score increases for FirstEnergy with 3.7 percentage points for Opex benchmarking and 6.7 percentage points for Totex benchmarking. The Opex relative efficiency of FirstEnergy is therefore 67.3 percent after correcting for unfavourable environmental conditions. These increases in the scores have a large absolute impact on the potential one-off cost savings. If we apply the new environmentally corrected Opex scores in the calculations from Table 5 the Opex savings would be US$367mln. instead of US$418mln.

Section 8: Overall results and Detailed analysis

At this stage of the process the final scores are calculated. Here we include the correction for measurement error (based on the peer stripping approach) and the environmental factors. The addition of these two corrections is not theoretically correct, but allows an explicit and understandable correction to the scores for measurement error – or rather compares the companies with second-best instead of first-best. The completion of this stage involves agreement that certain environmental variables are significant and should be corrected for. As we have seen this would be justified on the basis of empirical evidence. For some companies the upward adjustment of the relative efficiency score results in a final adjusted score that exceeds 100 percent. For the purposes of such a benchmarking exercise we would limit the scores to 100 percent.

In Table 11 we report the overall results for FirstEnergy.

[here table 11]

The customer-weighted average score for FirstEnergy is substantially higher with the environmental and second-best correction combined. FirstEnergy is 70.5 percent efficient and 87.5 percent efficient in terms of Opex and Totex costs respectively. This is a 6.9 percentage point and 11.6 percentage point increase respectively. The environmental correction is the main driver behind these increases.

The total Opex cost base for FirstEnergy is just over US$1 bln. Based on the raw efficiency analysis a total saving of US$418mln would be possible (see Table 12). Taking a comparison with second best into account (by frontier stripping) reduces this figure by US$30mln. Including a correction for non-average environmental conditions – in the case of FirstEnergy negative environmental conditions – reduces the headline figure by a further US$51mln. This leaves a total possible Opex saving for FirstEnergy of US$337mln. This is equivalent to 81 percent of the starting figure. Penn Electric has benefited most from the corrections. After correcting for measurement error and environment only 69 percent of the original possible saving remains.

[here table 12]

Once the results have been corrected for both measurement error and environmental factors, pure inefficiency attributable to management remains. The implementation of the potential savings is usually left to the company, rather than to the Holding company. The actual identification of how the savings might be achieved will require further and more detailed analysis of the processes within the company. This requires process benchmarking. One possible approach is to share information on such processes with other companies in the group or to approach the best-practice peer companies to learn from their approach.

Section 9: Discussion and conclusions

Consolidation of separate companies by a Holding company or larger company will only be fully successful if all the potential value is realised through efficiency savings. The identification of these potential savings poses a problem for Holding company management due to information asymmetry. The application of regulatory benchmarking techniques where national or regional data is available can overcome this information deficit.

In the benchmarking two aspects are important. First, the companies being benchmarked should be included in the benchmarking process. In other words, the benchmarking exercise needs to take into account their input and their views. This will create "buy-in" into the process and using our approach will create "lock-in". That is to say, once the benchmarking process is started, an efficiency target will eventually be set. Second, any identified inefficiency should be corrected for possible noise in the data, such as measurement error, and corrected for environmental factors. Both these factors are exogenous to company management and thus beyond their direct control. Allowing the company to propose the environmental factors that should be examined will increase their commitment to the final results. We have suggested a management friendly approach that draws on the literature on and practical experience of benchmarking by regulators.

In our example of FirstEnergy, we demonstrate that both the measurement error correction as well as correcting for environmental factors can substantially influence the identified inefficiency. The correction for measurement error is US$30 mln., which is equivalent to a 7 percent reduction in the headline US$418 mln. operational cost saving. The correction for unfavourable environmental conditions is even more substantial. The correction for environmental factors is US$51 mln., which is equivalent to a 12 percent reduction in the headline operational cost saving.

In our approach to correcting for measurement error we have “stripped” away the first layer of best-practice companies. Although this method is rather crude, it is appealing because it can demonstrate the stability of the DEA results and can help “sell” the results by stating that the companies will only be compared to second-best instead of first-best. As part of the benchmarking exercise it will be important to carefully choose a relevant peer group of companies and ensure that the data is consistent and reliable. This will increase the credibility of the outcome.

Environmental factors are usually brought forward by company management as significant cost drivers. In our example, many of the *a priori* environmental factors were not statistically significant and could therefore not explain the observed inefficiency. The question remains whether those statistically significant environmental factors can ultimately justify a higher cost base relative to other companies in different conditions.

As part of our analysis we also examined the environmental conditions of the top 25 performers, i.e. those 25 companies with the highest relative efficiency scores. The difference between the maximum and minimum of the environmental factor gives a sense of the spectrum across which the companies operate. *A priori* one would expect that the top 25 companies will have a narrower range of environmental conditions. That is to say, the environmental conditions will be more similar than for the total sample. In Table 13. we summarise the range of environmental factors faced by the top 25 performers and the total sample, whereas Figure 5 shows the scatterplots for the Opex efficiency scores against the eight environmental factors.

