Assessing the Impact of Plant Level Scale Economies, and Persistent & Transient Efficiency on the Cost of Sewage Treatment in the Large Sewage Plants of England & Wales.

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Abstract

A considerable number of academic and regulatory studies model the costs of water and sewage services at the company level and consider factors such as average population density in the served area as a determinant of input requirements, and hence efficient costs. However, with very limited exception, the previous literature has effectively assumed that such companies are single system operators. However, companies often operate multiple physically separate and distinct treatment, collection, and distribution systems, of which there are over 6,000 in England and Wales. Moreover, within and between such companies local operating characteristics can vary significantly, thereby influencing not only system level performance but also aggregated company performance. Thus, if we wish to provide more accurate models of company level costs, it is first necessary to better understand local system cost determinants. While evidence on the presence of scale economies in sewage treatment, and/or water supply is mixed, few studies examine the presence of scale economies in sewage treatment in isolation. Furthermore, limited consideration is given to the different treatment technologies used in sewage treatment plants. We therefore test and reject the assumption of a common technology for different treatment technologies. The chosen models therefore allow for plant level variable scale economies, plant level operating characteristics, and differences in treatment technologies.

The resulting analysis is based on regulatory data for sewage treatment plants that serve more than 25,000 population equivalent and therefore includes a sample of 328 plants in England and Wales over a 5-year period. By applying new generation Stochastic Frontier techniques in the Kumbhakar et al. (2014) approach to a four-way decomposition of the composed error from the standard panel data Random Effects model and extending to include heterogeneity in each of the four components, allows estimation of Persistent and Transient measures of cost efficiency, and whether these efficiencies have determinants – regulatory, or otherwise. By substantially addressing the shortcomings identified, the paper provides a robust plant level econometric benchmarking analysis of sewage treatment costs, and both estimates and determinants of transient **and** persistent efficiencies but will also inform future research aiming to properly account for the impact of disaggregated system characteristics on models of company level performance in the presence of multiple operating facilities.

Introduction

Benchmarking studies in the water industry which generally include some of the following: assessing the extent to which economies of scale and scope are present, measuring efficiencies, productivity related metrics, assessing the performance of utilities in newly privatised and regulated industries, and the impact of different types of regulatory regime on industry or firm performance, and are typically done at a company level of analysis. Further, while the water industry encapsulates both water supply and sewerage service provision, studies are more often done in the context of Water-only companies (WOCs) or Water and Sewerage Companies (WASCs), relatively little consideration is given to Sewage services in isolation, as investigated by Saal et al (2013).

Some of the first attempts at modelling the costs of water and/or sewage service provision, for example, by Ford & Warford (1969), Knapp (1978), Fraas and Munley (1984), and Hayes (1987) are by current standards rudimentary analyses, however, remain important having identified some key characteristics of water and sewage service provision. The removal of contaminants is a key cost driver in sewage treatment and various treatment technologies exist for this purpose. Another stylised fact is that the industry is made of firms who are producers of multiple outputs. One of the principal determinants of sewage treatment cost is the volume of the stream of wastewater flowing into the treatment plant, the population served or connected to the network, the number of industrial customers (where industrial waste is said to be exceptionally expensive and more difficult to treat), while the percentage of utilised capacity in treatment plants impacts operating cost.

Of the studies that solely consider Sewage treatment, the majority appear originate from Italian or Spanish regions using plant level data, studies such as Fraquelli and Giandrone (2003), Hernandez-Sancho and Sala-Garrido (2009), Hernandez-Sancho et al (2011), Molinos-Senante et al (2014, 2016), Guerrini et al (2016), Lledó Castellet-Viciano, et al. (2018). It is apparent that only one plant level study exists for the English and Welsh water and sewerage industry – Knapp (1978). Of the plant-level analyses, there are a number of limitations present, as such we wish to address some of these limitations to better examine the extent to which economies of scale and efficiency play a role in determining the costs incurred in sewage service provision in England and Wales.

Often plant level approaches fail to incorporate, or test for the validity of employing a flexible modelling approach that would allow one to examine for the presence of variable scale economies across the sample, thereby imposing a common scale elasticity across the sample. In the only published plant-level study of English and Welsh sewage plants: Knapp (1978) attempted to fit a quadratic function to explain average costs, however despite a large range in plant sizes treating approximately 1 to 40 million gallons of daily sewage flow, the squared output terms did not provide any additional predictive power for average costs. Elsewhere, Fraquelli and Giandrone (2003) assess the impact of plant sizes and economies of scale on the costs of operation in medium and large sized Italian sewage treatment plants – that is, plants with a population equivalent > 10, 000. The cross-sectional dataset of 103 plants, covering 11 Italian regions appears to show a general tendency for falling unit costs with an increase in output, although a number of limitations may be present in the Cobb-Douglas cost function that is employed, e.g., the sample is restricted to a common elasticity of scale – where a Cobb-Douglas output elasticity provides information regarding the average output of the plants that were sampled, but cannot supply sufficient information about scale economies in the full range of plant sizes. Moreover, despite the apparent availability of multiple output measures, only one is used (the volume of treated water).

In fact, the water (and sewage) industry has long been recognized as an industry where firms produce multiple outputs – e.g., water supply utilities produce retail and wholesale volumes, integrated utilities may produce both retail and wholesale volumes while also providing sewage services. The same should be said for sewage only utilities or plants, whereby sewage treated may be measured by Load received or Population equivalent, and Flow treated. This is a particularly important fact when one considers the nature of the sewers that each utility, and system uses, e.g., combined sewers collect both volumes of wastewater from households and industrial customers, while also collecting rainfall volumes – depending on the season and weather patterns, it is not hard to reconcile how a system or plant that also treats rainfall volumes faces different demand when compared to a system which does not treat rainfall volumes. By means of example, Hayes (1987) analysed the water supply industry and employed a generalized quadratic cost function, utilizing measures of water sold to retail customers, and volumes sold on wholesale markets to other utilities, in order to examine whether the water supply sector exhibited subadditivity – that is, examining whether the cost of jointly producing both retail and wholesale water volumes, is less than or equal to the cost of producing each of the retail and wholesale volumes separately. Elsewhere, Kim and Clark (1988) estimated individual and combined cost elasticities for residential and non-residential water supply by US water utilities.

Moreover, the presence (or lack thereof) of economies of scale, or the nature of the returns to scale available in water and/or sewage service provision is widely covered for a variety of outputs, e.g., water supply to households and/or wholesale volumes, sewage treatment, and potentially even leakages or network losses – as in Garcia and Thomas (2001). Further, it is apparent in some studies that these economies, if present, are exhausted beyond a certain size of utility – Kim and Clark (1988) suggest smaller US water supply utilities benefit from increasing returns, Torres and Morrison-Paul (2006) show that smaller US water supply utilities exhibit economies of size, however the sample-average and larger utilities display diseconomies of size.

Studies such as Saal and Parker (2000) & (2004), Ashton (2000), and Saal et al. (2007) have looked at the impact of privatization and regulation in the English and Welsh water industry specifically. Privatized in 1989, significant changes have taken place in the English and Welsh industry, including numerous mergers and consolidations. Saal and Parker (2000) & (2004), and Saal et al (2007) found that the costs incurred by the average Water and Sewerage Company (WASC) were characterized by diseconomies of scale (decreasing returns to scale: scale elasticities of between 0.83 - 0.88, depending on the restrictions imposed indicate that a 1 percent increase in inputs produced a 0.83-0.88 percent increase in Outputs). In contrast, Ashton (2000) employs a similar methodological approach for an overlapping period, from 1989- 1997 of English and Welsh water and sewerage companies. These findings suggest the industry was characterized by substantial economies of scale of 0.678 (whereby a 1 percent increase in output see the sum of inputs rise by only 0.678 percent). Similarly, Bottasso et al. (2011) studied the English and Welsh industry finding that WASCs exhibit scale economies of between 1.12 and 1.23, depending on specification.

Scale economies are said to exist in sewage treatment but likely exhausted at a certain size, seen in Knapp (1978), Fraas and Munley (1984), Fraquelli and Giandrone (2003) who impose restrictive functional forms. Sewage treatment plants cost efficiencies have also been analysed by employing nonparametric Data Envelopment Analysis approaches. Guerrini et al (2016) suggest that economies of scale are present in treatment plants located in Tuscany, Italy, where efficiency increases as treatment plant design capacity passes from 50 to approximately 13,000 Population Equivalent.

The region of Valencia, Spain has received considerable attention Hernández-Chover et al. (2018) provide an example of a DEA methodology which allows for variable returns to scale, the study of 217 plants provides calculations of both radial and non-radial efficiency measures. Radial DEA may provide a proportional shrinkage factor for all inputs, which would allow the same output to be produced, but with lower inputs, resulting in an increased efficiency score, however non-radial DEA allows the identification of a targeted and specific shrinkage factors for each input, also resulting in increased efficiency. Hernandez-Chover et al (2018) average efficiency results: for plants serving population equivalents of 500-8, 000 was 48 percent, while plants serving PE of 8,000 – 50, 000 exhibited 75 percent efficiency. Only 6 plants serving PE of above 50, 000 were analysed, showing efficiency results of 90%. The differences between average efficiency scores across plants are said to be the result of scale economies - this suggests that as population equivalent served increases (scale), unit costs decrease.

