18 March 2009

NIW Comparative Efficiency: An Econometric Analysis Using Panel Data A Report for NIAUR





# **Project Team**

# NERA Special Consultant

Professor Gordon Hughes

#### NERA

Dr Bill Baker

James Grayburn

Mathieu Pearson

NERA Economic Consulting 15 Stratford Place London W1C 1BE United Kingdom Tel: +44 20 7659 8500 Fax: +44 20 7659 8501 www.nera.com

# Contents

1.	Introduction	1
2.	Comparative Efficiency Measurement	
	Using Panel Data	3
2.1.	Introduction	3
2.2.	Ordinary Least Squares (OLS) Regression Analysis	4
2.3.	Stochastic Frontier Analysis (SFA)	7
2.4.	Assessing the Regression Model	9
3.	Panel Data Analysis of Ofwat COLS	
	Equations	11
3.1.	Introduction	11
3.2.	Data	12
3.3.	Ofwat Water Operating Cost Models	13
3.4.	Ofwat's Sewerage Operating Cost Models	20
4.	Panel Models of Aggregate Water	
	Operating Expenditures	24
4.1.	Introduction	24
4.2.	Water panel model estimates	24
4.3.	Sewerage panel model estimates	26
4.4.	Comparative Efficiency of E&W Companies Using	
	Aggregate Cost Panel Models	27
4.5.	Comparison with Ofwat Rankings	30
5.	Comparative Efficiency of NIW	33
5.1.	NIW Relative Efficiency	33
5.2.	Comparison with E&W companies	34
6.	Conclusions	36

# List of Tables

15
19
22
25
26
28
29
30
30
31
32
34
34

# 1. Introduction

NERA was commissioned by the Northern Ireland Authority for Utility Regulation (the "Utility Regulator" or UR) to provide advice on their efficiency analysis of Northern Ireland Water (NIW) up to and including the forthcoming price review, PC10, and on their associated submissions to the Minister responsible for NIW.

This report corresponds to the second task of output 3. This requires NERA to consider alternative techniques to the Ofwat COLS approach for assessing relative efficiency, including panel data techniques and stochastic frontier analysis (SFA), and to hold a workshop with NIAUR to discuss the analysis and results.<sup>1</sup> This report presents the results of our panel data analysis, which (as agreed with the UR) is restricted to only operating expenditure

In undertaking a panel data analysis of NIW's relative efficiency we draw on E&W company expenditure and operating characteristics data from the company "June returns", which are published annually by Ofwat. The E&W companies represent a good set of comparators for NIW as their operations are similar in nature and scope. Furthermore, the published June return information provides a rich source of data on these companies. Using the June returns data we construct a panel dataset consisting of data on cost drivers and operating expenditure for all E&W companies for the period 1997-98 to 2007-08.

Ofwat itself undertakes an annual comparative efficiency analysis of the E&W companies operating expenditure. Ofwat's analysis is based on cross sectional (single year) COLS regressions of functional (sub-service) level expenditure.<sup>2</sup> The key difference between the efficiency analysis undertaken by Ofwat and that we present in this report is that our analysis is based on panel data regression models. In addition (unlike Owat) we base our efficiency analysis on whole service (water or sewerage) regression models, although we also present the results from estimations of the Ofwat functional equations using panel data methods, to examine the robustness of the Ofwat approach in the panel context.

This report progresses as follows:

- **§** In Section 2 we describe how panel data techniques, including SFA, can be applied to comparative efficiency analysis;
- § In Section 3 we present a panel data analysis of Ofwat's COLS equations;
- **§** In Section 4 we present panel data models of total water and total sewerage operating expenses for E&W companies. We also present a comparative efficiency analysis of E&W companies based on our panel data models, and we present a comparison of the efficiency rankings obtained using our panel models to those obtained by Ofwat in their latest COLS analysis; and

<sup>&</sup>lt;sup>1</sup> The results from this report were presented at a workshop between NERA and NIAUR on the 11<sup>th</sup> February 2009.

<sup>&</sup>lt;sup>2</sup> Ofwat (January 2009), 'Relative efficiency assessment 2007-08'

- **§** In Section 5 we use our panel model to assess the relative operating cost efficiency of NIW and compare this with a recent analysis (of NIW's relative efficiency) based on Ofwat's 2006/07 COLS models.
- **§** In Section 6 we present our conclusions.

# 2. Comparative Efficiency Measurement Using Panel Data

#### 2.1. Introduction

The efficiency of a company can be defined as the extent to which it is able to minimise its costs for producing a given set and volume of outputs, taking into account the environment in which it operates (including demographic and geographical circumstances). A perfectly efficient company is one which has the lowest costs possible given the outputs that it produces and the environment in which it operates.

There are a variety of statistical techniques that can be used to assess the comparative efficiency of different companies. Statistical techniques use regression analysis to estimate a model, based on past data for different companies, that relates costs to different types of output (such as water delivered, sewage disposed, etc...) and environmental factors (network density, network size, urbanisation, etc...). In considering the most appropriate approach to take, it is important to examine the relative merits and drawbacks of the alternative techniques that could be used. This section looks at the most frequently used techniques and examines their main advantages and disadvantages when used in comparative efficiency assessments. Broadly the techniques that we discuss in this section can be classified under one of the following headings:

- **§** Ordinary least squares (OLS), of which the technique used by Ofwat (COLS) is a variant. OLS uses observations from a single point in time for a set of companies.
- § Panel data techniques which (unlike OLS) utilise datasets which include repeated observations over time from the same set of companies. The key advantages of using panel data techniques are: that they allow more observations for the same set of companies to be incorporated in the analysis (which should improve the robustness of the results); and that they take into account not only variation in the data between companies, but also within companies over time (therefore company specific effects that are persistent over time can be taken into account).
- **§** Stochastic frontier analysis (SFA), which can be used on a single cross section or on a panel dataset. (The SFA analysis in this report always uses a panel dataset). The key characteristic of SFA is that is that it attempts to distinguish between random error and genuine inefficiency.

One point that must be kept in mind is that the use of any statistical model necessarily implies the existence of random variation in the data. Since it is not possible to observe either variations in efficiency – over time or across companies – or random factors directly, the transition from statistical analysis to conclusions about company efficiency has to rest on assumptions about how variation in the data is divided between random factors and efficiency. These assumptions may be explicit, as in the case of the COLS approach, or they may be embedded in the structure of the statistical model. In discussing the various statistical methods that have been used we will highlight these assumptions, since understanding them is essential to any assessment of the robustness of the results which they generate.

## 2.2. Ordinary Least Squares (OLS) Regression Analysis

Ordinary Least Squares analysis is one of a variety of techniques which fall under the heading of regression analysis. It involves the identification of the statistical relationship between different variables. In the case of this study, therefore, the objective is to derive the relationship between total cost and a variety of exogenous cost drivers.

OLS regression analysis can be best understood through the use of a simple example. If the cost of building and operating a network (C) depended only on the network length (L), then each operator's level of costs and network length could be plotted on a graph, as in Figure 2.1 below, where each point represents a different operator.



Ordinary least squares regression analysis fits a line of "best fit" to these points, such that the line minimises the sum of the squared vertical distances of the observed company costs (represented by crosses) from the line.

The line of best fit can be written in equation form as:

$$C_i = a + bL_i + u_i$$

where *i* represents the observations for the different operators, *a* is the fixed cost involved in providing a network regardless of the network length, *b* is the cost of providing each additional unit of network length (the marginal cost), and *u* is the regression residual (the difference between actual costs and those "predicted" by the line of best fit).

If there are many companies in the sample, it is very unlikely that they would all lie on the best-fit line, but rather some would be above and others below. The best-fit line therefore represents the costs that a company of 'average' efficiency would be expected to incur at a given network length. Those companies with an observation above the line (for example, company A in Figure 2.1) have costs above those of a company of average efficiency with the same network. Such companies are, in this relative sense, inefficient. Conversely, those

companies that lie below the regression line (for example, company B) may be viewed as being relatively efficient (above average efficiency).

In practice, rather than plotting all the companies' observations on a graph, a computer program is used to estimate the regression coefficients (a and b) using the data on all the companies in the sample. Individual companies are then judged by substituting their actual output numbers into the equation to give a predicted level of costs, Z, as if the company were of average efficiency. If the company's actual cost level were larger than Z, then it would lie above the regression line and, therefore would be deemed inefficient (compared to "average performance"). Likewise, if its predicted costs were to exceed its actual costs, it would be judged to be efficient compared to "average performance".

The difference between a company's actual costs and its predicted costs is termed the residual. A positive residual therefore indicates inefficiency relative to the sample "average", and a negative residual indicates efficiency relative to the sample "average".

Most cost functions are likely to have more than one cost driver. OLS regression analysis deals with this through the use of multivariate regressions, which take the general form:

$$C_i = a + b_1 L_i + b_2 P_i + b_3 Q_i + \dots + u_i$$

As before, *a* represents the level of fixed costs,  $b_1$  measures the marginal cost of explanatory factor *L*, and *u* is the regression residual. However, in addition,  $b_2$  and  $b_3$  now measure the marginal cost of the new explanatory factors *P* and *Q* respectively (assuming in each case that the other two explanatory factors are held constant).

Ofwat use a version of OLS in their comparative efficiency analysis known as corrected ordinary least squares (COLS). As we discuss above the OLS method estimates the impact of cost drivers on costs at the mean not at the efficient frontier. However, Ofwat wish to compare the efficiency of the E&W companies to the efficient frontier, to enable them to set targets for cost reductions by companies so that they will "catch-up" to the frontier. Ofwat try to achieve this by comparing the relative efficiency of each company (the ratio of the company actual costs to the costs predicted for it by the OLS regression line) to the relative efficiency of a selected benchmark company. This benchmark company represents the most efficient company relative to the average and which meets certain additional criteria (such as comprising more than three percent of industry turnover by service).

More generally, efficiency analyses that rely upon OLS regression often assume that some proportion – say r% - of the deviations from the regression line is caused by random variation and the remainder by efficiency differences across companies. Thus, the efficiency difference between the benchmark firm with error  $u_b$  and firm i is  $[1-(r/100)]^*(u_i - u_b) / (C_i - u_i + u_b)$ . The value of r is clearly important, but it is also arbitrary unless there is independent evidence on the magnitude of efficiency differences relative to random errors. A more worrying consequence of this formulation is that the random error is perfectly correlated with the efficiency error, which seems highly improbable.