[Here Table 13]

[Here figure 5]

Table 13 demonstrates that the top 25 performing companies in our sample operate across an equally broad range of environmental conditions as for the total sample. The major difference seems to be the lower density of the top 25 performers (in terms of connections per line length, per service area and units transmitted per line length). This suggests that companies in unfavourable conditions can become best-practice, as opposed to viewing an environmental condition as exogenous. This suggests that, if anything, our environmental corrections (for underperforming units) are generous since they are based on average performance.

In our analysis we examined both operational and total cost efficiency. The benchmarking of total costs (i.e. including capital costs) avoids any potential capital-labour trade-off. The results differ substantially and suggest that examining only operational costs could influence the results. However, including capital costs in benchmarking is difficult due to a number of reasons. First, determining the appropriate stock of capital is difficult because of different accounting treatments between companies and because of technology or vintage differences. This implies that creating a consistent and comparable dataset for capital is laborious and time consuming. Second, determining an appropriate charge for the capital stock is not easy. This can be overcome by calculating the appropriate return required by the market. Third, the interpretation of the efficiency scores is not straightforward. The dollar savings need to be translated into real cash savings as removing part of the capital stock is not feasible. In our view the focus for Holding companies should be on operational cost savings. However some savings in actual capital expenditure may be possible if the Capex part of Totex is too high (see Jamasb and Pollitt, 2003, on the use of actual Capex in benchmarking). The influence of capital on operating costs has been included through some of the environmental factors, such as the age and the mix of customers (and hence assets).

This paper demonstrates that regulatory benchmarking can also be applied within a management setting and should not only be left to regulators. The similarity between a Holding company setting targets for daughter-companies and a regulator setting targets for regulated utilities under information asymmetry is strong. The approach we have demonstrated can be applied in any sector where there is good data available. Until now this approach has received little attention and has not been widely applied (certainly not in the utility sector), whereas the potential to assist Holding company managers in extracting operational efficiencies is large in our view as our particular example demonstrates.

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Figure 1: A suggested approach to benchmarking

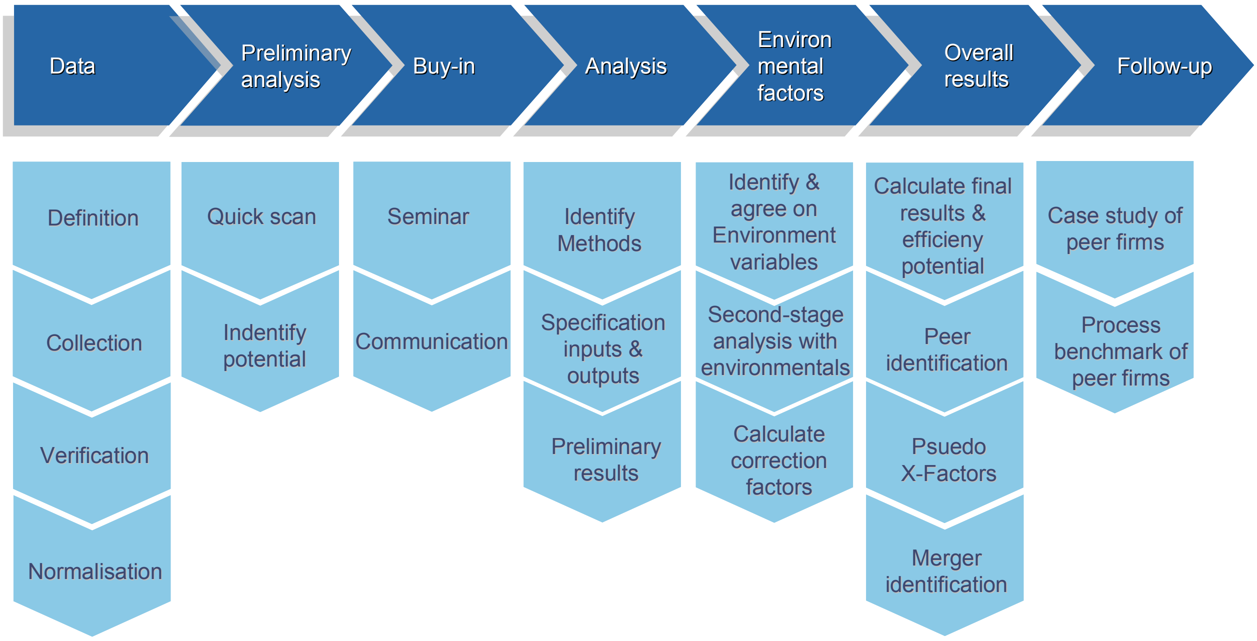
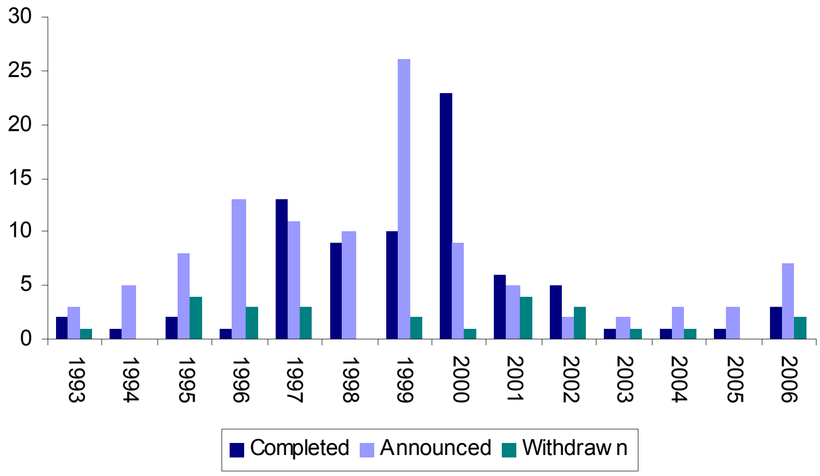