These results are broadly consistent with those of Hernandez-Sancho and Sala-Garrido (2009) using a similar DEA approach to analyse 338 plants, also in Valencia, Spain. Each plant uses the same technology – "secondary treatment", this common technology restriction is highlighted as a requirement for DEA, where DEA requires to compare apples with apples, because it may not account for technical or plant-specific characteristics (like the Z-vector of technical variables in translog modelling). Initial results suggest that the average WWTP displays a 41.87 percent input-efficiency, meaning that potential savings of 52-percent are available to exploit while maintaining the same level of output. The paper does not incorporate a calculation of scale economies – however it is clear that as plant size increases, the average efficiency of the WWTPs increases also. E.g., WWTP's treating 5, 000, 000 cubic metres) display input efficiency of 91 percent (Hernández-Sancho and Sala-Garrido, 2009). The authors suggest that the falling inefficiency is due to size of the operations.

Molinos-Senante et al (2014) employed a non-radial DEA approach with allowance for variable returns to scale. Results suggest that of the 192 plants in Valencia on average each WWTP could save 53-percent of operating costs if they operated on the efficient frontier. Further, 17- percent of WWTPs were found to be operating at an efficient level. Moreover, findings suggested that all inputs in the treatment process in plants are affected by economies of scale, while larger plants treating more than 400,000 cubic metres per year displayed higher levels of efficiency than smaller plants.

It is apparent that that company level studies of WASCs and Sewage only utilities do not give appropriate consideration to the variation in operating characteristics between or within companies. For example, Blaeschke and Haug (2018) studied a sample of municipal sewage treatment utilities in the State of Hessen, Germany and provide a better example of a study which considers the complexity of sewage systems. Where each municipality within the State bears responsibility for the treatment of wastewater. Employing a single proxy for output (flow measured in cubic metres), to capture some differences in the operating environment characteristics or the demand faced by each utility, population density is considered as a technical variable, along with a measure of population change, the number of villages in the municipality, and a proxy to control for industrial wastewater volumes. Some studies only include very basic considerations, typically controlling for population density, e.g., Renzetti (1999), Molinos-Senante and Maziotis (2019), Molinos-Senante et al (2020).

However often, even well-cited studies do not attempt to capture, or recognize, the complexity of the network systems employed by WASCs, e.g., Saal and Parker (2000, 2004), Ashton (2000), Saal et al (2007), Molinos-Senante and Maziotis (2017).

While these variables might go some way to controlling for the complexity in the network systems employed by the sewage utilities, there remains an underlying assumption that these utilities operate one single integrated network, which incorporates collection, transport, and treatment of sewage, while also treating and disposing of sludge. E.g., in England and Wales, the 10 WASCs actually operate over 6000 distinct systems for sewage collection and treatment within their respective service areas. The configuration of these systems, which vary in size from Beckton (~pop) to a minimum of (250 PE) are the product of numerous optimisation decisions. The geographic or spatial distribution of plants, and the size of these plants are based on the exogenous demand each firm faces, and how best to serve current and predicted future demand. Among the factors that must be considered, simple examples include trade-offs between transporting sewage by road, or pipelines – where pipelines could be energy powered, or gravity driven. Or trade-offs between building sewage treatment plants or extending existing network pipelines to accommodate rising customer demand – as seen in Converse (1972).

Urakami et al (2021) provide a similar narrative in their case study of the Hyogo prefecture in Japan. Overall, Japan presents quite a complex example of sewerage systems, but Japanese municipalities own and operate whole sewage systems that include collection and treatment of sewage, and treatment and disposal of sludge. Within these municipally operated systems, decision-making units often operate multiple sewage collection and treatment systems. As such, it should not be difficult to reconcile that companies do not operate one single sewerage system. Moreover, detailed plant level analysis of how individual plant operating characteristics, size of treatment plant, scale economies, and persistent and short-term inefficiencies influence operating costs within each company and across companies in the regulated industry, should be of interest to academics, managers, and regulators alike.

It is worth noting that some firm level studies focusing on water supply utilities offer a much-improved attempt to control for the complexity of the intensive network systems that companies operate, examples like Bottasso and Conti (2003) include a population density, and a measure of network pipeline length. Stand out examples come from Garcia and Thomas (2001), Torres and Morrison-Paul (2006), and Klien and Michaud (2019). Garcia and Thomas (2001) look at French water supply utilities and include technical variables which control for both the number of customers, and the number of municipalities supplied, along with variables which describe the capital-intensive network that utilities operate – these variables include network length, production capacity, stocking capacity, and pumping capacity. Torres and Morrison-Paul (2006) considered storage capacity and treatment capacity as capital network variables, and technical variables also included number of customers, service area, and length of pipeline network (although dropped from final analysis due to issues related to multicollinearity).

Given this discussion of literature, this paper aims to contribute to the literature as follows.

To satisfy the limitations identified in plant-level sewage treatment literature – allowing for variable scale economies, multiple outputs, controlling for treatment technologies (and testing the assumption of a common technology among treatment plants), and effluent quality controls, as well as other operating characteristics (utilised capacity). In doing so, extending the literature on the cost determinants of the largest sewage plants which form an important part of the complex sewage systems alluded to above.

Apply new generation stochastic frontier techniques which separate the composed error from panel data estimated models, in order to estimate persistent and transient (and therefore overall) efficiency scores, to investigate their determinants, and assess production risks associated with the English and Welsh industry's largest treatment plants. It is evident that a 4-way error decomposition has not been applied to sewage plants.

Assess how inter-company performance is evaluated when we consider the differences in plant sizes, plant technologies, and the quality of treatment used, and how these plant size/technology profiles differ across companies – e.g., if larger operations are expected to exhibit lower unit costs, relative to smaller operations, in the context where companies do not have equal access to the same scale economies/ scale of plant, without considering intercompany differences predicted costs and efficiency results will be biased.

Preliminaries and Regulatory Context

Given our earlier discussion of the previous literature we now consider Ofwat's 2019 Price Review, which set out the cost assessments for Asset Management Period 7 (AMP 7), covering 2020-25.

Ofwat employed aggregated cost modelling for wholesale water and wholesale wastewater services aims to identify drivers of 'Base Costs' – defined as operating costs plus capital maintenance costs (Ofwat, 2019). However, focusing on wastewater, the specified models include various limitations, some of which include: a non-varying elasticity of scale across all companies and extremely limited measures for controlling how the size and number of sewage treatment works (STWs) impacts company level costs, the insistence and choice of using Biological Load as the single-output, and little consideration of how choice of technology or removal of contaminants are a legitimate driver of costs.

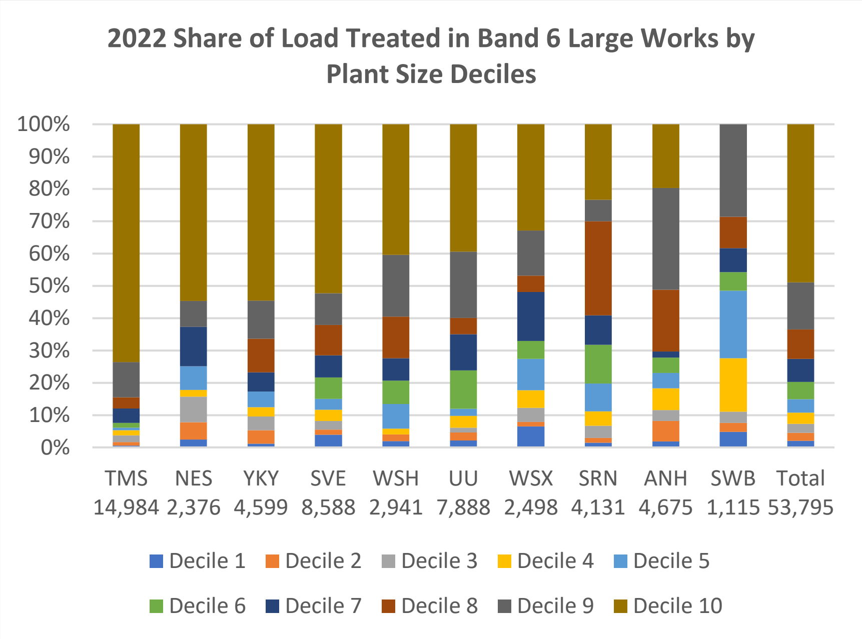
The models are estimated using a conventional panel data random effects estimator, where the estimated random effect is assumed to have resulted solely from inefficiency. As will become apparent in later sections, this is a misuse of random effects estimation. Historically and until the 2009 Price Review, Ofwat have undertaken water and sewerage service unit cost analysis for STWs with a population equivalent (PE) less than 25, 000. While costs of STWs with PE greater than 25,000 – namely a 'Band 6 work', were modelled similarly to current aggregate company models, with the same limitations. Thus, for example, Ofwat's 2003-04 operating expenditure large STW model (Ofwat, 2005) for works above 25,000 PE identified non-varying, but strongly increasing returns to scale, while unit cost analysis of smaller STWs (less than 25,000 PE) show clear decreases in unit cost as the size of STW increases. Furthermore, this historic unit cost analysis demonstrated that there is a clear understanding from Ofwat that the type of sewage treatment technology used impacts the nature of the unit costs. Nevertheless, current aggregate modelling takes account for the impact of scale economies by including the overall share of Load treated in a large plant (over 25,000 PE), all things considered this is an inadequate approach considering that it ignores substantial variation in the scale, and marginal and unit costs of operation within the large plants.