#### 2.2.1. Multi-year least squares regression analysis

The analysis described above uses data for a single year to assess how efficient one firm is compared to others. However, depending upon the number of firms for which data are available, such analysis has limitations with regards to accuracy and robustness. If, for example, a number of firms have low costs for spurious reasons (such as misreporting of accounting data in a particular year) this could skew the model significantly, making other firms look less efficient than they actually are. Also, the number of observations is limited to the number of companies for whom the required data are available.

Where a number of years of data are available, it is possible to create a data panel (or "pool"), which includes data for different companies over a number of years. This helps overcome problems associated with a limited number of observations, and reduces or eliminates the impact of peculiarities in the data, as these tend to "average out". The use of a panel dataset should therefore lead to a more robust and stable model. Furthermore, the availability of repeated data observations for the same company over time allows persistent unobserved effects on company costs to be taken into account in the analysis.

However, including more than one year's worth of data from any firm can lead to problems due to the existence of heterogeneity both within observations across time and between the different observations in the panel. This can lead to difficulties in obtaining efficient and unbiased estimates of the regression coefficients. In addition, panel data can also lead to problems of autocorrelation, if the within-observation heterogeneity is low (if the figures for each year for an observation do not differ by a large amount).

Ordinary Least Squares analysis is neither able to control for the heterogeneity both within and between observations, nor for the autocorrelation problems that can arise with panel data, and hence it is not an appropriate technique to use with this type of data. In its place a twostep Generalised Least Squares (GLS) approach can be used, which takes account of the repeat observations for each firm.

The model estimated using data for a number of years is similar to that used in single-year analysis, but has an additional term measuring the time trend. This variable, which effectively allows the constant term to change over time, takes account of technological progress, inflation, or other such items that cause changes in the costs of all companies over time. The regression equation in this case is:

$$C_{i,t} = a + b_1 L_{i,t} + b_2 P_{i,t} + b_3 Q_{i,t} + \dots + T + u_{i,t}$$

where T is the time trend, and  $L_{i,t}$  is the value of variable L for company i in time period t, and so on. Finally,  $u_{i,t}$  is the regression residual which indicates the gap between actual and predicted (average) efficiency for each company in each time period.

It is possible to run panel data analysis with an "unbalanced panel"; that is a dataset that does not contain an observation for each company in every year in the panel. If, for example, the panel covers eight years, it is possible to include firms in the panel, which are missing data

for some of those years (for example a firm which has data for only 5 of the 8 years), without the model being adversely affected.

The availability of multiple observations for the same firm in different periods permits the estimation of a specification that distinguishes the efficiency error from the random error. If the efficiency error is constant over time, the error  $u_{i,t}$  can be rewritten as the sum of a company-specific efficiency error  $w_i$  and a separate, independent random error  $v_{i,t}$  that is normally distributed. This is known as the panel fixed effects model and can be estimated using dummy variables for each company, whose coefficients capture the efficiency of the companies. An alternative specification assumes that the efficiency errors  $w_i$  are not fixed but are random variables drawn from (perhaps) heteroskedastic distributions – known as the random effects model. Thus, the relative importance of the efficiency and random errors depends upon the data and the model specification rather than being imposed by the analyst. Even so, one must bear in mind that the efficiency fixed effects capture not only differences in efficiency but also systematic differences between companies caused by explanatory factors that are not included in the model. This applies to the OLS and other specifications but the omission of relevant explanatory factors may be problematic with panel data.

#### 2.3. Stochastic Frontier Analysis (SFA)

A significant drawback of both OLS and GLS regression analysis is that they both implicitly assume that the whole of the residual that is obtained for any company in any period of time can be attributed to relative inefficiency (or efficiency). However, it is possible, if not probable, that the residuals from such an analysis will include unexplained cost differences that are the result of data errors and other factors affecting costs that have not been picked up in the regression equation. Stochastic Frontier Analysis (SFA) builds on the methodologies outlined above and aims to address this shortcoming.

There is an extensive academic literature on efficiency measurement using SFA, and this technique is increasingly being used by utility regulators to measure efficiency. It is based on regression analysis, but has two distinctive features:

- **§** In contrast to OLS and GLS regression analysis, SFA models incorporate the possibility that some of the model residual may result from errors in measurement of costs or the omission of explanatory variables, as opposed to the existence of genuine inefficiencies. This decomposition of residuals between 'error' and 'genuine inefficiency', which is based on assumptions made about the distributions of the 'error' and 'genuine inefficiency' terms, is intended to provide a more accurate reflection of the true level of inefficiency.
- **§** Secondly, the regression for SFA looks not at the average firm, but at the theoretically most efficient one.

In the case of data for just one year SFA estimates the equation:

 $C_i = a + b_1 L_i + \dots + v_i + u_i$ 

where '...' indicates the other variables included in the model.

The residual in a stochastic frontier model is assumed to have two components: the  $u_i$  component, which represents the genuine inefficiency; and the  $v_i$  component, which represents the genuine error. In econometrics literature,  $u_i$  is often referred to as the inefficiency term and  $v_i$  is often referred to as the random error.

In order to be able to decompose the residual into inefficiency and random error it is necessary to make assumptions about the distributions of its two components. For single year SFA models, the inefficiency term is assumed to follow a non-negative distribution (such as the half-normal or truncated normal distributions), whilst the genuine error term is assumed to follow a symmetric distribution. By making these assumptions the technique is able to decompose the residual by fitting the assumed non-negative distribution to the residuals to identify the proportion of the residuals that can be explained by this distribution.

Having to make such assumptions is a key disadvantage of single year SFA, as the appropriateness of these assumptions cannot accurately be measured.

#### 2.3.1. Multi-year stochastic frontier analysis

SFA can also be applied to panel data. This involves estimating a regression equation of the following form:

$$C_{i,t} = a + b_1 L_{i,t} + b_2 P_{i,t} + b_3 Q_{i,t} + \dots + T + v_{i,t} + u_{i,t}$$

where T is a time trend variable that identifies the change over time in the regression constant, i represents an individual company observation and t represents the time period. With this specification, residuals can be different for each firm and for each year. Once again, in a multi-year setting, SFA decomposes the residual between inefficiency and error by making assumptions about the statistical distributions of these two components of the residual.

The advantages of using panel data over simple cross-sectional data (single year data) is that, with cross-sectional data in SFA analysis, strong assumptions are required about the statistical distribution of the inefficiency component of the regression residuals and, in many practical cases when cross-sectional data are used, insufficient data are available to support these assumptions. There is often little evidence to suggest which statistical distribution is appropriate in constructing a model, and in many cases, more than one distribution may be deemed to 'fit' the data. The use of panel data, in contrast, allows for these distributional assumptions to be relaxed. By observing each firm more than once, inefficiency can be estimated more precisely as firm data is embedded in a larger sample of observations. Specifically, with panel data, it is possible to construct estimates of the efficiency level of each firm that are consistent as the number of time-series observations per firm (t) increases.

In early SFA panel data studies, however, the benefits described above came at the expense of another strong assumption, namely that relative firm efficiency does not vary over time (that is,  $u_{i,t} = u_i$ ). This may not be a realistic assumption, especially in long panels. Recent studies on this issue, however, have shown that this assumption of time-invariance can be tested, and can also be relaxed, without losing the other advantages of panel data.

Reflecting these points, NERA has applied two different possible parameterisations of the inefficiency term *u* to the SFA panel.

- **§** A time-invariant model where the inefficiency term is assumed to be constant over time within the panel; and
- **§** A parameterisation of time effects (time-varying decay model) where the inefficiency term is modelled as a random variable multiplied by a specific function of time:

 $u_{i,t} = \varepsilon_{i, \cdot} e^{\eta(t-T)}$ 

where *T* corresponds to the last time period in each panel and  $\eta$  is the decay parameter to be estimated.

Again, it is the specification that provides the basis for separation of efficiency and random errors. The equation above has the same error component structure as for the panel GLS model but it goes further (a) by assuming that the efficiency error can only take positive values, and (b) in the time-varying model by allowing the errors to follow some trend over time.

#### 2.4. Assessing the Regression Model

Before drawing conclusions about relative efficiency, it is essential to verify that the regression equation is theoretically and statistically valid and that it represents the best possible model, if there is more than one possibility. The types of questions likely to be raised in this context are:

- § How well does the cost model fit the observations? Is there a large proportion of cost variation that is left unexplained by the variation in the chosen explanatory factors? Under Ordinary Least Squares analysis this is measured by the coefficient of determination  $R^2$  (or a variation on it).
- **§** Are the coefficients sensible? For example, does the model predict that costs will rise (rather than fall) as the network length increases, as intuition and experience would suggest? Care must be taken here to consider the possible impact of multicollinearity, which may make some coefficients appear unintuitive when they in fact are closely related to other variables.
- **§** Are the coefficients statistically significant? In other words, can we be confident that the relationship described is a statistically valid one?

Even if the model appears to be satisfactory, there are several potential sources of inaccuracy. These concern:

- **§** Inaccuracies of functional form; it is unlikely that in practice the model's functional form is known exactly in advance. For example, are costs linearly related to the network length or is the functional form more complex? Does logarithmic transformation of explanatory factors give a better or worse fit?
- **§** The omission of relevant variables. The accuracy of regression analysis in measuring relative efficiency depends to a large extent on the degree to which all relevant explanatory factors have been included. If, for example, hilly countryside had a

significant adverse effect on costs but was ignored in the regression study, then those companies serving hilly terrain might appear to have unduly high costs simply because of their location rather than because of inefficiency; and

**§** A lack of independence among the cost drivers. For meaningful results, there need to be many more independent observations than the number of cost-driver coefficients being estimated (in econometric terms, there need to be many degrees of freedom).