Figure 2: overview of number of M&A deals involving IOUs



Source: EEI (2006)

Figure 3: Data envelopment analysis

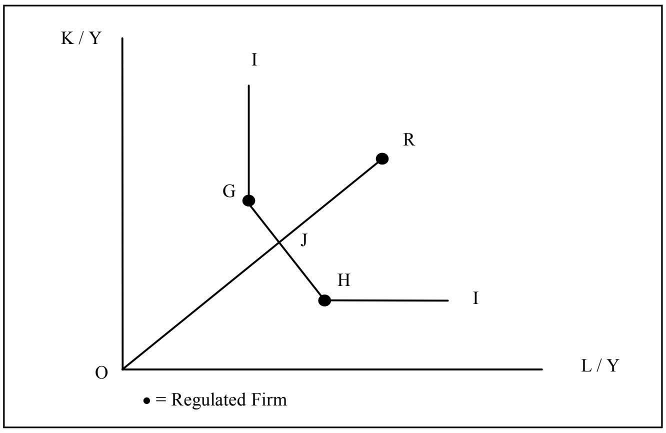


Figure 4: Scatterplots Opex efficiency score (Y-axis) against environmental factors (X-axis) Total sample

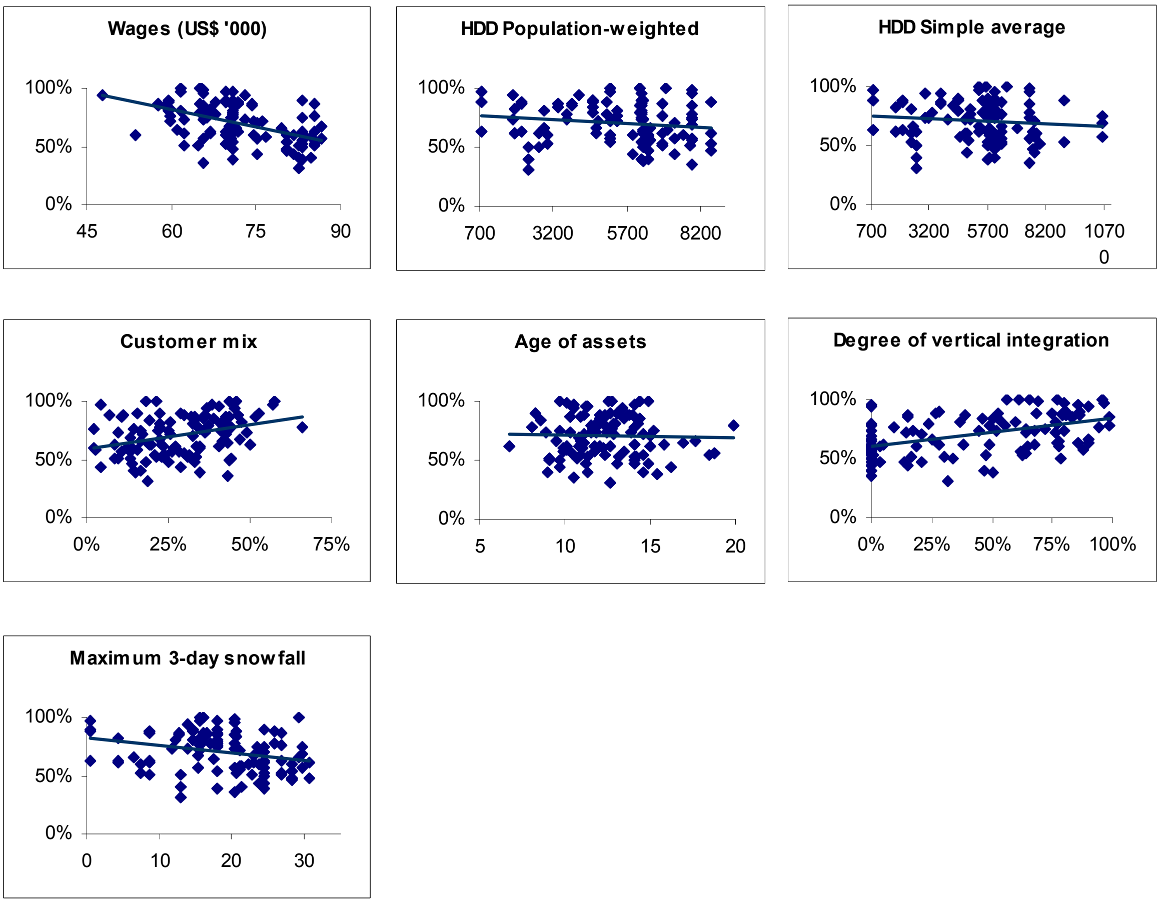


Figure 5: Environmental factor correction

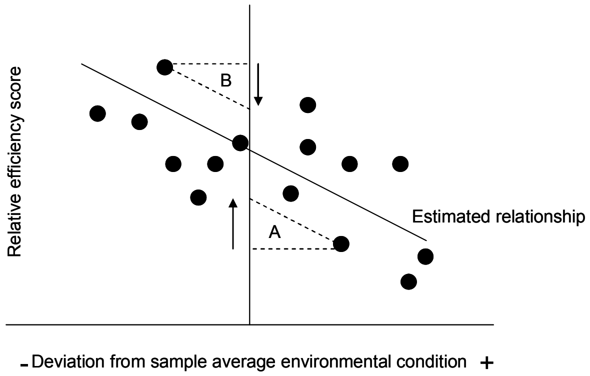