Consideration of the 2022 large works database demonstrates that there is not only substantial variation in the size of the companies themselves that should be accounted for but also substantial variation in the reliance on different plant scales, which matters if there are scale economies. Thus, the plant size by decile data in Table 1 demonstrates substantial variation across England and Wales, even for the large band 6 works.

Table 1: 2022 Band 6 Large Works – Plant Size Deciles

Decile Class	Pop. Equivalent (000s)	
	Min.	**Max.**
Decile 1	24.8	30.0
Decile 2	30.1	35.3
Decile 3	35.4	42.6
Decile 4	42.7	51.8
Decile 5	51.9	62.7
Decile 6	62.9	82.3
Decile 7	82.8	106.8
Decile 8	107.9	146.8
Decile 9	147.2	273.8
Decile 10	>273.8	

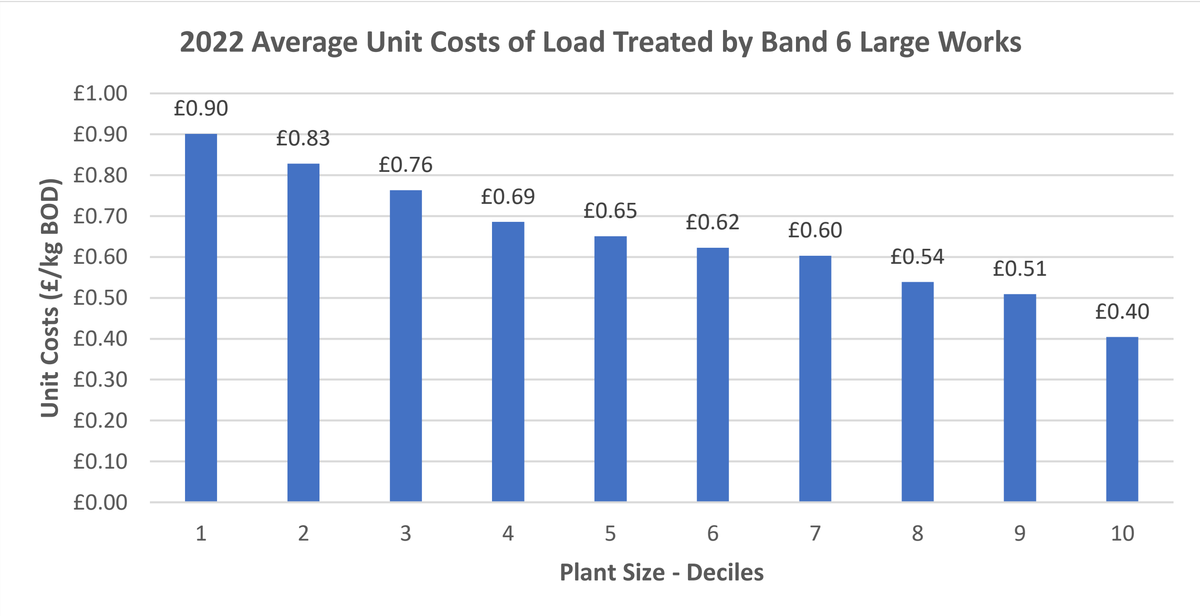
Figure 1



Moreover, Figure 1 demonstrates the considerable inter-company difference in the reliance on the largest plants even within Ofwat's Band 6 large plants category. For example, while SWB does not have access to any plants in decile 10, Thames Water treats in excess of 70 percent of its sewage load in plants categorized as decile 10.

This implication of the inter-company variation of plant scales on sewage treatment costs, is seen by the simple calculation of the underlying observed unit costs. E.g., the steadily declining average unit cost (2022 prices) by plant size decile suggests substantial economies of scale in sewage treatment, even amongst the largest plants in England and Wales.

Figure 2



Given this brief discussion of the English and Welsh regulatory context and the characteristics of the large works sewage treatment. We therefore turn to conduct a systematic analysis of cost determinants using the large works database to better understand the relationship between cost and scale for these large works.

Data Description

Ofwat's large works database is the best plant-level data that is available for England & Wales sewage works, despite its limitations. As Ofwat's database does not include any information on Capital stocks, we have supplemented the data available by incorporating plant-level Design Capacity data (measured in Population Equivalent) available via the European Commission Urban Wastewater Treatment Directive. This Design Capacity data is plant-specific, but time-invariant – measured in 2018. This data is incorporated into the analysis by defining a Capacity Utilisation variable, which is both plant and time-specific, defined as observed annual load divided by design capacity load (both measured in population equivalent). Operating Expenditures are defined as "Total Functional Expenditure" as in Ofwat's Large Works database, prices are adjusted to 2017/18 price base using CPIH data.

Efforts were made to construct input prices, while we succeeded in constructing prices that varied across companies and time period, however issues with the magnitude of second-order coefficient estimates and lack of variation in input prices across plants within companies resulted in the omission of the prices from the analysis.

Our analysis is carried out with a balanced five year panel database covering 2018-2022, which after excluding some data on quality grounds and excluding observations that are not observed in all years, includes 1640 observations for 328 large plants, of which 89 rely on Biological Secondary Treatment, and 239 rely on Activated Sludge. For reference, there are 396 large plants in Ofwat's raw database for 2022.

The primary distinction between plants is whether the secondary treatment technology is one of Activated Sludge or Biological treatment processes. As seen in Table 2, there are clear differences in the scale range of plants for each technology, where Biological plants display a PE range of 25,483 – 378,871. The largest Biological plant is one-tenth the size of the largest Activated Sludge plant. Activated Sludge plants range in size from 25,410 - 3,799,223 PE.

Table 2: Descriptive Statistics Non Categorial Variables

Variable	Units	Mean	SD	Min	Max
	Biological Sewage Treatment Works (N = 445)				
Functional Expenditure	(£,000s)	744	537	128	3,720
Biological Load	(kg BOD/day)	3,745	3,041	1,529	22,732
Population Equivalent	(units)	62,419	50,685	25,483	378,871
Flow Treated	(m^3/d)	18,900	16,007	4,488	105,115
Capacity Utilisation	(%)	0.893	0.132	0.365	1.17
UV Light	(mW/s/cm^2)	30.01	2.26	30	35
	Activated Sludge Sewage Treatment Works (N = 1195)				
Functional Expenditure	(£,000s)	1,830	2,829	221	43,756
Biological Load	(kg BOD/day)	10,056	19,413	1,525	227,953

Population Equivalent	(units)	167,598	323,549	25,410	3,799,223
Flow Treated	(m^3/d)	50,261	99,667	4,062	1,195,640
Capacity Utilisation	(%)	0.897	0.141	0.206	1.30
UV Light	(mW/s/cm^2)	33.32	10.88	16	63.24
		Total (N = 1640)			
Functional Expenditure	(£,000s)	1,536	2,479	128	43,756
Biological Load	(kg BOD/day)	8,343	16,880	1,525	227,953
Population Equivalent	(units)	139,058	281,329	25,410	3,799,223
Flow Treated	(m^3/d)	41,752	86,605	4,062	1,195,640
Capacity Utilisation	(%)	0.896	0.139	0.206	1.30
UV Light	(mW/s/cm^2)	33.28	10.17	16	63.24

The database also includes further information on treatment technology classification. As Table 3 demonstrates, within Activated Sludge and Biological treatment groups, management have choices: A treatment plant may undertake Secondary or Tertiary levels of treatment and it is clear that Biological plants rely more-heavily on Tertiary levels of treatment (80.4% of plants), versus 64.1% of Activated Sludge plants. Moreover, even within a Tertiary level of treatment, management have a choice between two sub-groups: namely, Group 1 Tertiary add-ons, or Group 2 tertiary add-ons.

There are also clear differences in the reliance on tertiary treatment and numerical consent compliance across Activated Sludge and Biological Plants.

Further to the data above, plants in England & Wales are subject to numerical consents imposed by the Environmental Agency (EA). These consents detail the permissible level (mg/Litre) of specific contaminants that each plant's treated effluent may contain. Where treated effluent is the final product of wastewater treatment and is ultimately released back into waterways. These controlled contaminants are Biological Oxygen Demand (BOD), Suspended Solids (SS), Ammonia , and Phosphorus – treatment plants may be subject to some, or all of these constraints. In addition, a minority of plants use UV Light as a treatment technique.

The data available for these consents include varying ranges – BOD consents range from 5-250 mg/litre, SS consents from 10-250 mg/litre, Ammonia consents from 1-65mg/litre, while Phosphorus consents range from 0.2-3mg/litre.

Given the nature of the data, dummy variables are constructed. For BOD, SS, and Ammonia consents the respective dummy variables =1 if a treatment plant has a consent inside the 1^{st} quartile, that is, 12mg/litre or less for BOD, 25mg/litre or less for SS, and 3mg/litre or less for Ammonia. For example, Table 3 shows that 28.8% of Biological plants operate with the harshest BOD consent, inside the 1^{st} quartile, while the corresponding proportion of Activated Sludge plants with a BOD consent inside the 1^{st} quartile is 25.6%. Therefore, on balance, 26.5% of the studied sample operates with a BOD consent of less than 12mg/L. The same interpretation is applied to Suspended Solids and Ammonia consents.