# 3. Panel Data Analysis of Ofwat COLS Equations

#### 3.1. Introduction

In this section we present the results of our econometric panel data analysis of the equations used by Ofwat in the COLS analysis of their relative efficiency of E&W companies. The Ofwat models are based on an analysis of the relationship between a variety of explanatory variables and operating costs (of E&W water companies) at the functional (sub-service) level for single cross section of data. In this section we take the equations (the functional form of the relationship between the explanatory variables and costs) that Ofwat have used as their "best models" in their latest relative efficiency analysis and re-estimated them using panel data techniques.<sup>3</sup>

The analysis presented in this section was the starting point in our process of building whole service operating costs panel data regression models. The analysis allowed us to examine what explanatory factors we might expect to be important in our models. In addition, as part of this analysis, we also tested the assumptions implicit in Ofwat's methodology that the relationship between the explanatory variables and functional operating costs is stable across companies, but not over time. These tests provide a good insight into whether there are substantial advantages to be gained from using panel data, rather than a single cross section as the basis for efficiency analysis. We also use our dataset to investigate the most appropriate functional from of the Ofwat water distribution functional expenditure model. This analysis follows a change in the functional form used by Ofwat between their latest relative efficiency analysis (corresponding to 2007/08) and that they published for 2006/7. The analysis of the specification of the water distribution model has a direct relevance to a claim for a special factor<sup>4</sup> put forward by NIW. The claim is for additional costs to be allowed because of the very high ratio of mains length to resident population in the area served by NIW compared to those observed in the areas served by the E&W companies.

The remainder of the section progresses as follows:

- **§** First we describe the dataset that we have used in the analysis presented in this section and in the reminder of this report.
- § We then present the results from panel GLS and SFA panel regression analysis of functional water service expenditure estimated using the broad functional form and explanatory factors associated with Ofwat's most recent COLS equations; this analysis also includes an investigation into the functional form of the Ofwat water distribution model.<sup>5</sup>
- **§** Finally we present the results of an equivalent analysis for the sewerage equations used in Ofwat's most recent efficiency analysis

<sup>&</sup>lt;sup>3</sup> Note that the latest Ofwat analysis draws on a single year of data for 2007/08, whereas our analysis use a panel of data from 1997/8 to 2007/08

<sup>&</sup>lt;sup>4</sup> A special factor is effectively an allowance for additional costs for a specific company in the relative efficiency analysis to take into account factors that are not accounted for in the efficiency model(s).

<sup>&</sup>lt;sup>5</sup> Ofwat (January 2009), '<u>RD 02/09: Relative efficiency assessment 2007-08</u>'.

#### 3.2. Data

We have constructed a panel dataset for the period 1997/98 to 2007/08 for all E&W WaSCs and WoCs from published June Return data. The dataset consists of water and sewerage operating expenditure and potential cost drivers. We sourced corresponding data for NIW for 2007/08 from NIW's annual information submission, AIR08.

The relative efficiency analysis undertaken by Ofwat is also based on the June returns data. However, there are some differences between the data used by Ofwat and the data we use in our analysis. We outline these differences below.

**§** Ofwat makes pre-modelling adjustments for differences in company policies with regard to the capitalisation of expenditure, and to allow for differences in expenditure which are caused by companies' taking a "pension holiday".<sup>6</sup>

We were unable to source data for the pre-modelling adjustments made by Ofwat for the entire time period of the panel dataset we have constructed. Therefore, to ensure the data were treated consistently over time, we used unadjusted data for every year. For the most part the size of the adjustments are relatively small and where they cause differences in expenditure which are persistent over time these will be automatically taken into account by the panel data methodology. We would therefore not expect a material difference in the results if we used a dataset that reflected all of the adjustments made by Ofwat over the period.

**§** Ofwat makes a number of post modelling adjustments to the data to take into account atypical costs and special factors in their assessment of company relative efficiency.

We do not make special factor adjustments to our dataset. (We do estimate regression models with and without company atypical costs as identified in their June returns included in the definition of total service operating costs, see Section 4.1 for more detail). However, because the special factor adjustments are post modelling adjustments they would not be the cause of any differences between our panel models and Ofwat's COLS models.<sup>7</sup>

The absence of special factor adjustments might be thought to be a cause of differences between our relative efficiency assessments (which we present in Sections 4 and 5) and those of Ofwat. This is because special factors are excluded by Ofwat from company costs before they are compared to the benchmark. However, where these special factors have a persistent effect on company costs over time they will be treated as company specific effects (and thus excluded from the assessment of relative (in)efficiency) by the panel data methodology we employ.

**§** Ofwat uses data reported at the sub-company level in their sewerage operating expenditure COLS models.

<sup>&</sup>lt;sup>6</sup> For more details see Ofwat (January 2009) op. cit. p. 26

<sup>&</sup>lt;sup>7</sup> For more details see Ofwat (January 2009) op. cit. p.26

The E&W water and sewerage companies report data on sewerage expenditure and operating characteristics at the sub-company level (i.e. for each WaSC the same categories of data will be reported for several sub-areas of its total operating area). Ofwat estimates its COLS models using the sub-company data, thereby increasing the number of observations available. Our models all use data that has been reported at the whole company level, however because our models make use of a panel of data they do not suffer in comparison to those of Ofwat in terms of the number of observations available for use in estimation.

#### 3.3. Ofwat Water Operating Cost Models

In this sub-section we first present the results of our estimation of Ofwat's models using panel GLS and SFA and pooled random coefficient models. We then use our panel dataset to investigate the functional form of Ofwat's water distribution expenditure model.

#### 3.3.1. Re-estimation of Ofwat's models using panel data methods

Ofwat's latest models for comparing the efficiency of water companies with respect to their water service operating expenses are:

1. Water distribution

Ln (Opex / Total number of connections) =  $\alpha + \beta *$  Ln(Total length of mains / Total number of connections)

2. Resources & treatment

Opex / Total winter population =  $\alpha + \beta *$  (No of sources / Distribution input) +  $\gamma *$  (Proportion of supplies from boreholes)

3. Power

Ln (Opex) =  $\alpha + \beta * \ln$  (Distribution input \* Average pumping head)

4. Business activities

Ln (Opex) =  $\alpha + \beta * \ln$  (Total no of billed properties)

We have tested the Ofwat's equations by estimating panel versions of them, or slightly more generalised versions of them  $^8$ .

For each equation we have estimated three econometric specifications of the basic model using panel data for the years 1997-2007. In each case a time trend is added to capture the

<sup>&</sup>lt;sup>8</sup> In the case of equation 2 this has involved converting the equation into log-log form, which is a slightly more general form of the Ofwat equation. Ofwat's specifications force the coefficients on certain variables to take specific values – e.g. in the log-log version of the resources and distribution equation, the coefficient on log(Total winter population) is - 1 and the coefficient on distribution input is -β. In generalising we do not impose these constraints. Ofwat's assumptions can be tested and there is no good reason to impose them a priori.

impact of inflation, technical change and other factors that may have influenced the development of costs over time. These are:

**§** A GLS version of each equation assuming an error structure with heteroskedastic errors across companies and a uniform autocorrelation coefficient over time. <sup>9</sup>

The GLS estimator fits an equation around the mean of the distribution of costs. The coefficients from these models can be interpreted as the marginal impact of the cost drivers on the <u>mean</u> expenditure of E&W companies.

**§** A stochastic frontier specification assuming time-invariant inefficiency.<sup>10</sup>

The SFA estimator fits an equation at the cost frontier. The coefficients from these models can be interpreted as the marginal impact of the cost drivers on the <u>efficient</u> expenditure of E&W companies.

**§** Random coefficient models designed to test the pooling assumption across companies and over time.

The random coefficient estimator, like the GLS estimator, fits an equation at the mean of the distribution of costs. However, unlike the GLS estimator, the random coefficient allows the coefficients to vary across companies or time periods. The GLS specifications assume the coefficients (the relationship between cost and the cost drivers) on the dependent variables are the same across companies and over time, i.e. the relationship between expenditure and the explanatory variables is consistent over time and across companies, and therefore that the panel data set can be "pooled" over companies and over time. The random coefficient model allows us to relax these assumptions. We undertake two tests for pooling in our panel data set, these are: 1) pooling across companies;<sup>11</sup> and 2) pooling across time.

We present the results from these models, including the results of the tests for pooling across time and companies in Table 3.1 below

<sup>&</sup>lt;sup>9</sup> This error structure has been tested against simpler assumptions and is consistently accepted for each of the equations.

<sup>&</sup>lt;sup>10</sup> We have estimated versions of these SFA model without the assumption of time invariant efficiency. However, these models were unstable and produce implausible results.

<sup>&</sup>lt;sup>11</sup> This test assumes that we estimate a set of T COLS-type equations across N companies for each year t = 1 to T treating each coefficient b[t] as a random variable with a mean b[mean] and a standard deviation b[sd]. The equation errors are assumed to be stable and independent over time. The test then examines whether the assumptions are consistent with the evidence.

<sup>&</sup>lt;sup>12</sup> This second, more difficult, test assumes that we estimate a set of N time series equations for each company using data for the time periods t = 1 to T and then test equivalent assumptions about each coefficient b[n] treated as drawn from a random distribution with mean b[mean] and standard deviation b[d]. This test is more difficult because T = 10 or 11 and N = 22, so that the time series equations are bound to be less satisfactory than the cross-section equations. There is also the question of company fixed effects, which would be reflected in the constant terms of the time series equations, but if correlated with the explanatory variables could be a cause of variation in the individual company coefficients.

<sup>&</sup>lt;sup>13</sup> It should be noted that it is not possible to estimate the time trends using the pooling over time specification, so the dependent variables are adjusted by imposing the value of the time trends derived from the panel GLS specifications.