Figure 6: Scatterplots Opex efficiency score against environmental factors Top 25 companies

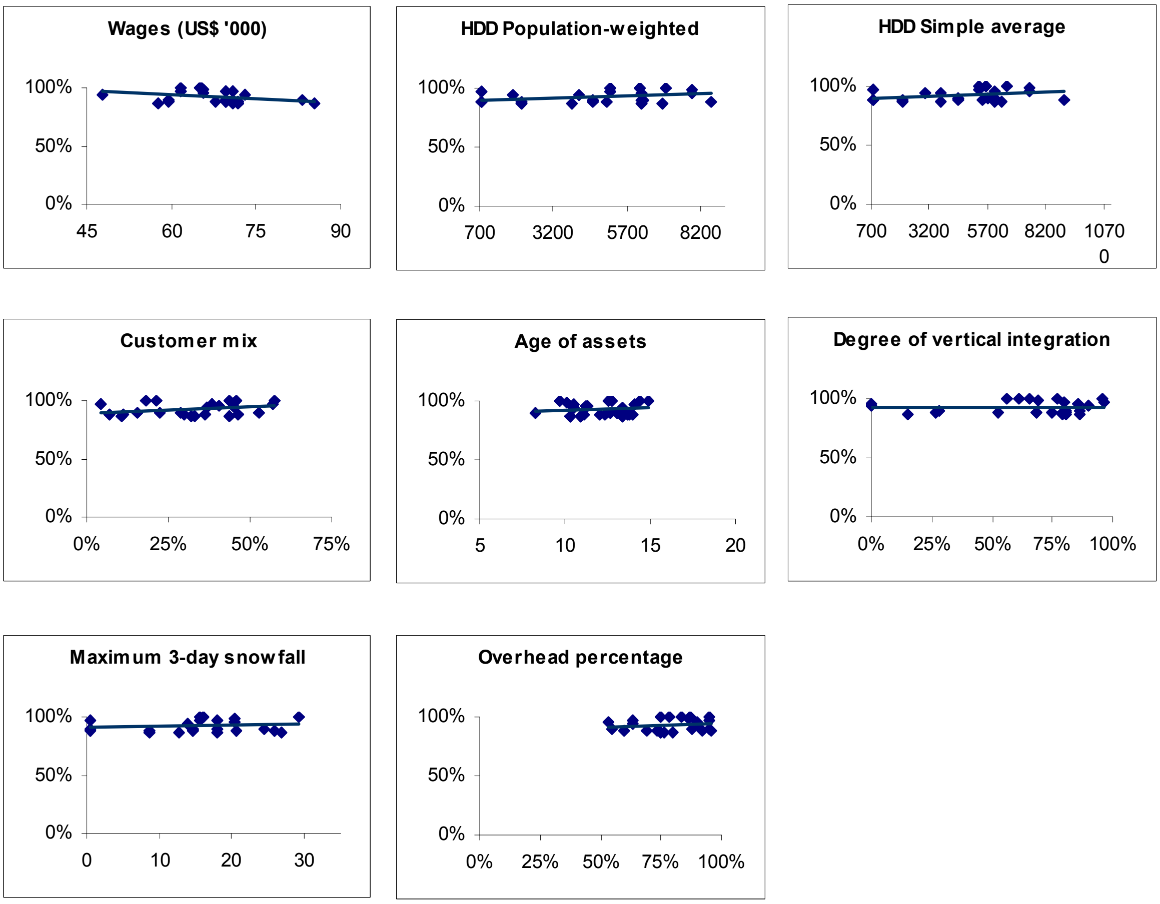


Table 1: Descriptive statistics Total sample benchmarking dataset

		Total		
Variable	Unit	Mean	Min	Max
Opex	US$	145,795,930	2,375,449	1,007,519,597
Totex	US$	282,540,145	3,365,055	1,960,446,867
Customer numbers	#	763,553	8,631	4,862,430
Units transmitted	MWh	18,715,631	154,470	98,913,912
Network length	km	21,214	296	122,670
Sample size		109		