While for Phosphorus, the dummy variable =1 if the treatment plant has any consent within the total 0.2-3 mg/litre range, the rationale for different treatment comes from the belief that Phosphorus removal is expensive, while it is clear that there is not enough variation in the data to construct a quartiles approach. Therefore, 66.5% of Biological plants, and 43% of Activated Sludge plants operate with a Phosphorus consent. Dummy variables are constructed for each permutation of treatment technology classification also, e.g., Tertiary add-on Group 2 will =1 when a treatment plant employs a Tertiary level of treatment via a Group 2 add-on. As seen below, 59.5% of Activated Sludge plants employ a Tertiary level of technology, using a Group 2 add-on, while Biological plants rely more heavily on Tertiary Group 2 treatment processes (over 75% of the sample).

Table 3: Treatment Plant Characteristics (%)

Variable	Sample		
	Biological	Activated Sludge	Overall
Secondary Level Treatment	0.196	0.359	0.315
Tertiary Add-on Group 1	0.054	0.046	0.048
Tertiary Add-on Group 2	0.751	0.595	0.637
Activated Sludge	0	1	0.729
BOD consent dummy	0.288	0.256	0.265
Ammonia Consent dummy	0.328	0.321	0.323
SS consent dummy	0.281	0.318	0.308
Phosphorus Consent dummy	0.665	0.43	0.494
UV Light	0.067	0.165	0.138

Methodology

Given our stated research agenda, our methodology aims to firstly test the validity of the assumption of a common technology across sewage treatment plants, where the primary division of technology is allocated as being either: Activated Sludge processes, or Biological processes.

Secondly, we seek to determine the Overall Cost Efficiency of the large sewage treatment plants in England and Wales, in doing so exploiting the nature of panel data and disentangling persistent and residual (time-varying) elements of efficiency, unobserved plant heterogeneity, and random noise – this is done by implementing a new generation Stochastic Frontier approach developed by Kumbhakar, et al (2014).

Initially, a variable cost function (defined as Total Functional Expenditure) is specified as:

$$lnVC_{it} = f(Y_{it}, K_{it}, Z_{it};\ \theta) + \alpha_i + \epsilon_{it} \tag{1}$$

This cost function is estimated with a conventional random effect. Where, $lnVC_{it}$ is the natural log of Total Functional Expenditure, for Plant *i,* at Time *t.* The vector of outputs is denoted Y_{it}, the two outputs are Biological Load (kg BOD Received per day) and Flow Treated (M^3 of Flow Treated per day). K_{it} is Capacity Utilisation (Population Equivalent of Load Received divided by Population Equivalent of plant Design Capacity), and Z_{it} is a vector including a fully interactive time trend and non-interactive operating characteristics dummy variables – including numerical consents, and technology dummies for levels of Tertiary treatment, and type of treatment technology, e.g., Biological or Activated Sludge (where applicable).

In their 3-step approach Kumbhakar et al. (2014) encourage an initial estimation of a conventional panel data random (or fixed) effects model as Step 1 - which provides estimates of β, α_i , ϵ_{it}. The terms α_i and

ϵ_{it} which collectively form the 'composed error' from random effects modelling, may both be decomposed.

Step 2 involves running an SFA model on the error term (ϵ_{it}) from Step 1. This allows a decomposition into two distinct components also, namely, residual (time-varying) inefficiency – which is one-sided, time and plant specific. The second element is a true random shock, also time and plant specific.

Step 3 involves running an SFA model on the random effect (α_i) component, this allows the decomposition of the random effect into two distinct components, namely, Persistent Efficiency and an Unobserved Plant Heterogeneity component. That is, the random effect α_i contains a one-sided time-invariant but plant specific inefficiency component, as well as a two-sided time-invariant unobserved plant heterogeneity element (which should not otherwise be considered as inefficiency). The unobserved heterogeneity is said to capture time-invariant inputs, e.g., in sewage treatment these inputs may include the physical geography of the served area.

Following Kumbhakar et al (2014), equation *(1)* then becomes:

$$lnVC_{it} = f(Y_{it}, K_{it}, Z_{it};\, \theta) + \mu_i + \eta_i + u_{it} + v_{it} \qquad (2)$$

Where: μ_i is the unobserved plant heterogeneity, η_i is persistent (time-invariant) inefficiency, u_{it} is residual (time-varying) inefficiency, and v_{it} is the random shock element.

As always the choice of functional form is a necessary and important part of any cost modelling exercise, as such we choose a starting point of the popular and flexible translog functional form proposed by Christensen et al (1973).

A particular benefit of this specification in our application is that it does not restrict the sample plants or companies to common elasticities of scale. We therefore initially estimate a translog form model for each sample, Pooled, Activated Sludge, and Biological, and then test the validity of restricting each sample to a simpler and more restrictive log-linear model, resembling a Cobb-Douglas functional form where a variable elasticity of scale is not permitted.

By employing a balanced panel and then manipulating the data such that the data are normalised around their respective mean values, allows clear and straightforward interpretation, such that the first order coefficients may be interpreted as the cost elasticities for the sample average plant.

The initial Pooled translog specification for Plant *'i'* at Time *'t'* is estimated as:

$$
\begin{aligned}
\ln VC_{it} = {} & \beta_0 + \sum_{L}(\beta_L \ln Y_{Lit}) + \sum_{F}(\beta_F \ln Y_{Fit}) + \sum_{K}(\beta_K \ln K_{it}) + \sum_{R}(\beta_R\, R_{it}) + \frac{1}{2}\sum_{L}\sum_{L}\beta_{LL} \ln Y_{Lit} \ln Y_{Lit} \\
& + \frac{1}{2}\sum_{F}\sum_{F}\beta_{FF} \ln Y_{Fit} \ln Y_{Fit} + \frac{1}{2}\sum_{K}\sum_{K}\beta_{KK} \ln K_{it} \ln K_{it} \\
& + \frac{1}{2}\sum_{R}\sum_{R}\beta_{RR}\, R_{it}\, R_{it} + \sum_{L}\sum_{F}\beta_{LF} \ln Y_{Lit} \ln Y_{Fit} + \sum_{L}\sum_{K}\beta_{LK} \ln Y_{Lit} \ln K_{it} + \sum_{L}\sum_{R}\beta_{LR} \ln Y_{Lit}\, R_{it} \\
& + \sum_{F}\sum_{K}\beta_{FK} \ln Y_{Fit} \ln K_{it} + \sum_{F}\sum_{R}\beta_{FR} \ln Y_{Fit} R_{it} + \sum_{D}\sum_{R}\beta_{DR} \ln K_{Dit} R_{it} + \beta_{BOD}\, Dum_{BOD} \\
& + \beta_{SS}\, Dum_{SS} + \beta_{AMM}\, Dum_{AMM} + \beta_{PHOS}\, Dum_{PHOS} + \beta_{UV}\, UV + \beta_{Ter}\, Dum_{Ter} \\
& + \beta_{Group2}\, Dum_{Group2} + \beta_{Bio}\, Dum_{Bio} + \alpha_i + \epsilon_{it}
\end{aligned}
$$

Where outputs are denoted Y_L for biological load received, and Y_F for flow treated. Capacity utilisation is denoted K, and R denotes a time trend variable. Non-interactive dummy variables for are also included, where Dum_{BOD}, Dum_{SS}, Dum_{AMM} will equal 1 only if a plant operates with a Biological Oxygen Demand, Suspended Solids, or Ammonia numerical consent in the 1st quartile – as earlier defined. Dum_{PHOS} equals 1 if a plant has any Phosphorus consent. If a plant operates a Tertiary level of treatment Dum_{Ter} equals 1 (conversely Dum_{Ter} equals 0 if a secondary level of treatment is used), if the tertiary level of treatment uses 'Tertiary add-on 2' from earlier, then Dum_{Group2} equals 1. Finally, Dum_{Bio} equals 1 if the classification of treatment used in a plant are Biological processes – for obvious reasons, this drops out of/ or is irrelevant in models which split the sample of STWs into Activated Sludge and Biological technologies. UV is a non-interactive control for the quantity of UV light used.

The parameters to be estimated are β_0, β_L, β_F, β_K, β_R, β_{LL}, β_{FF}, β_{KK}, β_{RR}, β_{LF}, β_{LK}, β_{LR}, β_{FK}, β_{FR}, β_{DR}, β_{BOD}, β_{SS}, β_{AMM}, β_{PHOS}, β_{UV}, β_{Ter}, β_{Group2}, and where applicable: β_{Bio}.

A number of distributional assumptions are made in Kumbhakar et al (2014) approach – later dubbed the 'Homoscedastic model'. The heterogeneity component, and random shock terms are independently and identically distributed (i.i.d), taken from standard normal distributions, with constant variances. In addition, both inefficiency terms (residual and persistent) are independently and identically distributed, while restricted to half-normal (non-negative) values, with constant variances. Kumbhakar et al. (2014) note that it is possible to extend this methodology to allow for non-zero means in inefficiency distributions, and/or to allow for heteroskedasticity in the variances.

As such, we follow a similar approach to Badunenko and Kumbhakar (2017) – while Badunenko and Kumbhakar (2017) applied an approach to estimating the same four components (firm effects, random noise, persistent, and transient efficiency), the paper employed a different methodology proposed by Colombi et al (2014). Instead, we extend the Kumbhakar et al (2014) methodology to allow the variance of Plant Heterogeneity (μ_i) to be determined by a vector of numerical consent variables, denoted $Z_{\mu i}$ below. The numerical consents (BOD, Ammonia, SS, Phosphorus, and UV light) are as defined earlier. The variance of the random shock term (v_{it}) is considered to be determined by company dummies, denoted Z_{vit} .