	Pa	anel GLS	1	Pa	nel SFA		Random coefficient pooling over time		cient – time	Ofwat 2007/08
	Coeff	SE	Ζ	Coeff	SE	Ζ	Coeff	SE	z	Coeff
							(Chi^2)	(DF)	(P)	
A. Water distribution										
Length of mains / Total connections	02297	.0077	0.00	02146	.0079	0.00				-0.713
Time	0069	.0046	0.14	0075	.0031	0.02				N/A
Constant	-3.6998	.1106	0.00	-3.9261	.1302	0.00				-2.066
Autocorrelation	0.7168									
Sigma U2				0.1650	0.2681					
Sigma V2				0.0225	0.0021					
Test for pooling across panels										
Test for pooling over time										
B. Resources & treatment										
% from boreholes	-0.6117	0.0841	7.28	-0.4846	0.2107	2.30	-0.7446	0.0879	8.47	N/A
Ln (No of sources)	0.1179	0.0352	3.35	0.0268	0.0552	0.49	0.2699	0.0492	5.48	N/A
Ln (Distribution input)	-0.2269	0.0381	5.95	-0.1741	0.0755	2.31	-0.3901	0.0474	8.23	N/A
Time	0.0072	0.0041	1.75	0.0102	0.0024	4.32				N/A
Constant	-3.8470	0.1526	25.20	-4.6429	0.4127	11.25	-3.4701	0.1694	20.48	N/A
Autocorrelation	0.796									
Sigma_u^2				0.0937	0.0324					
Sigma_v^2				0.0119	0.0011					
Test for pooling across panels							3761.0	84	0.00	
Test for pooling over time							8.7	40	1.00	
C. Power consumption										
Ln (Distribution input)	0.9402	0.0209	45.03	0.9490	0.0201	47.16	0.9458	0.0093	101.24	0.907
Ln (Average pumping head)	0.6312	0.0808	7.81	0.6361	0.0993	6.41	0.7633	0.0425	17.96	0.907
Time	0.0512	0.0058	8.78	0.0536	0.0041	13.08				N/A
Constant	-7.1295	0.4029	17.70	-7.6275	1.0427	7.32	-7.8471	0.2215	35.43	-8.104
Autocorrelation	0.660									
Sigma_u^2				0.0098	0.0048					
Sigma_v^2				0.0406	0.0039					
l est for pooling across panels							288.7	63	0.00	
l est for pooling over time							263.8	30	0.00	
D. Business activities	0.0407	0.0450	00.40	0.0400	0.0044	07.00	0.0404	0.0440		0.040
Ln (I otal no of bills)	0.9427	0.0156	60.42	0.9498	0.0344	27.63	0.9481	0.0143	66.22	0.918
	0.0325	0.0040	8.03	0.0289	0.0024	12.13	0.7055	0.0000	40.04	N/A
	-3.7322	0.1043	35.79	-4.3444	0.2531	17.17	-3.7655	0.0920	40.91	-3.506
	0.708			0.0262	0.0110					
				0.0362	0.0119					
Signa_V'2				0.0136	0.0013		2164.6	40	0.00	
Test for pooling over time							77	42 20	0.00	
Source: NERA estimates	I	l			1		1.1	20	0.99	I

Table 3.1 **Evaluation of Ofwat's Water COLS Models Using Panel Data** 

Source: NERA estimates.

The key points from the estimation of the GLS and SFA panel versions of Ofwat equations are outlined below.

- **§** For the most part the explanatory variables used by Ofwat in the various equations are statistically significant drivers of functional expenditure. With the exception of the percentage of water obtained from boreholes in the water resources and treatment model, all of the explanatory factors used by Ofwat in their water operating costs models are statically significant at least at the 10% level in our panel versions. This suggests that the collection of explanatory variables used in the Ofwat models represent a reasonable basis from which to develop a whole service water operating cost model.
- § Where direct comparison can be made the GLS and SFA panel model coefficients estimates are similar to those obtained by Ofwat for its latest COLS models. However this finding is not necessarily supportive of the Ofwat approach. For the power consumption and business activities models the coefficient estimates from the GLS and SFA panel models are very similar to the Ofwat COLS coefficients. The water distribution model the coefficient on the length of main/total connections variable for the GLS, SFA and Ofwat COLS models all have the same (negative) sign, however there is a large difference between the size of the coefficients from the SFA and GLS models (-0.022 and -0.021) and that from the Ofwat COLS model (-0.713).<sup>14</sup>

On the face of it this finding my be taken to be somewhat supportive of the Ofwat approach (in that for some of the Ofwat models there is evidence that switching from cross-sectional to panel estimation does not radically alter the relationship between costs and the explanatory variables). However, as we explain below, there is evidence to suggest that these relationships are not consistent across companies, and therefore an alternative approach (to functional expenditure equations) may be preferable.

- **§** The difference between the level of costs at the average and at the frontier is largely captured by the constant term. For most of the variables the differences between the values of the coefficients estimated using the alternative (GLS and SFA) specifications are small. As discussed above the panel GLS model coefficients correspond to the average efficiency of companies in the sample, whereas the SFA coefficient estimates reflect the most efficient firm. However, the shift between the level of costs at the average and the level of costs at the frontier is largely captured by the differences in the constant terms (of the various specifications) rather than differences in the coefficients for the explanatory variables.
- § The SFA models suggest that inefficiency (as a proportion of the error term) is large for water distribution, resources & treatment and business activities but small for power consumption. The estimates of sigma\_u^2 and sigma\_v^2 are reported because u is the (truncated normal) efficiency error, while v is the (normal) random error. Thus, the ratio of the sigma\_u^2 to sigma\_v^2 represents the importance of efficiency differences relative to unexplained and random variation. This is large for water distribution, resources & treatment and business activities but small for power consumption.

<sup>&</sup>lt;sup>14</sup> Because we use a log-log specification for our panel estimations of the resources and treatment model the coefficient estimate we obtain are not directly comparable with the Ofwat COLS coefficients.

In Table 3.1 we also present the results of our tests for pooling across companies and time using the random coefficients model. We summarise the key conclusions from the tests for pooling across companies and across time below.

§ The test for pooling over time is supportive of the pooling of the panel data set across time, thus reinforcing the case for using panel data methods. For the test of pooling across time, for most of the functional expenditure models, the assumption of pooling over time cannot be rejected. Whilst this assumption is rejected for the power consumption we consider that it would be possible to re-specify the equation to deal with the problem by including power prices or something similar.<sup>15</sup> In other words the test is supportive of the pooling of the panel data set over time. The findings of this test reinforces the case for pooling over time so as to get better estimates of the coefficients on the cost drivers.

Pooling across time is something that is implicitly rejected by the Ofwat methodology, which is to estimate a series of cross-sectional equations over time, thus allowing the model coefficients to change over time.

**§** The test for pooling over companies suggests that the pooling of the panel data set across companies cannot be taken for granted. Our results suggest that the hypothesis of pooling across companies can be rejected for each of the models. (Although, as we note above, the power of this test is less than the test for pooling across time given the relatively fewer observations and the complication of company specific fixed effects).

Implicitly Ofwat assumes that it is reasonable to pool companies at a point in time. This assumption has been challenged by some academic commentators who have argued that the data supports the view that the WOCs and the WASCs do not face the same cost frontier. Our results suggest that some richer specification, taking account of differences between companies, may be required.

§ Whilst some degree of pooling across companies is necessary to enable efficiency comparisons to be made, the evidence from the panel data analysis does not support pooling across companies at the level of functional expenditure. Pooling across companies is necessary because efficiency comparisons would not be possible if we jettison comparisons across companies, but it is not strongly supported by the evidence presented in Table 3.1 (although we cannot conclusively reject this given the caveats to this test). This finding is, perhaps, not surprising but it is not very helpful because it challenges the whole basis for efficiency comparisons. It appears that the functional expenditure equations do not fit the data very well. The results presented in Table 3.1 suggest that one ought to be examining different specifications and ways of carrying out efficiency comparisons, such as the whole service operating cost panel models that we present in Section 4.

<sup>&</sup>lt;sup>15</sup> The effect of power prices on power expenditure could be to some extent picked up in the other regression coefficients, the apparent changes in these coefficients over time could in fact be a result of changes in power prices. Power prices tend to be fairly volatile over time and the effect of this volatility on power expenditure may not by fully captured by adjusting the expenditure variable by the implied time trend from the GLS or SFA models.

#### 3.3.2. Functional form of water distribution model

Between the publication of Ofwat's latest relative efficiency analysis and its previous<sup>16</sup> relative efficiency analysis Ofwat have altered the functional form of its water distribution model. For 2006/07 Ofwat used the equation:

Ln (Opex / Resident population) =  $\alpha + \beta$  \* (Proportion of mains > 300/320 mm).

There are several points to note about the revision:

- **§** The scale variable has been changed from resident population to the total number of connections. This has some intuitive justification since many analyses of water costs and tariffs assume that the number of connections is a basic factor in total network costs. However, there are equally plausible arguments for use of resident population as the key cost driver.
- **§** The proportion of large diameter pipes in the total network has been dropped as a driver. Again, this is surprising since it has an intuitive appeal – large diameter pipes are more expensive to maintain and are generally older than small pipes – and the variable has proved robust in the past.

Ofwat use cross-sectional data for a single year which means, as we discuss above, Ofwat implicitly rejects the pooling of the data from companies over time. However, because the many potential cost drivers may be highly correlated or may be subject to random reporting errors the Ofwat approach can lead to instability in the basic equations over time. Use of panel data is, therefore, particularly appropriate as a way of identifying an appropriate equation specification. For this reason we have used panel data techniques to examine alternative specifications of the water distribution equation to test whether the new equation is, indeed, an improvement on the old equation. This analysis has a direct relevance to a claim for a special factor<sup>17</sup> put forward by NIW based on their very high ratio of mains length to resident population compared to the E&W companies.

Table 3.2 shows the results of estimating a generalised specification of the Ofwat water distribution model which includes the log variant of the pipe length variable, the proportion of large mains variable and either or both of total connections and resident population as the scale variable. The starting equation is:

Ln (Opex) =  $\alpha + \beta 1*\ln(\% \text{ large mains}) + \beta 2*\ln(\text{Length of mains}) + \beta 3*\ln(\text{Total connections}) + \beta 4*\ln(\text{Resident population}).$ 

The results are obtained using a GLS panel estimation with heteroskedastic panels and a common AR1 autocorrelation over time with different sets of cost drivers.<sup>18</sup> The chi-square statistic provides a basis for comparing the performance of the different models. These

<sup>&</sup>lt;sup>16</sup> Ofwat (December 2007), '*RD21/07 Relative efficiency assessment 2006-07*'

<sup>&</sup>lt;sup>17</sup> A special factor is effectively an allowance for additional costs for a specific company in the relative efficiency analysis to take into account factors that are not accounted for in the efficiency model(s).

<sup>&</sup>lt;sup>18</sup> Alternative simpler specifications for the error term have been tested and are consistently rejected.

models presented above are directly comparable with Ofwat's regression models, in that the coefficients estimate the impact of the variables on cost at the average.