Table 2: Overview of firstenergy companies

Company	Opex (US$)	Totex (US$)	Customer numbers (#)	Units transmitted (MWh)	Network length (km)
Cleveland Electric Illuminating Co.	178,435,938	274,437,779	1,220,543	26,504,398	24,214
Jersey Central Power & Light Co.	309,470,174	492,902,045	1,044,024	20,770,050	17,764
Metropolitan Edison Co.	119,265,233	210,664,182	512,290	12,981,565	14,434
Ohio Edison Co.	204,378,504	296,995,408	1,315,861	32,313,405	27,750
Pennsylvania Electric Co.	137,582,462	247,105,283	583,136	13,356,649	20,258
Pennsylvania Power Co.	53,171,590	71,205,948	155,361	4,252,233	5,232
FE Total	1,002,303,900	1,593,310,644	4,831,215	110,178,300	109,652

Table 3: FirstEnergy input-output ratio results

	Opex			Totex		
Company	per customer	per kWh	per network	per customer	per kWh	per network
Cleveland Electric Illuminating Co.	79.3%	58.0%	30.0%	100.0%	70.9%	37.7%
Jersey Central Power & Light Co.	39.1%	26.2%	12.7%	47.6%	30.9%	15.4%
Metropolitan Edison Co.	49.8%	42.5%	26.8%	54.7%	45.2%	29.3%
Ohio Edison Co.	74.7%	61.8%	30.0%	99.6%	79.9%	39.9%
Pennsylvania Electric Co.	49.2%	37.9%	32.6%	53.1%	39.7%	35.0%
Pennsylvania Power Co.	33.9%	31.2%	21.8%	49.1%	43.8%	31.4%
FE Customer-weighted average	61.2%	47.2%	26.0%	76.5%	57.4%	32.1%

Table 4: Results raw efficiency scores FirstEnergy companies

Company	Opex efficiency	Totex efficiency
Cleveland Electric Illuminating Co.	80.6%	100.0%
Jersey Central Power & Light Co.	39.3%	47.6%
Metropolitan Edison Co.	54.0%	57.6%
Ohio Edison Co.	78.9%	100.0%
Pennsylvania Electric Co.	52.8%	57.2%
Pennsylvania Power Co.	38.1%	54.9%
FE Customer-weighted average	63.7%	77.6%

Table 5: FirstEnergy potential Opex savings (raw efficiency scores)

Company	Opex (US$)	Opex efficiency score	Potential opex saving
Cleveland Electric Illuminating Co.	178,435,938	80.6%	34,598,728
Jersey Central Power & Light Co.	309,470,174	39.3%	187,848,396
Metropolitan Edison Co.	119,265,233	54.0%	54,885,860
Ohio Edison Co.	204,378,504	78.9%	43,226,054
Pennsylvania Electric Co.	137,582,462	52.8%	64,952,680
Pennsylvania Power Co.	53,171,590	38.1%	32,929,166
FE Total	1,002,303,900		418,440,884
Per customer	207		87

Table 6: FirstEnergy Raw versus Stripped scores

Company	Raw		Stripped		Difference	
	Opex efficiency	Totex efficiency	Opex efficiency	Totex efficiency	Opex	Totex
Cleveland Electric Illuminating Co.	80.6%	100.0%	85.7%	100.0%	5.1%	0.0%
Jersey Central Power & Light Co.	39.3%	47.6%	42.0%	54.9%	2.7%	7.3%
Metropolitan Edison Co.	54.0%	57.6%	56.2%	64.6%	2.2%	7.0%
Ohio Edison Co.	78.9%	100.0%	81.7%	100.0%	2.9%	0.0%
Pennsylvania Electric Co.	52.8%	57.2%	54.8%	64.0%	2.0%	6.7%
Pennsylvania Power Co.	38.1%	54.9%	40.2%	58.9%	2.1%	4.1%
FE Customer-weighted average	63.7%	77.6%	66.9%	80.8%	3.2%	3.3%

Table 7: Desctiptive statistics environmental variables

Variable	Unit	Total Mean	Min	Max
Wages	US$ '000	71,544	47,897	86,676
Heating Degree Days (HDD) (population weighted)	#	5,385	768	8,550
HDD (simple 30-year average)	#	5,292	785	10,632
Customer mix (industrial units versus total)	%	28%	2%	66%
Age of assets	years	12	7	20
Degree of vertical integration	%	43%	0%	98%
Connection density (# connections per km network)	#	39	14	124
Connection density (# connections per service area)	#	121	3	2,573
Load density (units transmitted per km network)	#	1,000	248	3,158
Snowfall (average 3-day maximum)	inches	19	1	31
Percentage overhead network	%	75%	25%	100%