As below:

$$\mu_i \sim N\left(0,\ \sigma_{\mu i}^2\right) \ where\ \sigma_{\mu i}^2 =\ \sigma_\mu^2\ exp(Z_{\mu i}\gamma_\mu) \tag{3}$$

$$v_{it} \sim N\left(0,\ \sigma_{vit}^2\right) \ where\ \sigma_{vit}^2 =\ \sigma_v^2\ exp\ (Z_{vit}\gamma_v) \tag{4}$$

As noted in Badunenko and Kumbhakar (2017), one may interpret the variance of the time-invariant plant effects (unobserved heterogeneity component) and the variance of random shock as being production risks. Specifically, the variance of plant effects can be viewed as persistent and plant-specific production risks, and the variance of the random shock is a time-varying and plant-specific production risk.

The variance of the residual (time-varying) inefficiency (u_{it}) is determined by Year dummies (where 2018 dummy is the financial year ending 2018 and 2022 dummy is dropped) denoted Z_{ui}.

$$u_{it} \sim N^+\left(0,\ \sigma_{uit}^2\right) \ where\ \sigma_{uit}^2 =\ \sigma_u^2\ exp(Z_{ui}\gamma_u) \tag{5}$$

As such, $E(u_{it}) = \sqrt{\left(\frac{2}{\pi}\right)}\,\sigma_{uit}$

We allow the distribution of the persistent inefficiency (η_i) to be a truncated normal, whereby the mean is not restricted to zero, but the variances are constant, furthermore the mean (mu_i) is a function of company dummy variables.

$$\eta_i \sim N^+\left(mu_i,\ \sigma_\eta^2\right) \tag{6}$$

As such, $E(\eta_i) =\ mu +\ \sigma_\eta\varphi(\alpha_i)/(1 -\ \phi(\alpha_i))$

Where φ is the probability density function for a normal distribution, ϕ is the cumulative distribution function for a normal distribution, and α_i = $(\eta_i - mu)/\sigma_\eta$)

Predictions of residual inefficiency $\hat{u}_{it}$ are obtained by using the Jondrow et al (1982) procedure, residual efficiency is then calculated using the Battese and Coelli (1992) estimator as $\exp(\hat{u}_{it}|\epsilon_{it})$ Similarly, predictions of persistent inefficiency ($\hat{\eta}_i$) are obtained via Jondrow et al (1982) procedure, then persistent efficiency is calculated with Battese and Coelli (1992) estimator as $\exp(\hat{\eta}_i)$. Finally, Overall Cost Efficiency is simply the product of residual efficiency and persistent efficiency estimates.

Results

We begin our analysis by testing if a pooled model including both Activate Sludge and Biological plants is appropriate. Thus, in this step two full translog models are estimated, the first results column presents the pooled "common" technology specification, whereby the only control for difference in technology is a Biological dummy variable. The second model represents a jointly estimated cost function, whereby individual technology-specific parameter coefficients are permitted. These parameters are tested via a Chow test, whereby the null hypothesis assumes no differences exist between the technology-specific parameter coefficients. As seen in Table 4, we may reject the null hypothesis (Chi2 statistic of 68.72, statistically significant at 1%) and conclude that the common technology assumption that is built into a pooled cost model is violated.

Moreover, the specification tests in Table 4 go further to investigating the differences between Activated Sludge and Biological technologies. We find that two different functional forms are required. Beginning at a translog (variable elasticity) model, we statistically test the validity of restricting the Pooled technology to a log-linear model. Rejection of the null hypothesis (Chi2 statistic of 16.61, significant at 5%) effectively suggests that if we naively model with a pooled sample, both Activated Sludge and Biological plants operate with variable returns to scale. However, given that we reject the common technology assumption, we test this restriction for Activated Sludge and Biological technologies separately. We find that the restriction to log-linear from translog with Activated Sludge plants is statistically rejected – Chi2 statistic of 20.34 significant at 1%, among other things, suggests that variable returns to scale are present in Activated Sludge plants. The same is not true for Biological plants – we find that restricting to a simpler log-linear specification for these plants is merited (Chi2 statistic 5.00 was not statistically significant at any reasonable level).

Table 4: Specification Tests for Pooled and Jointly Estimated Models.

Specification	Pooled	Pooled Allowing for Different Technologies	
Technology	Common	Activated Sludge	Biological
Specification Hypothesis Tests:			
Restricting to log-linear specification			
Wald test Chi2	16.61**		25.34**
(Deg. F)	(7)		(14)
Restricting to the Pooled Technology			
Chow test Chi2			68.72***
(Deg. F)			(22)
Restricting to log-linear specification			
Wald test Chi2		20.34***	5.00
(Deg. F)		(7)	(7)

*** p<.01", "** p<.05", "* p<.1

Given the rejection of the pooled assumption, Table 5 (below) seeks to specify technology specific models. As such, we systematically test down an initial "full" model for each technology sample. By testing the joint significance of the terms that are not directly significant, any terms that are not jointly significant are removed – by removing variables before testing joint-significance we miss out on the additional potential explanatory power in the models.

As a highlight, we find that the numerical consents are legitimate drivers of cost to a greater or lesser extent in different technology samples. It is also clear that a higher level of utilised capacity in the sample average plant sees lower operating costs. Furthermore, Flow treated is a legitimate cost driver, and moreover the importance of Flow levels increases over the sample period, while the relative importance of Load received falls (negative lnLOADt coefficients illustrate this dynamic).

Table 5: Estimated Models for the Pooled and Separately Estimated Activated Sludge and Biological Plants

	(Pooled Translog)	(Pooled Final)	(AS Translog)	(AS Final)	(BIO Translog)	(BIO Log-linear)	(BIO Final)
lnLOAD	0.676***	0.658***	0.680***	0.660***	0.627**	0.501***	0.515***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)
lnFLOW	0.067	0.083	0.065	0.085	0.072	0.159*	0.171**
	(0.244)	(0.138)	(0.301)	(0.160)	(0.711)	(0.053)	(0.037)
lnCaputil	-0.289***	-0.224***	-0.265**	-0.181**	-0.314	-0.277*	-0.284**
	(0.010)	(0.003)	(0.032)	(0.036)	(0.334)	(0.062)	(0.040)
t	0.024***	0.023***	0.026***	0.025***	-0.004	-0.004	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.799)	(0.793)	(0.793)
lnLOADsqr	-0.146	-0.219	-0.186	-0.265	-0.012		
	(0.395)	(0.186)	(0.346)	(0.162)	(0.980)		
lnFLOWsqr	-0.342**	-0.336**	-0.365**	-0.349**	-0.209		
	(0.023)	(0.024)	(0.038)	(0.046)	(0.482)		
lnCaputilsqr	0.108		-0.093		0.988		
	(0.716)		(0.774)		(0.163)		
tsqr	0.015**	0.015**	0.023***	0.024***	-0.010		
	(0.027)	(0.021)	(0.004)	(0.003)	(0.372)		
lnLOADlnFLOW	0.286*	0.309**	0.316*	0.338*	0.131		
	(0.056)	(0.037)	(0.070)	(0.050)	(0.687)		
lnLOADt	-0.047***	-0.047***	-0.050***	-0.052***	-0.060**	-0.054**	-0.034***
	(0.002)	(0.002)	(0.008)	(0.005)	(0.026)	(0.036)	(0.005)
lnFLOWt	0.035**	0.036**	0.042**	0.043**	0.028	0.019	
	(0.012)	(0.011)	(0.021)	(0.015)	(0.211)	(0.361)	
lnCaputilt	0.028		0.027		0.049	0.021	
	(0.189)		(0.278)		(0.255)	(0.604)	
lnCaputillnFLOW	0.031		0.251		-0.508		
	(0.880)		(0.282)		(0.272)		
lnCaputillnLOAD	-0.162		-0.405		0.335		
	(0.487)		(0.128)		(0.556)		
Tertiary	0.011		-0.066		0.272	0.279*	0.326***
	(0.905)		(0.527)		(0.101)	(0.086)	(0.001)
Tertiary add-on 2	0.053		0.057		0.063	0.050	
	(0.550)		(0.593)		(0.664)	(0.722)	
Biological	-0.253***	-0.249***					
	(0.000)	(0.000)					
BOD consent	0.116*	0.128**	0.140*	0.119**	0.099	0.099	
	(0.067)	(0.043)	(0.062)	(0.048)	(0.406)	(0.395)	
AMM consent	0.095*	0.099**	0.097*	0.093	0.091	0.104	
	(0.054)	(0.047)	(0.095)	(0.105)	(0.351)	(0.271)	
PHOS consent	0.089**	0.120***	0.036		0.131*	0.142**	0.145**
	(0.039)	(0.000)	(0.494)		(0.075)	(0.049)	(0.028)
SS consent	-0.102*	-0.096*	-0.056		-0.179	-0.196*	
	(0.069)	(0.081)	(0.374)		(0.124)	(0.084)	
UV Light	0.005**	0.006***	0.006***	0.006***	-0.003	-0.002	
	(0.012)	(0.000)	(0.001)	(0.000)	(0.556)	(0.677)	
Intercept	-0.127***	-0.104***	-0.090**	-0.086**	-0.586***	-0.617***	-0.591***
	(0.002)	(0.005)	(0.030)	(0.017)	(0.000)	(0.000)	(0.000)
Within R2	0.075	0.072	0.064	0.059	0.159	0.144	0.141
Between R2	0.822	0.823	0.841	0.840	0.623	0.622	0.601
Overall R2	0.776	0.776	0.790	0.788	0.577	0.574	0.555
No. Observations	1640	1640	1195	1195	445	445	445
No. Groups	328	328	239	239	89	89	89
deg. freedom	22	16	21	13	21	14	7
Sigma	0.384	0.386	0.373	0.374	0.407	0.398	0.396
Sigma_u	0.317	0.319	0.297	0.298	0.358	0.348	0.346
Sigma_e	0.218	0.218	0.226	0.226	0.193	0.193	0.192
rho	0.679	0.682	0.633	0.634	0.775	0.766	0.765
chi2	1596.57	1578.55	1295.699	1286.68	191.67	190.68	185.85
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*** p<.01", "** p<.05", "* p<.1