Variable		Model A	Model B	Model C
		Depen	dent variable: L	n(opex)
% large mains	Coeff	3.546	2.432	3.188
	SE	0.753	0.779	0.716
I p(I anoth of mains)	Coeff	-0.153	-0.270	-0.206
	SE	0.108	0.114	0.098
In(Total connections)	Coeff	-0.514	1.196	
	SE	0.491	0.115	
I n(Regident population)	Coeff	1.593		1.131
	SE	0.456		0.099
Time	Coeff	0.000	-0.006	-0.002
	SE	0.004	0.004	0.004
Constant	Coeff	-4.695	-3.036	-4.160
Constant	SE	0.558	0.345	0.235
Test statistics:				
Chi-square		3832.32	3196.00	3679.55
No of degrees of freedom		5	4	4
Probability		0.000	0.000	0.000

 Table 3.2

 Panel GLS estimates of general version of water distribution model

Source: NERA estimates

The key points from the results presented in Table 3.2 are:

- **§** The proportion of large mains is an important cost driver independent of length of mains, total connections or resident population. The coefficient on the percentage of large mains has a large positive coefficient significant at the 5% level whenever it is included with one or other of pipe length variables or with any of the scale variables.
- **§** The implied coefficient in the general models on the variable length of mains/resident population variable is negative. This finding is consistent with the negative coefficient on this variable in the Ofwat equation. One important consequence of this is that the claim by Northern Ireland Water for a special factor adjustment for water distribution opex on the grounds that it has a particularly high value for length of mains per person is clearly not consistent with these models. Indeed, including ln(pipe length/resident population) is associated with a lower cost per person.
- **§ Resident population is clearly better than total connections as the scale variable.** In contrast with total connections or length of main, whether it is included on its own or together with the other scale variables, the coefficient on resident population is always large, positive and significant.

## 3.4. Ofwat's Sewerage Operating Cost Models

Ofwat's latest models for comparing the sewerage operating cost efficiency of E&W companies are:<sup>19</sup>

1. Sewer network

 $\label{eq:linear} \begin{array}{l} \text{Ln} \left( \text{Opex/Sewer length} \right) = \alpha + \beta * \ln \left( \text{Area/Sewer length} \right) + \gamma * \ln \left( \text{Resident} \right. \\ \left. \begin{array}{l} \text{population/Sewer length} \right) + \delta * \text{Holiday population/Resident} \\ \left. \begin{array}{l} \text{population} \end{array} \right) \end{array}$ 

2. Sewage treatment (for large treatment plants)

Ln (Opex) =  $\alpha + \beta * \ln$  (Total load) +  $\gamma *$  Activated sludge +  $\delta *$  Tight effluent consent

3. Sewage treatment (for small treatment plants)

Opex/Total Load = A [varying across treatment type]

In equation 2, the last two variables are dummy variables that apply to large sewage treatment plants relating to the use of activated sludge treatments and the severity of the effluent consent constraints at large works. As we discuss above we do not have data available at the same disaggregated level as that used by Ofwat so we are unable to replicate these variables at that level. At the aggregate level of the data that we use, the activated sludge variable can be proxied by the proportion of sewage that is subject to secondary or tertiary treatment, since the use of the activated sludge method of sewage treatment is invariably associated with secondary or higher levels of treatment. We are unable to proxy the tight efficient constraint variable at the aggregate level. For equation 3 we do not have data available on the breakdown of small sewage treatment plants by size and type of treatment.

Because of the above data issues for sewage treatment we have estimated a panel model for all sewerage treatment expenditure at the aggregate company level. The aggregation over all sewage treatment plants introduces the number of sewage treatment plants as a variable, which represents the average fixed cost per plant. For consistency with the treatment of water resources and treatment expenses we have used the natural logarithm of the number of sewage treatment plants as the explanatory variable. The equation we use for aggregate sewerage expenditure is:

 $Ln (Opex) = \alpha + \beta * ln (Total load) + \gamma * Ln (No. sewage treatment plants) + \delta * \% of sludge receiving secondary treatment.$ 

4. Sludge treatment and disposal

Opex/Weight of sludge = A [varying across disposal methods]

<sup>&</sup>lt;sup>19</sup> Ofwat (January 2008), Op. cit.

We do not have detailed figures on the proportions of sludge disposed of in different ways, so that the best that can be done is to calculate an average cost of disposal. The equation we use for sludge treatment and disposal expenditure is:

 $Ln (Opex) = \alpha + ln (Weight of sludge)$ 

5. Business activities

Opex/Total no of billed properties = A

{Equivalent specification:  $Ln(Opex) = \alpha + ln(Total no of billed properties)$ }

The results from estimating these equations for the components of sewerage operating expenses are shown in Table 3.3.<sup>20</sup> As a consequence of the relatively small number of WASCs it was not possible to obtain reliable results on pooling time series equations across companies, so the test for pooling across panels is not shown.

<sup>&</sup>lt;sup>20</sup> Because the specification of the models presented in Table 3.3 are either more general versions of the Ofwat models or a slightly modified speciation (because our dataset does not comprise directly compatible data), we do not present the coefficients for the Ofwat sewerage operating costs models in the table.

	Pa	anel GLS	;	Pa	anel SFA		Rando pooli	m coefficing over	cient – time
	Coeff	SE	Ζ	Coeff	SE	Ζ	Coeff	SE	Ζ
							(Chi^2)	(DF)	(P)
A. Sewer network									
Ln (Sewer length)	-0.1650	0.2134	0.77	-0.1750	0.2965	0.59	-0.7024	0.3177	2.21
Ln (Area)	0.2916	0.0879	3.32	0.3741	0.1452	2.58	0.4857	0.0977	4.97
Ln (Resident population)	0.9821	0.1979	4.96	0.9686	0.2743	3.53	1.4362	0.2816	5.10
Holiday population/Resident population	1.0959	1.5618	0.70	1.6400	2.5438	0.64	-0.4520	1.5018	0.30
Time	0.0211	0.0059	3.61	0.0257	0.0047	5.42			
Constant	-6.6332	0.5586	11.87	-7.6167	1.0958	6.95	-6.8080	0.4585	14.85
Autocorrelation	0.58								
Sigma U2				0.0131	0.0075				
Sigma V2				0.0224	0.0032				
Test for pooling over time							51.0	50	0.44
B. Sewage treatment									
Ln (Total BOD load)	0.6490	0.0481	13.50	0.5252	0.1172	4.48	0.6959	0.0491	14.18
Ln (No of sewage treatment plants)	0.3807	0.0595	6.39	0.8341	0.1209	6.90	0.3431	0.0680	5.04
% of sewage with secondary treatment	-0.0872	0.1607	0.54	-0.1526	0.1138	1.34	-0.9135	0.7783	1.17
Time	0.0500	0.0067	7.50	0.0542	0.0047	11.46			
Constant	-6.7306	0.5472	12.30	-8.4298	0.9582	8.80	-6.1772	0.5942	10.40
Autocorrelation	0.71								
Sigma U2				0.6533	2.7283				
Sigma V2				0.0117	0.0017				
Test for pooling over time							46.7	40	0.22
C. Sludge disposal									
Ln (Weight of sludge)	0.0231	0.0140	1.65	0.0460	0.0264	1.74	0.7763	0.0860	9.03
Time	0.0591	0.0125	4.71	0.0685	0.0058	11.77			
Constant	2.6312	0.1083	24.29	1.5220	0.1463	10.41	-0.8888	0.3916	2.27
Autocorrelation	0.78								
Sigma U2				0.4522	0.3405				
Sigma V2				0.0333	0.0047				
Test for pooling over time							173.6	20	0.00
D. Business activities									
Ln (I otal no of bills)	0.8578	0.0492	17.43	0.9724	0.1027	9.47	0.9391	0.0498	18.86
	0.0354	0.0060	5.86	0.0353	0.0035	10.00			
Constant	-3.5652	0.3733	9.55	-4.7591	0.7432	6.40	-4.1298	0.3788	10.90
	0.88								
Sigma U2				0.1090	0.1136				
Sigma V2				0.0130	0.0018		ļ		
LI est for pooling over time							4.8	20	1.00

 Table 3.3

 Estimates of equations for Ofwat's sewerage operating expenses

Source: NERA estimates.

The key conclusions from the results presented in Table 3.3 are outlined below.

- **§** Some of Ofwat's explanatory variables are not statistically significant when used in a panel context. Both the ratio of holiday population to resident population and the percentage of sewage receiving secondary or higher levels of treatment could be dropped from their respective equations.
- § The assumptions, implicit in the Ofwat unit costs models, that operating expenses for sludge disposal and business activities are directly proportional to the weight of sludge and the total number of billed properties respectively, are clearly rejected by our analysis. This is demonstrated by the coefficients on these variables in their respective models being clearly different from 1. In fact, the weight of sludge performs poorly in explaining sludge disposal costs in the panel GLS and panel SFA equations. This reflects the very strong time trend in these equations, which is consistent with the dominant influence of regulatory factors driving the cost of sludge disposal.
- **§** The test statistics for pooling over time from the random coefficient do not reject pooling in three out of the four equations, though the power of this test is likely to be quite poor. This finding is consistent with the results of similar tests performed on the water operating costs panel models and is supportive of the use of panel data to obtain coefficient estimates that are pooled over time. However, given the even smaller number of observations compared with the water operating cost equations, and the still present issue of company fixed effects, the power of this test is likely to be quite poor.

# 4. Panel Models of Aggregate Water Operating Expenditures

#### 4.1. Introduction

In this section we first derive equations for whole water service operating expenditure using a panel SFA estimator. We derive these equations by starting with a general model of water operating expenditure based on the set of explanatory variables used by Ofwat in their COLS equations. We then move to a simpler model by excluding those variables that do not appear to be significant drivers of total water operating costs. We repeat this process to derive and equation for whole service sewerage operating costs. We use our models to obtain water and sewerage service efficiency rankings for the E&W companies and then compare these rankings with those obtained by Ofwat in its latest relative efficiency analysis.

#### 4.2. Water panel model estimates

In this sub-section we estimate panel models for two definitions of total operating expenses:

- 1. "Controllable operating expenses" The sum of Ofwat's separate opex categories, excluding "uncontrollable" expenses, i.e. local authority rates, service charges, third party services and exceptional items.
- 2. "Total operating expenses" The sum of all operating expenses including rates, service charges, third party services and exceptional items.

The distinction between controllable and uncontrollable expenses is not a clear one. Local authority rates are a tax on property values – including the value of the water network - but both the amount of property used by a company and its valuation can be affected by decisions made by the company. Similarly, both service charges and third party services can be influenced to some degree by the operator.