Table 8: Tobit regression Opex

COEFFICIENT	
Wage	-0.00644***
	(0.00192)
Customer mix	0.248***
	(0.106)
Vertical Integration	0.149***
	(0.0479)
Constant	1.032***
	(0.156)
Observations	109
Uncensored observations	104
right-censored observations	5

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Tobit regression Totex

COEFFICIENT	
Customer mix	0.345***
	(0.101)
Vertical Integration	0.119***
	(0.0413)
Constant	0.583***
	(0.0328)
Observations	109
Uncensored observations	100
right-censored observations	9

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: FirstEnergy Raw versus Environmental correction

	Raw		Environment correction		Difference	
Company	Opex efficiency	Totex efficiency	Opex efficiency	Totex efficiency	Opex	Totex
Cleveland Electric Illuminating Co.	80.6%	100.0%	77.9%	*100.0%*	-2.7%	0.0%
Jersey Central Power & Light Co.	39.3%	47.6%	48.7%	64.1%	9.4%	16.5%
Metropolitan Edison Co.	54.0%	57.6%	59.3%	72.2%	5.3%	14.6%
Ohio Edison Co.	78.9%	100.0%	79.1%	*100.0%*	0.2%	0.0%
Pennsylvania Electric Co.	52.8%	57.2%	65.5%	71.3%	12.7%	14.0%
Pennsylvania Power Co.	38.1%	54.9%	43.1%	51.7%	5.0%	-3.2%
Customer-weighted average	63.7%	77.6%	67.3%	84.3%	3.7%	6.7%

** the scores for CEIC and Ohio are set to 100% in totex with environmental correction. These would otherwise exceed 100%.*

Table 11: FirstEnergy companies overall results

Company	Opex				Totex			
	Raw score	Measurement correction	Environmental correction	New score	Raw score	Measurement correction	Environmental correction	New score
Cleveland Electric Illuminating Co.	80.6%	5.1%	-2.7%	83.1%	100.0%	0.0%	0.6%	*100.0%*
Jersey Central Power & Light Co.	39.3%	2.7%	9.4%	51.4%	47.6%	7.3%	16.5%	71.4%
Metropolitan Edison Co.	54.0%	2.2%	5.3%	61.5%	57.6%	7.0%	14.6%	79.2%
Ohio Edison Co.	78.9%	2.9%	0.2%	82.0%	100.0%	0.0%	5.6%	*100.0%*
Pennsylvania Electric Co.	52.8%	2.0%	12.7%	67.5%	57.2%	6.7%	14.0%	78.0%
Pennsylvania Power Co.	38.1%	2.1%	5.0%	45.2%	54.9%	4.1%	-3.2%	55.7%
Customer-weighted average	**63.7%**	3.2%	3.7%	**70.5%**	**77.6%**	3.3%	8.4%	**87.5%**

** the scores for CEIC and Ohio are set to 100% in totex with environmental correction. These would otherwise exceed 100%.*

Table 12: FirstEnergy companies opex savings

Company	Actual Opex	Reduction based on raw results	Correction for measurement error	Correction for environmental factors	Final possible cost reduction	Final as % of raw
Cleveland Electric Illuminating Co.	178,435,938	- 34,598,728	9,135,920	- 4,774,642	- 30,237,450	*87%*
Jersey Central Power & Light Co.	309,470,174	- 187,848,396	8,417,589	29,002,400	- 150,428,407	*80%*
Metropolitan Edison Co.	119,265,233	- 54,885,860	2,635,762	6,295,197	- 45,954,901	*84%*
Ohio Edison Co.	204,378,504	- 43,226,054	5,906,539	481,264	- 36,838,251	*85%*
Pennsylvania Electric Co.	137,582,462	- 64,952,680	2,792,924	17,492,926	- 44,666,830	*69%*
Pennsylvania Power Co.	53,171,590	- 32,929,166	1,116,603	2,675,080	- 29,137,483	*88%*
Total	1,002,303,900	- 418,440,884	30,005,337	51,172,225	- 337,263,322	*81%*

Table 13: Difference maximum and minimum environmental conditions top 25 versus Total sample (Opex)

	Top 25		Total	
Environmental factor	Min	Max	Min	Max
Wage ('000$)	48	85	48	87
HDD POP	768	8,550	768	8,550
HDD Simple	785	8,998	785	10,632
Customer mix	4%	57%	2%	66%
Age (years)	8	15	7	20
Vertical integration	0%	96%	0%	98%
Connection density (#/line)	14	64	14	124
Connection density (#/area)	13	353	3	2,573
Load density (kWh/line)	277	1,673	248	3,158
Snowfall	1	29	1	31
Overhead percentage	53%	96%	25%	100%

Difference between maximum and minimum
Bold indicates statistically significant in total sample

Appendix 1

In Table A1. we provide an overview of all the data that was collected and the sources that were used. The label column is used in this appendix to "road-map" the calculation of a number of variables we use in our analysis.