Table 5 regression output suggests that Activated Sludge plants are operating with strong economies of scale, displayed in the lnFLOWsqr coefficient significant at 5%. The same is not true for Biological plants, however we do observe the importance of Flow treated as an important cost driver (lnFLOW coefficient of 0.171 significant at 5% suggests Flow treated is attributable to additional real costs of 17.1%. The importance of Flow treated is reiterated by the Load interaction with time trend, and the Flow interaction with time trend – these both suggest that the relative importance of Flow increases over the sample period (positive coefficients on lnFLOWt), while the relative importance of Load is dropping (negative lnLOADt coefficients)

Furthermore, Capacity Utilisation, although not statistically significant as an interactive term, the linear form (lnCaputil) shows intuitive and highly significant coefficients in each final model – in particular, suggesting that higher utilised capacity in Activated Sludge plants sees lower operating costs of 18.1% in the sample average plant, while this is even greater at 28.4% in the Biological sample. The passage of time (time trend variable) presents an interesting dynamic whereby costs in Activated Sludge plants are rising on average 2.5% a year.

Other notable points include the costly nature numerical consents. E.g., if one were to naively pool every treatment plant and perform cost modelling exercises, as Ofwat does, BOD, Ammonia, and Phosphorus consents all legitimately increase sewage treatment costs. While looking at Phosphorus consents in Biological plants, these are seen to attribute an additional 14.5% to real operating costs, while the use of UV light, Ammonia and BOD consents seen to increase costs in Activated Sludge plants (noting that Ammonia is not directly significant, but highly jointly significant therefore relevant in explaining higher costs – see specification tests in Table 6).

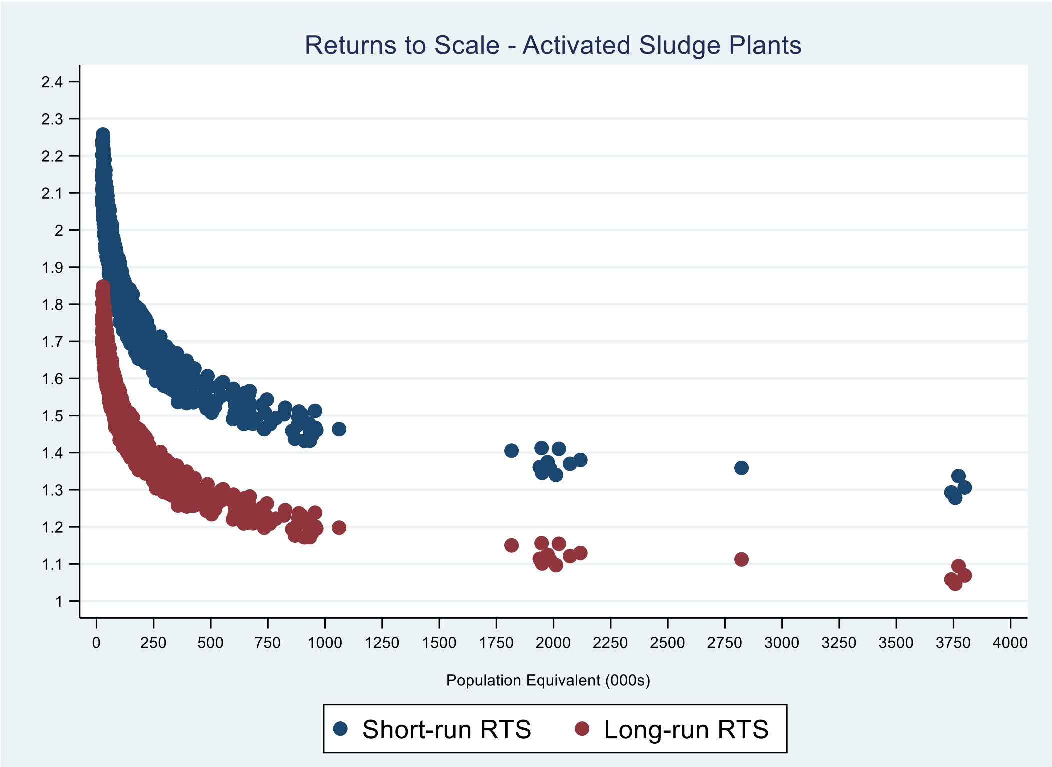
Table 6: Specification Hypothesis Tests:

	(Pooled Translog)	(Pooled Final)	(AS Translog)	(AS Final)	(BIO Translog)	(BIO Log-linear)	(BIO Final)
Joint Significance Chi2 Wald tests							
Time and interactions	65.44***	65.40***	48.80***	49.17***	20.45***	25.49***	25.95***
(Deg. F)	(5)	(4)	(5)	(4)	(5)	(4)	(2)
LOAD and interactions	141.65***	144.89***	120.80***	121.43***	20.74***	21.44***	27.99***
(Deg. F)	(5)	(4)	(5)	(4)	(5)	(2)	(2)
FLOW and interactions	18.06***	17.85***	14.20**	13.99***	6.90	4.72*	N/A
(Deg. F)	(5)	(4)	(5)	(4)	(5)	(2)	
Capacity Utilization and interactions	12.05**	N/A	8.68	N/A	8.14	3.49	N/A
(Deg. F)	(5)		(5)		(5)	(2)	
Restricting to log-linear specification							
Wald test Chi2	16.61**	N/A	20.14***	N/A	6.17	N/A	N/A
(Deg. F)	(7)		(7)		(7)		
Restricting to Final specification							
Wald test Chi2	4.97	N/A	5.00	N/A	16.00	5.76	N/A
(Deg. F)	(6)		(5)		(11)	(7)	

*** p<.01", "** p<.05", "* p<.1

Given one of the key differences between Activate Sludge and Biological technologies is the variable scale elasticity, Figure 3 (below) shows the strong economies of scale in Activated Sludge plants:

Figure 3



Further discussion about these results to follow below..

Given our stated methodology, using the estimated random effects models presented in Table 5 we decompose the Random Effects into two components – firstly a one-sided Persistent Efficiency, and secondly Unobserved Plant Heterogeneity (which should not be considered as inefficiency). Table 7 demonstrates that there is clearly a Company element to long-term (persistent) inefficiency, where management decision-making influences plant level efficiency. As company dummies were not a significant determinant of the plant level unobserved heterogeneity component, this suggests the company dummies are capturing inefficiency and not regional operating effects. In contrast, the numerical consents are highly significant in determining the unobserved heterogeneity component.

Table 7: Persistent Inefficiency Coefficients – SFA on the random effect

	Pooled	Activated Sludge	Biological
Observations	1,640	1,195	445
Wald chi2(1)	47.82***	38.37***	80.36***
Log likelihood	-190.59	-48.34	-0.083
Frontier			
Constant	-0.247***	-0.188***	-0.271**
Mean			
ANH	-0.449***	-0.418***	-0.562
NES	-0.221***	-0.157***	-0.433***
SRN	-0.164***	-0.136**	-0.134**
SVE	-0.977**	-2.466	-0.571
SWB	-0.275***	-0.466**	0.015
TMS	-0.059*	-0.330***	-0.070
UU	-0.231***	-0.365***	-0.104**
WSH	-0.411***	-0.044	-0.481***
YKY	-0.207***	-0.194***	-0.231***
Constant	0.458***	0.325***	0.508***
Variance			
Constant	-3.510***	-3.285***	-5.665**
Unobserved Plant Heterogeneity			
BOD consent			
Ammonia consent	-0.698***	-1.210***	
Phosphorus consent		-0.500***	0.419***
SS consent		0.579***	
UV light	-0.014***	-0.023***	
Constant	-2.613***	-2.529***	-2.964***

The decomposition of the Error term (from the conventional random effects models estimated earlier) into a one-sided time-varying efficiency, and a two-sided true random shock term in Table 8, shows that there is a significant time element to firm's short-term efficiency. More specifically, the time-varying (in)efficiency measures how each plant, and therefore company, reduces its short-term rigidities. Year dummies show this dynamic, 2022 dummy is omitted due to the presence of a constant. It is clear that there is a strong company-specific effect in determining the size of the random shock element.

Furthermore, the parameterization of the variances of the Plant heterogeneity component (above, Table 7) with numerical consents, and the parameterization of the variance of random shock component (below, Table 8) with company dummies, allow the identification of factors that may increase, or decrease production risks. Where the variance of plant heterogeneity component may be considered as time-constant production risk, and the variance of the random shock term may be considered as time-varying production risk (Badunenko and Kumbhakar, 2017).