We note that some of the Ofwat water operating expenditure equations are specified in terms of expenditure per person, while others refer to total expenditure without population as a scale variable. For aggregate expenditure our generalised model treats resident population as an explanatory variable while the dependent variable is total operating expenditure.

In Table 4.1 we present our SFA analysis of total water operating expenses.

									/ /			
	C	Controllable operating expenses						Total	operat	ing expe	nses	
	Ν	lodel 1			Model 2		N	lodel 3			Model 4	
	Coeff	SE	Ζ	Coeff	SE	Z	Coeff	SE	Ζ	Coeff	SE	Z
% large mains	0.614	0.616	1.00				0.504	0.573	0.88			
% from boreholes	-0.234	0.072	3.27	-0.212	0.063	3.38	-0.217	0.069	3.12	-0.189	0.122	1.55
Ln (Average pumping head)	0.116	0.069	1.67	0.097	0.068	1.42	0.065	0.049	1.32			
Ln (Total no of sources)	0.059	0.034	1.72	0.060	0.033	1.80	0.041	0.033	1.24			
Ln (Input volume)	0.124	0.152	0.82				-0.011	0.145	0.07			
Ln (Total no of bills)	-0.428	0.356	1.20				-0.707	0.339	2.09			
Ln (Resident population)	1.171	0.346	3.39	0.881	0.036	24.52	1.631	0.337	4.83	0.949	0.025	37.52
Time	0.020	0.003	7.85	0.018	0.002	9.65	0.022	0.002	8.99	0.019	0.002	11.49
Constant	-4.011	0.508	7.90	-3.766	0.369	10.21	-4.158	0.417	9.97	-3.344	0.244	13.70
Log-likelihood	224.4			223.3			237.0			233.1		
Sigma_u^2	0.028	0.020		0.030	0.022		0.022	0.015		0.015	0.008	
Sigma_v^2	0.007	0.001		0.007	0.001		0.006	0.001		0.006	0.001	

 Table 4.1

 SFA equations for controllable and total water operating expenses

Source: NERA estimates.

Table 4.1 shows the SFA equations that have been estimated for controllable and total operating expenses.

- **§** For controllable operating expenses, the coefficients on the percentage of large mains, input volume and the total number of bills are insignificant, so that these variables have been dropped from the simplified version of the model (Model 2).
- **§** For total operating expenses, the percentage of large mains, average pumping head, the number of water sources, input volume and the total number of bills have been dropped from the simplified version of the model (Model 4) because they are insignificant. The coefficient on the total number of bills is significant when all of the variables are included (Model 3), but it becomes insignificant once the other variables are dropped.

The key conclusions for our SFA model of whole service water operating expenses are outlined below.

- **§** After taking into account scale, company specific effects and time, the observable characteristics of water company operations explain little of the differences in total operating expenses between companies. The only explanatory variables that are consistently significant in the models that we have estimated are the proportion of supply from boreholes and resident population as well as the time trends. This could suggest that there are a number of (unobserved) cost drivers of water service expenditure which are not captured by the set of Ofwat variables. Alternatively this result may be indicative that after taking into account the scale of water company operations then a relatively small proportion of water service operating expenses are driven by other factors.
- **§** Resident population is a more relevant cost driver for total water operating expenditure than total mains length. We note that we have also estimated versions of the equations presented in Table 4.1 which use total mains length as the scale variable rather than the resident population. In these equations the coefficient on total mains length is small and insignificant.

#### 4.3. Sewerage panel model estimates

Table 4.2 shows our estimate of the stochastic frontier equations for controllable and total sewerage operating expenses. The definitions of controllable and uncontrollable operating expenses for sewerage cost are the same as for water costs. Again models 2 and 4 are simplified version of the more general model after variables which appeared to be insignificant drivers of costs were removed.

SFA equations	SFA equations for controllable and total sewerage operating expenses											
	Co	ontrolla	ible ope	erating	expens	ses		Total	operati	ng exp	enses	
		Model	1		Model :	2		Model	3	ſ	Vodel 4	1
	Coeff	SE	Z	Coeff	SE	Z	Coeff	SE	Z	Coeff	SE	Z
Holiday population /												
Resident population	6.743	0.936	7.20	5.535	0.762	7.26	6.785	0.970	7.00	5.872	0.798	7.36
% of sewage with												
secondary treatment	0.198	0.075	2.62	0.201	0.073	2.75	0.140	0.081	1.72	0.152	0.080	1.91
Ln (Sewer length)	0.265	0.179	1.48				0.252	0.204	1.23			
Ln (Area)	-0.149	0.165	0.90				-0.220	0.153	1.44			
Ln (Resident population)	-0.097	0.312	0.31				-0.024	0.337	0.07			
Ln (No of sewage treatment												
plants)	0.282	0.113	2.50	0.211	0.033	6.45	0.339	0.104	3.26	0.207	0.032	6.57
Ln (Total BOD load)	0.282	0.199	1.42				0.549	0.199	2.76	0.481	0.172	2.79
Ln (Weight of sludge)	-0.002	0.010	0.16				-0.010	0.011	0.95			
Ln (Total no of bills)	0.513	0.355	1.45	0.894	0.023	39.65	0.213	0.385	0.56	0.425	0.164	2.59
Time	0.037	0.004	9.95	0.034	0.003	11.39	0.043	0.004	10.69	0.041	0.004	11.07
Constant	-5.552	0.910	6.10	-4.164	0.229	18.21	-6.336	0.948	6.69	-6.053	0.795	7.61
Log-likelihood	127.4			125.2			121.2			119.2		
Sigma_u^2	0.453	4.126		0.029	0.075		0.718	5.163		0.262	1.780	
Sigma_v^2	0.005	0.001		0.005	0.001		0.005	0.001		0.006	0.001	

 Table 4.2

 SFA equations for controllable and total sewerage operating expenses

Source: NERA estimates.

The important points to note are:

- **§** A larger number of explanatory variables are significant in the sewerage aggregate cost panel model than was the case for the water model. This suggests that there may be less of an issue with unobserved cost drivers for sewerage operating expenditure.
- **§** Analysis of individual components of expenses may not provide a reliable guide to the behaviour of the total, especially if some of the component equations perform poorly. For example even though neither the ratio of holiday population to resident population nor the percentage of sewage receiving secondary or higher treatment are significant in our SFA regressions for the components of sewerage operating expenses, both of them are highly significant in the aggregate cost equation.
- **§** As a consequence of multi-collinearity between alternative scale variables in a small dataset several variables can be omitted because their coefficients are not significant and/or the signs of the coefficients do not make sense. For example some apparent cost drivers have negative coefficients. In the case of total operating expenses this might

have lead to the exclusion of all variables reflecting population size in the simplified model, though the total BOD load is an imperfect substitute. For this reason, we retained the log of the total number of billed properties, whose coefficient becomes very significant when other scale variables are excluded.

**§** The time trends for both controllable (3.4% per year) and total operating expenses (4.1% per year) are quite large and highly significant. This reinforces the earlier point that regulatory factors together with discharge fees and taxes are very important drivers of sewerage operating costs in England and Wales. Since these are exogenous in the short run, it may be important to consider how far the companies have the capacity and incentive to minimise the impact of taxes and regulations on the cost of their operations and what is passed on to customers.

#### 4.4. Comparative Efficiency of E&W Companies Using Aggregate Cost Panel Models

In this sub-section we present relative efficiency ranking of the E&W water companies using our simplified SFA whole service operating cost models.

#### 4.4.1. Water Service Efficiency

The simplified SFA models for controllable and total water operating expenses, presented in Section 4.2, have been used to rank the companies in the sample by their efficiency relative to the frontier. The results for controllable operating expenses are shown in Table 4.3.

Rank	C.ref	Company	Estimated i	nefficiency (%	) relative to:
			Frontier	Best	Decile
1	PRT	Portsmouth Water	2.2%	0.0%	-1.4%
2	YKY	Yorkshire Water	3.1%	0.9%	-0.5%
3	DVW	Dee Valley Water	3.6%	1.4%	0.0%
4	WSX	Wessex Water	5.0%	2.7%	1.3%
5	SRN	Southern Water	6.9%	4.7%	3.2%
6	SST	South Staffordshire	12.6%	10.2%	8.7%
7	ANH	Anglian Water	12.6%	10.2%	8.7%
8	SVT	Severn Trent Water	13.4%	11.0%	9.5%
9	NES	Northumbrian	15.2%	12.7%	11.2%
10	MKT	Mid Kent Water	16.7%	14.2%	12.6%
11	SWT	South West Water	17.3%	14.8%	13.2%
12	NWT	North West Water	17.5%	15.0%	13.4%
13	BWH	Bournemouth & West Hampshire Water	17.8%	15.3%	13.7%
14	CAM	Cambridge Water	22.6%	19.9%	18.3%
15	MSE	South East Water	28.3%	25.6%	23.9%
16	SES	Sutton & East Surrey Water	30.5%	27.7%	25.9%
17	BRL	Bristol Water	31.3%	28.5%	26.7%
18	TVN	Three Valleys Water	34.9%	32.0%	30.2%
19	THD	Tendring Hundred Water	38.5%	35.5%	33.6%
20	WSH	Welsh Water	45.1%	42.0%	40.1%
21	TMS	Thames Water	50.5%	47.3%	45.2%
22	FLK	Folkestone & Dover Water	61.4%	57.9%	55.8%

Table 4.3SFA ranking of companies by efficiency for controllable operating expenses

Source: NERA estimates derived from Model 2 in Table 4.1.

There is a considerable dispersion in the efficiency of water companies in terms of their controllable operating expenses. Large and small companies – as well as WOCs and WASCs – appear at the top and the bottom of the distribution of companies by efficiency, so that there are no obvious factors that differentiate those which are relatively efficient from those which are relatively inefficient.

Table 4.4 shows the efficiency ranking of companies in terms of their total operating expenses. The ranking of the companies is not identical to that in Table 4.3. For example, Thames Water moves from a rank of 21 for controllable operating expenses to one of 15 for all operating expenses. Wessex Water moves from a rank of 4 for controllable operating expenses to a rank of 10 for all operating expenses. The correlation between the rankings for the two definitions is 0.79. This is high but it remains the case that any conclusions about relative efficiency depend upon the measure of expenses that is used. Portsmouth Water and Dee Valley Water – two rather small companies – are ranked in 1<sup>st</sup> and 3<sup>rd</sup> for both measures, while Yorkshire Water is 2<sup>nd</sup> for controllable expenses and 4<sup>th</sup> for total expenses. Similarly, the Tendring Hundred Water, Welsh Water and Folkestone & Dover Water are consistently at the bottom of the efficiency rankings.