Variable	Description	Source	Constructed	Label
Wages production	Wages in production	FERC 354/18		1
Wages transmission	Wages in transmission	FERC 354/19		2
Wages distribution	Wages in distribution	FERC 354/20		3
Wages customer accounts	Wages in customer accounts	FERC 354/21		4
Wages customer information	Wages in customer info	FERC 354/22		5
Wages sales	Wages in sales	FERC 354/23		6
Wages administrative & general	Wages in administration & general	FERC 453/24		7
Distribution allocation key	Percentage allocated to distribution activity		Y	8
Distribution opex	Distribution opex	FERC 322/126		9
Administrative & general operations	Administrative and general operations opex	FERC 323/165		10
Administrative & general maintenance	Administrative and general maintenance opex	FERC 323/167		11
Regulatory costs	Regulatory costs	FERC 323/160		12
Customer account total	Total customer account expenses	FERC 322/134		13
Customer service information total	Total service and information expenses	FERC 322/141		14
Customer information total (demand side management)	Customer information (demand side management) expenses	FERC 322/138		15
Customer service information less customer information	Total service and information excl customer information expenses		Y	16
Sales expenses Total	Total sales expenses	FERC 322/148		17
Pension & benefits	Pensions & benefits costs	FERC 323/158		18
Initial value distribution assets	Initial value distribution assets	FERC 207/75/g		19
Initial value general plant assets	Initial value general plant assets	FERC 207/90/g		20
Cumulative depreciation distribution	Cumulative depreciation distribution	FERC 219/26/b		21
Cumulative depreciation general plant	Cumulative depreciation general plant	FERC 219/27/b		22
Distribution depreciation	Depreciation of distribution	FERC 336/8/b		23
General plan depreciation	Depreciation of general plant	FERC 336/9/b		24
Assets to distribution	Assets attributable to distribution activity		Y	25
Administrative & general to distribution	Administrative and general costs attributable to distribution activity		Y	26
OPEX	Opex attributable to distribution activity		Y	27
DEPRECIATION	Depreciation attributable to distribution activity		Y	28
RETURN	Calculated return on total distribution assets		Y	29
TOTEX	Total cost (OPEX + Depreciation + return)		Y	30
Overhead line length	Overhead line length	Platts		31
Underground line length	Underground line length	Platts		32
Total length	Total line length		Y	33
Service area	Service area	Platts		34
Residential sales	Total residential sales	FERC/EIA/PUC		35
Commercial sales	Total commercial sales	FERC/EIA/PUC		36
Industrial sales	Total industrial sales	FERC/EIA/PUC		37
Total sales	Total sales		Y	38
Residential customers	Total residential customers	FERC/EIA/PUC		39
Commercial customers	Total commercial customers	FERC/EIA/PUC		40
Industrial customers	Total industrial customers	FERC/EIA/PUC		41
Total customers	Total customers		Y	42
Net generation	Net Generation	FERC		43
Total purchased power	Total Purchases	FERC		44

Wages	Average annual payment 2003 for the power generation and supply sector	US Dept of Labor		45
Heating Degree Days (population)	State heating degree days 2003 population weighted	Nat. Oceanic and Atmos. admin.		46
Heating Degree Days (simple average)	State heating degree days 30-yr simple state-wide average	Nat. Oceanic and Atmos. admin.		47
Customer mix	Industrial units delivered as percentage of total units delivered		Y	48
Age of assets	Age of assets		Y	49
Degree of vertical integration	Own generation as percentage of own generation and purchased power		Y	50
Connection density per km network	Number of connections per network length		Y	51
Connection density per service area	Number of connections per service area		Y	52
Load density	Total units delivered per line length		Y	53
Snowfall	Average 3-day maximum snowfall (inches)	Nat. Oceanic and Atmos. admin.		54
Overhead percentage	Percentage overhead network		Y	55
Percentage opex	Percentage Opex of total costs		Y	56

Constructed variables

Distribution allocation key (8)

FERC specifies distribution activities and costs. However, certain overhead or general costs should also be allocated to the distribution activity. In order to do this we define an allocation key. This key is called the “distribution allocation key” and is derived from the wage costs in the different activities. We define the distribution allocation key as follows:

Distribution allocation key (8) = [(3) + (4) +(5) + (6)] / [(3) + (4) + (5) + (6) + (1) + (2)]

Assets to distribution (25)

The distribution allocation key is applied to calculate the total assets that can be attributed to the distribution activity. To calculate this we include a portion of the depreciated value of general plant assets to account for housing etc.