Focusing firstly on the coefficients of the numerical consents from Table 7, in Biological plants the elasticity of time-constant production risk with respect to Phosphorus consents is positive and statistically significant (0.419***). This interpretation suggests that a Phosphorus consent will increase time-constant production risk in Biological plants. In contrast, the elasticity of time-constant production risk with respect to Phosphorus consents is negative in Activated Sludge plants. It may be said that a Phosphorus consent reduces time-constant production risk in Activated Sludge plants. Similar results are seen in the negative and statistically significant coefficients of Ammonia and UV light - for an Ammonia consent (in the 1st quartile, as defined earlier) and the increased use of UV light, these factors also decrease production risk in Activated Sludge plants.

The coefficients of company dummy variables in Table 8 (where WSX drops out, due to the presence of a constant) suggest that three companies have a positive (increasing) and statistically significant time-varying production risk in both Activated Sludge and Biological plants, namely ANH, SRN, and SWB. Many companies have a positive and significant time-varying production risk in one type of plant, e.g., NES, SVE, TMS, UU, and WSH coefficients in Biological plants are statistically significant at worst, at a level of 5%. WSH and WSX are the only two companies who display significant and negative coefficients in any type of treatment plant.

Note, if one were to (naively) assume a common technology among treatment plants, e.g., the pooled estimates in Table 8, it is clear that with the exception of WSX, every company is facing an increasing time-varying production risk.

Table 8: Residual Inefficiency Coefficients – SFA on the error term.

	Pooled	Activated Sludge	Biological
Observations	1640	1195	445
Wald chi2(1)	73.25	49.14	164.54
Log likelihood	501.69***	360.33***	4.730**
frontier			
Constant	-0.101***	-0.099***	-0.032*
Variance			
2018 Dummy	-0.723***	-0.583**	-2.348
2019 Dummy	-0.351*	-0.365	1.719
2020 Dummy	-1.241***	-1.206***	-33.967
2021 Dummy	-1.120***	-1.220***	0.510

Constant	-3.451***	-3.516***	-6.351
Noise			
ANH	1.369***	0.570***	0.619*
NES	0.673**	-0.389	0.963**
SRN	2.273***	1.747***	0.797**
SVE	0.952***	-0.215	0.714**
SWB	2.910***	2.135***	1.449***
TMS	0.876***	0.821***	0.357
UU	1.713***	0.201	0.919***
WSH	1.317***	-0.829***	1.271***
YKY	1.980***	1.318***	0.352
Constant	-5.076***	-4.215***	-4.298***

We next consider how the Overall Cost Efficiency estimates, Scale Economies, predicted Unit Costs, and Cost Change dynamics differ across the years in the sample.

Table 9: Sample Average Estimates by Year

	Activated Sludge					Biological				
Year	**SR Scale**	**LR Scale**	**Overall CE**	**Unit Cost**	**Cost Change**	**SR Scale**	**LR Scale**	**Overall CE**	**Unit Cost**	**Cost Change**
2018	1.813	1.484	0.763	0.564	-0.021	1.329	0.952	0.770	0.496	0.030
2019	1.84	1.506	0.753	0.558	0.001	1.391	0.996	0.721	0.513	0.029
2020	1.871	1.531	0.783	0.569	0.029	1.459	1.045	0.778	0.540	0.029
2021	1.903	1.558	0.783	0.594	0.053	1.534	1.099	0.746	0.557	0.029
2022	1.932	1.581	0.744	0.627	0.074	1.617	1.158	0.753	0.576	0.029
Total	1.872	1.532	0.765	0.582	0.027	1.466	1.05	0.753	0.536	0.029

Where: ***SR Scale*** is the short-run estimate of scale economies***,*** ***LR Scale*** is long-run estimate. ***Overall CE*** is Overall Cost Efficiency (the product of Persistent Efficiency and Time-varying Efficiency)[1]. ***Unit Cost*** is predicted unit cost (£/kg BOD) and expressed in 2017/18 prices. ***Cost Change*** is the partial derivative with respect to the Time trend variable.

Table 9 (above) displays an increasing trend in Unit Costs across each type of plant over the period 2018-2022. While Cost Change (the partial derivative w.r.t time) suggest that costs across the industry's largest plants are rising rapidly, averaging 2.7% and 2.9% a year in Activated Sludge and Biological plants, respectively. It is also clear that Biological plants are operating with long run economies of scale in 2020-2022, while operating with decreasing returns in 2018, and 2019 (although marginally different from constant returns). Significant economies of scale are present in Activated Sludge plants, as high as 1.9% in 2022 short run estimate. Finally, it is clear that yearly averages of Overall Cost Efficiency estimates in both samples are quite stable, between 72 and 78%.

[1] Overall Cost Efficiency is bound between 0 (perfectly inefficient) and 1 (perfectly efficient) – thus may be expressed as a decimal or percentage. Persistent and Time-varying efficiencies are also bound between 0 and 1.

Given that the estimates of scale economies and unit costs vary significantly, we break out the plant sizes (measured in Population Equivalent) into deciles to test how these differences influence company performance. Table 10 shows that there are significant differences across plant sizes. Unit Costs are clearly seen to fall as plant size increases. Further, economies of scale strong, while strong, fall as Activated Sludge plant size increases. Indicating that even the 10th decile of large plants with a PE (thousands) of greater than 301.93 operate with economies of scale.

Table 10: Average Estimates by Population Equivalent Plant Size Decile

	Deciles by Plant Size (PE)										
	1	2	3	4	5	6	7	8	9	10	**Total**
Biological											
Short Run RTS	1.466	1.466	1.466	1.466	1.466	1.466	1.466	1.466	1.466	1.466	1.466
Long Run RTS	1.050	1.050	1.050	1.050	1.050	1.050	1.050	1.050	1.050	1.050	1.050
Overall Cost Efficiency	0.785	0.730	0.809	0.802	0.691	0.726	0.737	0.779	0.648	0.650	0.753
Predicted Unit Cost[2]	0.673	0.582	0.566	0.520	0.512	0.487	0.445	0.410	0.433	0.300	0.536
Annual Cost Change	0.050	0.043	0.039	0.033	0.025	0.018	0.008	0.001	-0.009	-0.033	0.029
Activated Sludge											
Short Run RTS	2.132	2.090	2.047	2.001	1.954	1.906	1.850	1.788	1.713	1.542	1.872
Long Run RTS	1.745	1.710	1.675	1.638	1.599	1.560	1.514	1.463	1.402	1.262	1.532
Overall Cost Efficiency	0.783	0.757	0.762	0.767	0.792	0.761	0.753	0.758	0.769	0.756	0.765
Predicted Unit Cost	0.794	0.721	0.706	0.691	0.651	0.564	0.563	0.497	0.468	0.378	0.582
Annual Cost Change	0.036	0.033	0.032	0.034	0.031	0.031	0.030	0.022	0.023	0.010	0.027
Total											
Short Run RTS	1.890	1.787	1.765	1.871	1.801	1.773	1.733	1.749	1.705	1.537	1.762
Long Run RTS	1.492	1.390	1.372	1.495	1.428	1.406	1.373	1.413	1.391	1.249	1.401
Overall Cost Efficiency	0.784	0.744	0.785	0.776	0.760	0.751	0.748	0.761	0.765	0.749	0.762
Predicted Unit Cost	0.750	0.653	0.638	0.649	0.608	0.541	0.528	0.487	0.467	0.374	0.570
Annual Cost Change	0.041	0.038	0.035	0.034	0.029	0.027	0.023	0.019	0.022	0.007	0.028
Decile Boundaries (Population Equivalent 000s) – 5 Year Panel											
Decile	1	2	3	4	5	6	7	8	9	10	All Plants
Min	25.91	31.39	37.30	43.58	54.92	65.42	84.46	113.34	146.72	301.93	25.91
Median	28.94	34.28	39.48	48.31	58.81	73.29	95.87	125.16	185.75	441.86	64.87
Max	31.32	37.06	43.50	54.51	64.33	84.18	112.92	146.39	296.64	3578.43	3578.43

With Table 10 results in mind and considering the substantial variation in the size of plants across English and Welsh companies, we now focus on how these factors legitimately influence company level performance and benchmarking. Table 11 (below) shows the share of each Company's overall sewage load that is treated in each Plant size, by decile band. The substantial variation of each Company's access to exceptionally large treatment plants can be seen where Thames (TMS) treats 80.5% of its overall load in Plants of sizes of PE (thousands) 301.93 to 3,578.43 while Anglian (ANH)

[2] As earlier, Unit Costs (£/kg BOD) are expressed in 2017/18 prices.

treats only 21.7% of load in plants with the same characteristics. Alarmingly, South West and Bournemouth (SWB) do not have access to any plant with PE (thousands) greater than 296.64. Nor do Southern Water (SRN) in the cleaned balanced sample dataset – note: ordinarily Southern Water does have access to a large decile 10 plant, but due to incomplete data, this plant dropped out in the cleaning process.