Rank	Cref	Company	Estimated in	nefficiency (%	) relative to:
			Frontier	Best	Decile
1	PRT	Portsmouth Water	3.1%	0.0%	-8.8%
2	DVW	Dee Valley Water	8.8%	5.5%	-3.7%
3	SST	South Staffordshire	13.0%	9.6%	0.0%
4	YKY	Yorkshire Water	13.1%	9.7%	0.1%
5	SRN	Southern Water	16.6%	13.0%	3.2%
6	BWH	Bournemouth & West Hampshire Water	18.5%	14.9%	4.9%
7	SVT	Severn Trent Water	21.0%	17.3%	7.1%
8	NWT	North West Water	22.3%	18.6%	8.2%
9	CAM	Cambridge Water	23.0%	19.3%	8.8%
10	WSX	Wessex Water	23.2%	19.5%	9.0%
11	NES	Northumbrian	25.4%	21.6%	11.0%
12	MKT	Mid Kent Water	27.6%	23.8%	13.0%
13	TVN	Three Valleys Water	27.8%	23.9%	13.1%
14	BRL	Bristol Water	28.2%	24.4%	13.5%
15	TMS	Thames Water	34.9%	30.8%	19.3%
16	ANH	Anglian Water	35.3%	31.2%	19.7%
17	SWT	South West Water	35.4%	31.3%	19.8%
18	SES	Sutton & East Surrey Water	36.0%	31.9%	20.3%
19	THD	Tendring Hundred Water	36.5%	32.4%	20.8%
20	MSE	South East Water	39.2%	35.0%	23.2%
21	WSH	Welsh Water	62.8%	57.8%	44.0%
22	FLK	Folkestone & Dover Water	64.8%	59.9%	45.9%

Table 4.4SFA ranking of companies by efficiency for total operating expenses

Source: NERA estimates derived from Model 4 in Table 4.1.

#### 4.4.2. Sewerage Service Efficiency

The efficiency rankings of the sewerage operators are shown in Table 4.5 and Table 4.6 for controllable and total operating expenses respectively. The dispersion of efficiencies relative to the frontier is much less than for water operating expenses. This may be a consequence of unobserved cost drivers for water operations, which is reflected in fewer significant explanatory variables in this model (compared with the sewerage model). Less dispersion of efficiencies may also indicate that the larger average size of sewerage operations has the effect of averaging out differences that cause dispersion in the observed efficiency of water operations.

The differences in the efficiency rankings for the two measures of cost are relatively minor. Three companies – Northumbrian, North West and Southern – are clearly less efficient than the other 7 companies for both controllable and total operating expenses.

Rank	Cref	Company	Estimated ine	fficiency (%)	relative to:							
			Frontier	Best	Decile							
1	WSX	Wessex Water	1.7%	0.0%	-0.4%							
2	SVT	Severn Trent Water	2.4%	0.7%	0.4%							
3	TMS	Thames Water	2.6%	0.9%	0.6%							
4	SWT	South West Water	2.8%	1.1%	0.8%							
5	ANH	Anglian Water	2.9%	1.1%	0.8%							
6	YKY	Yorkshire Water	8.8%	6.9%	6.5%							
7	WSH	Welsh Water	10.0%	8.2%	7.8%							
8	NES	Northumbrian	16.5%	14.5%	14.1%							
9	NWT	North West Water	21.2%	19.2%	18.8%							
10	SRN	Southern Water	23.9%	21.8%	21.3%							

Table 4.5Efficiency ranking of companies for controllable sewerage operating expenses

Source: NERA estimates based upon Model 2 in Table 6.

Effi	Efficiency ranking of companies for total sewerage operating expenses										
Rank	Cref	Company	Estimated ine	fficiency (%)	relative to:						
			Frontier	Best	Decile						
1	WSX	Wessex Water	1.3%	0.0%	-0.2%						
2	ANH	Anglian Water	1.7%	0.4%	0.2%						
3	TMS	Thames Water	2.2%	0.9%	0.7%						
4	WSH	Welsh Water	2.8%	1.5%	1.3%						
5	SVT	Severn Trent Water	2.9%	1.5%	1.3%						
6	SWT	South West Water	3.2%	1.8%	1.6%						
7	YKY	Yorkshire Water	3.4%	2.1%	1.9%						
8	NES	Northumbrian	9.3%	7.9%	7.7%						
9	NWT	North West Water	11.2%	9.7%	9.5%						
10	SRN	Southern Water	23.8%	22.2%	21.9%						

 Table 4.6

 Efficiency ranking of companies for total sewerage operating expenses

Source: NERA estimates based upon Model 4 in Table 6.

#### 4.5. Comparison with Ofwat Rankings

Table 4.7 compares the efficiency rankings for water services derived from the SFA models of controllable and total water operating expenses with the rankings assigned by Ofwat for 2007-08. The Ofwat rankings for 2007-08 exclude Mid Kent Water following their merger with South East Water. Our rankings include a separate ranking for Mid Kent and South East based on their (separately) reported June return data for the period 1997-98 to 2007-08. The calculation of the rank correlations reported in the table excludes Mid Kent and South East.

The rank correlations between the SFA ranks and the Ofwat ranks are 0.74 for controllable operating expenses and 0.52 for total operating expenses. We expect that the correlation between our SFA for controllable opex and Ofwat's rankings to be higher since the Ofwat rankings are based upon the components of controllable expenses.

There are some important differences between the SFA panel ranking for controllable operating expenses and the Ofwat COLS rankings.

- **§** The difference in rankings (Excluding Mid Kent and South East) for 6 companies is more than 5 places. 5 ranking place represents the width of a quartile in the rankings, thus a change in ranking of 5 places represents a significant shift in a company's ranking.
- § The companies which have a difference in ranking of more than five places are: Dee-Valley (minus 10 places); South West Water (minus 8); Bournemouth (plus 6); Cambridge (minus 6); Thames Water (plus 5); and Sutton & East Surrey (plus 5).
- **§** The average absolute value of the difference in ranks is 3.00 which is equivalent to slightly less than one-half of the class width for Ofwat's A, B, C classification.

		Controllal exp	ole operating enses	Total exp	operating enses	Ofwat ranking
		Rank	Decile	Rank	Decile	
ANH	Anglian Water	7	8.7%	16	19.7%	3
BRL	Bristol Water	17	26.7%	14	13.5%	14
BWH	Bournemouth & West Hampshire Water	13	13.7%	6	4.9%	6
CAM	Cambridge Water	14	18.3%	9	8.8%	19
DVW	Dee Valley Water	3	0.0%	2	-3.7%	13
FLK	Folkestone & Dover Water	22	55.8%	22	45.9%	21
MKT	Mid Kent Water	10	12.6%	12	13.0%	N/A
MSE	South East Water	15	23.9%	20	23.2%	11
NES	Northumbrian	9	11.2%	11	11.0%	9
NWT	North West Water	12	13.4%	8	8.2%	12
PRT	Portsmouth Water	1	-1.4%	1	-8.8%	1
SES	Sutton & East Surrey Water	16	25.9%	18	20.3%	10
SRN	Southern Water	5	3.2%	5	3.2%	7
SST	South Staffordshire	6	8.7%	3	0.0%	5
SVT	Severn Trent Water	8	9.5%	7	7.1%	8
SWT	South West Water	11	13.2%	17	19.8%	18
THD	Tendring Hundred Water	19	33.6%	19	20.8%	17
TMS	Thames Water	21	45.2%	15	19.3%	15
TVN	Three Valleys Water	18	30.2%	13	13.1%	20
WSH	Welsh Water	20	40.1%	21	44.0%	16
WSX	Wessex Water	4	1.3%	10	9.0%	4
YKY	Yorkshire Water	2	-0.5%	4	0.1%	2
	Rank correlations with Ofwat ranking	0.78		0.59		

 Table 4.7

 Summary of SFA and Ofwat efficiency rankings for water services

Source: NERA estimates derived from Model 4 in Table 2 and Ofwat (January 2009) 'relative efficiency' assessment 2007-08'

Table 4.8 compares the efficiency rankings for sewerage services derived from the SFA equations for controllable and total sewerage operating expenses with the rankings assigned by Ofwat for 2007-08. The rank correlations between the SFA ranks and the Ofwat ranks are 0.75 for controllable operating expenses and 0.66 for total operating expenses. Again, we would expect the correlation to be higher for controllable expenses since the Ofwat rankings are based upon the components of controllable expenses.

For sewerage the company with the biggest difference in efficiency ranking for controllable operating expenses is Yorkshire water which is 6<sup>th</sup> in the ranking based on our panel SFA

analysis but 2<sup>nd</sup> in the Ofwat rankings. The average absolute value of the difference in ranks between Ofwat's analysis and the SFA analysis is 2.2, again about one half of the class width for Ofwat's A, B, C classification.

		Controllable operating expenses		Total operating expenses		Ofwat ranking			
		Rank	Decile	Rank	Decile				
ANH	Anglian Water	5	0.8%	2	0.2%	4			
NES	Northumbrian	8	14.1%	8	7.7%	7			
NWT	North West Water	9	18.8%	9	9.5%	10			
SRN	Southern Water	10	21.3%	10	21.9%	9			
SVT	Severn Trent Water	2	0.4%	5	1.3%	5			
SWT	South West Water	4	0.8%	6	1.6%	6			
TMS	Thames Water	3	0.6%	3	0.7%	1			
WSH	Welsh Water	7	7.8%	4	1.3%	8			
WSX	Wessex Water	1	-0.4%	1	-0.2%	3			
YKY	Yorkshire Water	6	6.5%	7	1.9%	2			
	Rank correlations with Ofwat ranking	0.75		0.66					

 Table 4.8

 Summary of SFA and Ofwat efficiency rankings for sewerage services

Source: NERA estimates derived from Models 2 & 4 in Table 7 and Ofwat (January 2009) 'relative efficiency' assessment 2007-08'

# 5. Comparative Efficiency of NIW

The final stage in our analysis of the efficiency of water and wastewater service operators is to include Northern Ireland Water (NIW) in the analysis. We use the simplified water and sewerage total and controllable operating cost SFA panel models presented in Sections 4.2 and 4.3 to estimate the efficiency of NIW. We do not include data from NIW in our estimation of the SFA model, this ensures that the model coefficients are not influenced by the object of the comparative efficiency exercise.<sup>21</sup> This section progresses as follows:

- § We first present the results of our relative efficiency assessment of NIW's water and sewerage operating expenditure in 2007/08 using our simplified SFA models. We compare these results to a recent assessment of NIW's relative efficiency based on Ofwat's 2006/07 COLS models<sup>22</sup> and;
- **§** We then compare our SFA results for NIW with the SFA results for E&W companies presented in Section 4.