Total distribution assets (25) = [(19) – (21)] +(8)*[(20) – (22)]

Administrative & general to distribution

The distribution key is applied to calculate the share of administrative and general costs that can be allocated to distribution operational costs. To calculate this we add administrative & general operations and maintenance, subtract regulatory costs and pension & benefits costs; this sum is then multiplied with the allocation key.

Administrative & general to distribution (26) = (8) * [(10) + (11) – (12) – (18)]

We exclude costs associated with regulation and pensions & benefits. Notably pensions & benefits vary substantially over time, therefore potentially influencing the costs positively or negatively in a particular year. Regulatory costs are determined by the regulator and reflect charges to pay for the regulatory agency.

OPEX (27)

Based on the allocation of costs we can construct a figure for the total operational expenses of the distribution activity. The OPEX includes the direct distribution opex figure from FERC, customer account expenses, customer service costs (excluding customer information as this reflects state mandated demand side management programmes), sales expenses, and administrative & general to distribution.

OPEX (27) = (9) + (13) + (16) + (17) + (26)

DEPRECIATION (28)

The depreciation attributable to the distribution activity is calculated by:

DEPRECIATION = (8) * (24) + (23)

RETURN (29)

The return on invested capital is calculated by multiplying the *assets to distribution* by a standard rate of return. In our analysis we use a 6 percent return. This is to normalise the effective rental cost of capital facing firms in the sample

.

TOTEX (30)

The total cost of distribution is calculated by adding OPEX, DEPRECIATION, and RETURN.

Total Sales (38) and Total customers(42)

In some States there is retail competition. The customer number and kWh volume data collected by FERC does not take this into account. We have therefore supplemented this data using information on Electric Service Providers (ESP) from the Energy Information Agency (EIA)[20] and data from PUC websites. We have taken two steps to clean and adjust customer number and kWh volume data.

In step 1 we compare EIA customer data with PUC customer data. When this is of similar order of magnitude we included the IEA data on customer numbers and kWh's. In step 2 we cross check average ESP consumption with the average consumption for the incumbent retail utility on residential customers. When figures were in the same order of magnitude the ESP data was used in our analysis. When no PUC information was available, no additional figures were included, even when EIA data was available.

Age of assets (49)

The age of assets is estimated by comparing the depreciated book value with annual depreciation charges. The age is calculated by dividing the cumulative depreciation by the annual depreciation charge.

Age (49) = (21)/(23)

[20] EIA Form-861. This return contains a significant amount of the same data as collected by FERC.

Data adjustments

Table A2 shows the specific adjustments made where reported data made no economic sense. In the majority of cases the effect of any assumptions relative to a plausible true figure is likely to be small.

Table A2: Data adjustments per company.

Alabama Power	Overhead percentage set at sample average. No split available in total line length.
Cambridge Electric Light	Cumulative depreciation general plant is negative. This is therefore set to zero.
Cleveland Electric Illuminating	Overhead percentage set at sample average. No split available in total line length.
Conneticut Valley Energy Co	No figure available for service area. Figure is based on *pro rata* service area of PSC of North Hampshire that owns Connecticut Valley Energy and operates in the State and similar area.
Entergy Arkansas	Wages for administrative & general are negative. This is therefore set to zero. Overhead percentage set at sample average. No split available in total line length.
Entergy Louisiana	Cumulative depreciation general plant is negative. This is therefore set to zero. Wages for administrative & general are negative. This is therefore set to zero.
FPL	Administrative and general maintenance expenses are negative. This is therefore set to zero.
Illinois Power	Overhead percentage set at sample average. No split available in total line length.
Jersey Central P&L	Negative net generation figure. This is therefore set to zero. Overhead percentage set at sample average. No split available in total line length.
Metropolitan Edison	Negative net generation figure. This is therefore set to zero. Overhead percentage set at sample average. No split available in total line length.
Northwestern Energy	Overhead percentage set at sample average. No split available in total line length.
Ohio Edison	Overhead percentage set at sample average. No split available in total line length.
PECO	Administrative and general maintenance expenses are negative. This is therefore set to zero.
Pennsylvania Electric	Overhead percentage set at sample average. No split available in total line length.
Pennsylvania Power	Overhead percentage set at sample average. No split available in total line length.
PG&E	Regulatory costs are negative. This is therefore set to zero. Customer service information less customer information is negative. This is therefore set to zero.
PPL	Administrative and general maintenance expenses are negative. This is therefore set to zero.
PSC of Colorado	Overhead percentage set at sample average. No split available in total line length.
PSC of Oklahoma	Overhead percentage set at sample average. No split available in total line length.
South Beloit	Wages for production are negative. This is therefore set to zero. Cumulative depreciation general plant is negative. This is therefore set to zero.
Southwestern Public Service Company	Overhead percentage set at sample average. No split available in total line length.
Westar energy	No figure for available service area. Figure is based on information from Westar website which states service area as 10,130 sq miles.
Wheeling power	Wages for transmission are negative. This is therefore set to zero.
Wisconsin P&L	Customer service information less customer information is negative. This is therefore set to zero.