#### 5.1. NIW Relative Efficiency

In Table 5.1 below we present the results of NIW's operating cost efficiency in 2007/08 assessed using our SFA panel models. We also present the results of a comparative efficiency assessment of NIW operating costs in 2006/07 undertaken using the Ofwat COLS approach. Both sets of results presented in Table 5.1 compare NIW's costs to the efficiency frontier. The SFA estimation technique directly estimates that cost frontier for total operating costs. The Ofwat COLS method estimates the cost frontier for each sub-model as a selected benchmark company's level of efficiency,<sup>23</sup> and total service efficiency for each company is a product of its efficiency relative to the benchmark for each of the sub-models.

The key points from the results presented in Table 5.1 are summarised below.

- **§** For controllable opex, the SFA panel results show that NIW is very inefficient relative to the cost frontier. With controllable water and sewerage opex equal to 193% and 173% of the frontier company's costs respectively.
- **§** For total opex NIW is also very inefficient, but less so than for controllable opex. For total opex, NIW's water and sewerage costs are equal to 158% and 124% of the frontier company's costs respectively. These results could indicate that NIW faces lower charges for some items of expenditure classified as uncontrollable, for example local

<sup>&</sup>lt;sup>21</sup> To undertake this procedure using Stata NIW is assigned a very low weight in estimating the stochastic frontiers. The low weighting means that estimated equations are identical to those reported in Table 4.1 above, but this allows Stata to produce a relative efficiency score for NIW using these equations. The reason is that Stata's xtfrontier procedure is not able to generate predictions of efficiency for out-of-sample panel units, so it is necessary to include NIW in the frontier estimation if one is interested in calculating its efficiency relative to other companies.

<sup>&</sup>lt;sup>22</sup> See NERA (January 2009), 'Setting Efficiency Targets for NIW for 2009-10: A Final Report for NIAUR'

<sup>&</sup>lt;sup>23</sup> The benchmark company is selected as roughly as the least cost company relative to average level of efficiency in E&W. A number of other criteria are used in the selection of the benchmark company including that the company must comprise at least 3% of industry turnover (by service) and there must be no "special characteristics" that are outside the control of management" or "special concerns about the consistency of the benchmarks company's data.

authority rates or abstraction/discharge fees, if this is indeed the case. The results could also reflect differences in NIW's allocation of costs to the uncontrollable categories compared with E&W companies.

§ NIW's relative operating efficiency for uncontrollable and controllable operating costs are of a similar order for our 2007/08 SFA assessment and an assessment for 2006/07 based on Ofwat. The relative efficiency assessment of NIW's operating cost performance for 2006-07 using the Ofwat COLS models, finds that NIW's level of operating costs for water and sewerage are, respectively 219% and 156% of what they would be if NIW was at the frontier.

# Table 5.1 Comparison of NIW Operating Cost Efficiency Using SFA and COLS

Service	NIW Costs Relative to Efficiency Frontier Using:						
	SFA'		SFA	Ofwat COLS <sup>2</sup>			
	(Total, uncontrollable 2007/08)	inc.	(Controllable 2007/08)	(Controllable 2006/07)	-		
Water	158%		193%	219% <sup>3</sup>			
Sewerage	151%		173%	156% <sup>4</sup>			

Notes: (1) Source - NERA estimates; (2) Source - NERA (January 2009), 'Setting Efficiency Targets for NIW for 2009-10: A Final Report for NIAUR'; (3) NIW actual water operating expenditure (exc. Business activities costs) for 2006/07 was £79.04m, the benchmarked (frontier) cost for NIW suggested by Ofwat's 2006/07 COLS models was £36.14m; (4) NIW actual sewerage operating expenditure (exc. Business activities costs) for 2006/07 was £65.37m, the benchmarked (frontier) cost for NIW suggested by Ofwat's 2006/07 COLS models was £41.94m.

#### 5.2. Comparison with E&W companies

In Table 5.2 we compare the assessed relative efficiency of NIW using our SFA panel models, with the SFA efficiency scores of E&W companies presented in Section 4.4.

# Table 5.2Comparison of NIW Operating Cost Efficiency with E&W Company Using PanelSFA: Estimated Inefficiency

	NIW	Worst Ranked E&W Company
Water		
Controllable	193%	159% (Folkestone)
Total	158%	157% (Folkestone)
Sewerage		х, , , , , , , , , , , , , , , , , , ,
Controllable	173%	123% (Southern)
Total	151%	124% (Southern)
Courses NEDA on alusia		

Source: NERA analysis

From the comparison between the SFA efficiency results for NIW and those for the E&W companies we find that:

**§** For both water and sewerage controllable opex, NIW is the least efficient company of all companies. For example, for controllable water opex. NIW's costs are 193% of

what they would be if they were at the frontier whereas the worst ranked E&W company (Folkestone) has costs that are 159% of their efficient costs.

§ For total water and operating costs (i.e. including uncontrollable items), NIW is still the least efficient company although its performance is not as poor. For example, for total water opex, NIW's costs are 158% of what they would be if they were at the frontier whereas the worst ranked E&W company (again Folkestone) has costs that are 157% of their efficient costs. The improvement in its efficiency score implies that NIW has lower uncontrollable operating expenses relative to E&W companies, e.g. lower abstraction charge/ local authority rates.

# 6. Conclusions

In this report we have presented an econometric panel data analysis of the water and sewerage operating costs of the E&W WoCs and WaSCs. This analysis was based on a panel data set that we constructed specifically for the purpose of this analysis. The dataset consists of data on the operating expenditure and operating characteristics of the E&W companies drawn from their annual data submissions ("June returns") to the E&W water regulator, Ofwat. In the report we also presented a comparative efficiency analysis of NIW's water and sewerage operating expenditure. This analysis was based on whole service (water or sewerage) panel data models of operating costs that we developed from analysis of our dataset. In this section we summarise the main conclusions from our analysis.

§ In Section 3 we presented a panel data analysis, using GLS, SFA and random coefficients models, of the equations used by Ofwat in its latest report on the relative efficiency of E&W water companies. This analysis produced good evidence that the relationship between costs and cost drivers is stable over time. This would suggest that Ofwat's efficiency analysis would benefit from using panel data methods. Using a dataset that is pooled over time will allow a greater number of observations to be used in the analysis, which should lead to improvements in the robustness and reliability of the results. Panel data methods also allow variation in the data both between and within firms to be taken into account. This means that company specific effects which are persistent over time can be taken into account in the efficiency analysis.

Our analysis of Ofwat's equations also provided some evidence that for the functional expenditure equations used by Ofwat the relationship between costs and cost drivers was not stable across companies. (Although because the test that we used had fairly low power due to the relatively small number of companies and the complication of firm specific effects, we cannot completely discount the hypothesis of pooling across companies). This finding is problematic because some comparison across companies is necessary for relative efficiency assessments to be made. One conclusion from this is that efficiency assessments might be improved if some richer specification of the relationship between costs and costs drivers were used, such as the whole service operating costs models that we present in Section 4.

- § The whole service operating costs panel regression models that we present in Section 4, using SFA analysis, show that the relationships observed between costs and cost drivers at the level of functional operating expenditure do not translate straightforwardly to whole service expenditure. In our water service model only a small number of the set of cost drivers used by Ofwat in their COLS equations entered our SFA whole service equations as statistically significant variables, although a greater number were significant in the functional expenditure SFA equations. For sewerage a greater proportion of the Ofwat variables (or approximations of them) were significant in the SFA whole service equations. Indeed, a number of the variables did not appear to be significant in the functional sewerage SFA equations, but were highly significant in the whole service equations.
- **§** There were strong correlations between the "controllable" (as defined by Ofwat) operating cost efficiency rankings for E&W companies obtained using our whole service SFA models and the rankings obtained by Ofwat in its latest relative efficiency analysis.

The correlations were 0.78 for water and 0.75 for sewerage. However, there were some large differences in the ranking of individual companies.

- § In Section 5 we present an assessment of NIW's relative efficiency for 2007/08 for both "controllable" and "total" water and sewerage operating costs. NIW assessed efficiency for both services and definitions of operating costs is very poor, if slightly less poor for total operating costs. In each case NIW was significantly less efficient than the worst performing E&W company (with NIW's costs being at least 150% of what they would be if NIW was at the efficient frontier). The scale of NIW's assessed inefficiency using our SFA model was of a similar order to the assessed operating cost inefficiency of NIW for 2006/07 when that is based on Ofwat COLS regression models for 2006/07.
- **§** Whilst the conclusion from our analysis is that by any definition NIW's operating cost performance is clearly inefficient compared to that of E&W companies, we would caution against the inference that all of this assessed inefficiency can be caught-up, especially over a small number of years. Any efficiency comparison is limited to an extent by the available data and the statistical techniques which can be brought to bear on the problem. It is likely that there will be significant unobserved factors which cause heterogeneity in companies' costs, and it is the case that the potential complications that these factors can have for efficiency comparisons cannot be completely resolved by the available statistical techniques. In particular very large gaps to the efficiency frontier should be treated with some care. They may be the result of factors outside of managerial control or perhaps the steps necessary to resolve the assessed inefficiency may in fact not be optimal in the overall context of the company's operations. An example the second of these could occur when the manner of the historical development of a company's network requires the company to incur higher operating costs than would be suggested by the efficiency frontier. In this case the network imperfections could be resolved but the required additional capex to achieve this may outweigh any operating cost savings.

The required "catch-up" efficiency target of a company should also not be based solely on a company's comparative efficiency score but also draw on evidence of the achieved year on year reductions in unit costs by similar companies.



NERA Economic Consulting 15 Stratford Place London W1C 1BE United Kingdom Tel: +44 20 7659 8500 Fax: +44 20 7659 8501 www.nera.com

Marsh & McLennan Companies