Table 11: Share of Sample Population Equivalent Load by Load Size Decile

	Share of Total Sample Load Per Decile Class										**5 Year Avg. Total Sample Pop Equiv. Load**
Company	1	2	3	4	5	6	7	8	9	10	
ANH	0.041	0.047	0.067	0.046	0.040	0.015	0.066	0.210	0.252	0.217	4338.60
NES	0.026	0.029	0.082	0.021	0.025	0.058	0.039	0.051	0.096	0.573	2332.30
SRN	0.037	0.027	0.000	0.042	0.125	0.150	0.120	0.278	0.221	0.000	2440.74
SVE	0.038	0.030	0.027	0.042	0.050	0.065	0.084	0.102	0.099	0.463	5877.00
SWB	0.028	0.035	0.039	0.184	0.233	0.076	0.106	0.000	0.299	0.000	1054.29
TMS	0.006	0.014	0.014	0.020	0.000	0.022	0.025	0.044	0.050	0.805	14321.88
UU	0.023	0.016	0.024	0.046	0.038	0.117	0.125	0.061	0.232	0.319	6342.32
WSH	0.011	0.000	0.000	0.019	0.060	0.074	0.072	0.133	0.305	0.327	2844.68
WSX	0.012	0.061	0.018	0.040	0.130	0.066	0.124	0.053	0.148	0.347	2260.38
YKY	0.023	0.035	0.065	0.026	0.031	0.000	0.080	0.100	0.104	0.536	3798.92
Total	0.021	0.025	0.029	0.035	0.042	0.053	0.070	0.092	0.143	0.489	45611.20

In Table 12 (below), Actual Unit Cost refers to the average observed cost (in £s) for each Company of treating each kilogram of BOD received, across their respective plants in the 5-year balanced panel. While Predicted Unit Costs give an indication of what the cost models suggest "should" be the average cost (£) of treating each kilogram of BOD, for each Company across the same suite of plants. The predicted costs consider operating environment characteristics, such as scale economies, technology (activated sludge versus biological), tertiary level treatments, numerical consents and utilized capacity.

It is important to note that neither Actual nor Predicted Unit Costs calculated from the random effects models (in Table 5 consider the impact of inefficiency, as inefficiencies are calculated in steps thereafter).

Table 12 : Arithmetic and Load Weighted Company Average Cost and Efficiency Estimates

- Unit Costs (£/kg BOD) are expressed in 2017/18 prices.

Company	Actual Unit Cost Average	Actual Unit Cost Weighted Avg.	Predicted Unit Cost Average	Predicted Unit Cost Weighted Avg.	Annual Cost Change Average	Annual Cost Change Weighted Avg.	Overall Cost Efficiency Average	Overall Cost Efficiency Weighted Avg.
ANH	0.544	0.494	0.576	0.493	0.021	0.016	0.831	0.818
NES	0.660	0.625	0.637	0.534	0.033	0.019	0.765	0.706
SRN	0.646	0.600	0.526	0.479	0.024	0.020	0.701	0.706
SVE	0.484	0.393	0.571	0.473	0.028	0.019	0.913	0.904
SWB	0.695	0.616	0.658	0.613	0.033	0.031	0.781	0.791
TMS	0.731	0.454	0.577	0.376	0.023	0.005	0.643	0.658
UU	0.617	0.492	0.556	0.466	0.032	0.022	0.736	0.752
WSH	0.509	0.399	0.516	0.423	0.034	0.027	0.815	0.810
WSX	0.753	0.614	0.606	0.500	0.029	0.020	0.636	0.643
YKY	0.586	0.508	0.533	0.444	0.029	0.023	0.739	0.730
All E&W	**0.611**	**0.498**	**0.569**	**0.467**	**0.028**	**0.019**	**0.762**	**0.761**

	Rank - Actual Unit Cost Average	Rank - Actual Unit Cost Weighted Avg.	Rank - Predicted Unit Cost Average	Rank - Predicted Unit Cost Weighted Avg.	Rank - Annual Cost Change Average	Rank - Annual Cost Change Weighted Avg.	Rank - Overall Cost Efficiency Average	Rank - Overall Cost Efficiency Weighted Avg.
ANH	3	5	6	7	1	2	2	2
NES	7	10	9	9	8	3	5	8
SRN	6	7	2	6	3	5	8	7
SVE	1	1	5	5	4	4	1	1
SWB	8	9	10	10	9	10	4	4
TMS	9	3	7	1	2	1	9	9
UU	5	4	4	4	7	7	7	5
WSH	2	2	1	2	10	9	3	3
WSX	10	8	8	8	5	6	10	10
YKY	4	6	3	3	6	8	6	6

Focusing on weighted average Actual and Predicted costs rankings, Severn Trent are the standard bearer (1^{st} in class for Actual Unit costs) compared to their Predicted Unit cost, which would have placed SVE in the middle of the pack. This is interpreted as SVE being a low unit cost producer, despite its 'average/middle of the road' operating environment.

Similarly, given their operating environment (particularly the availability of the Industry's largest plants) Thames are predicted to be the lowest unit cost producer (Predicted Unit Cost, Weighted Avg. rank 1), however reality suggests despite their favourable operating characteristics the observed unit cost weighted average rank is 3^{rd}.

In contrast, Anglian present actual unit costs which are middle of the pack (weighted avg. rank 5) – despite predicted unit costs suggesting their operating environment is worthy of the 7th highest unit costs in the industry (weighted avg. rank 7). This low predicted ranking is almost certainly caused by the same factor driving Thames' high predicted ranking – that is, access to scale economies present in the largest industry plants. Where Anglian's largest plant is equipped to treat $1/10^{th}$ of the Population Equivalent of Thames' largest plant.

Both Annual Cost Change, and Overall Cost Efficiency metrics measure the trend in costs over the 5-year panel, and rate of overall cost efficiency displayed by each company. Overall cost efficiency is the product of persistent (long-term) efficiency, and time-varying (short-term) efficiency. Annual cost change suggests that on average, within the sample, which firms are doing best on keeping cost growth for functional expenditure best under control. The industry weighted average for the period is 1.9% per year; Anglian (1.6%) and Thames (0.5%) are the only two companies below the industry weighted average.

Annual cost trends and efficiency may go some way to explaining the difference between Predicted and Actual Unit Cost rankings for the Industry. Derived Annual Cost Change suggest TMS face costs that are increasing at the smallest average rate of 0.5% (weighted avg. rank 1), this would not support the higher Actual Unit Cost ranking, relative to Predicted Unit Cost ranking. It is likely that this difference is related to TMS low Overall Cost Efficiency (rank 9, in both Average and Weighted Avg. metrics). As a result, by means of industry benchmarking, Thames is a low unit cost, low efficiency producer. The opposite may be true for Anglian, a relatively higher unit cost, high efficiency producer – detailed estimates, by Plant size decile indicate just how efficiency ANH is as a producer. Again, Severn Trent provide the benchmark – consistently first in efficiency across plant sizes.

Detailed estimates of Actual Unit Costs, Predicted Unit Costs, Cost trends, and Efficiency are provided, by plant size deciles (as defined in Table 9) and Company in Appendix A1-A4.

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Appendix

Table A1: Actual Unit Cost by Company and Plant Size Decile

- Unit Costs (£/kg BOD) are expressed in 2017/18 prices.

Company	1	2	3	4	5	6	7	8	9	10	Total
ANH	0.641	0.638	0.586	0.480	0.659	0.260	0.497	0.507	0.474	0.408	0.544
NES	0.698	0.860	0.720	0.564	0.807	0.437	0.553	0.353	0.472	0.768	0.660
SRN	0.767	0.673		0.616	0.410	0.867	0.644	0.709	0.345		0.646
SVE	0.617	0.504	0.474	0.519	0.564	0.441	0.475	0.432	0.468	0.293	0.484
SWB	1.152	0.986	0.931	0.728	0.607	0.475	0.726		0.410		0.695
TMS	0.828	0.871	0.794	0.971		0.749	0.903	0.612	0.794	0.398	0.731
UU	0.936	0.668	0.793	0.649	0.584	0.701	0.596	0.457	0.445	0.310	0.617
WSH	1.303			0.316	0.632	0.346	0.537	0.508	0.432	0.280	0.509
WSX	1.178	0.831	0.755	0.723	0.703	0.886	0.815	0.384	0.670	0.396	0.753
YKY	0.974	0.588	0.519	0.422	0.636		0.582	0.603	0.523	0.471	0.586
All E&W	0.794	0.706	0.653	0.653	0.597	0.635	0.628	0.538	0.504	0.394	0.611

Company Ranks based on Average Actual Unit Cost

Company											
ANH	2	3	3	3	7	1	2	5	7	6	3
NES	3	7	4	5	9	3	4	1	6	8	7
SRN	4	5	#N/A	6	1	8	7	9	1	#N/A	6
SVE	1	1	1	4	2	4	1	3	5	2	1
SWB	8	9	8	9	4	5	8	#N/A	2	#N/A	8
TMS	5	8	7	10	#N/A	7	10	8	10	5	9
UU	6	4	6	7	3	6	6	4	4	3	5
WSH	10	#N/A	#N/A	1	5	2	3	6	3	1	2
WSX	9	6	5	8	8	9	9	2	9	4	10
YKY	7	2	2	2	6	#N/A	5	7	8	7	4

Table A2: Predicted Unit Cost by Company and Plant Size Decile

- Unit Costs (£/kg BOD) are expressed in 2017/18 prices.

Company	1	2	3	4	5	6	7	8	9	10	Total
ANH	0.754	0.681	0.654	0.570	0.730	0.543	0.526	0.463	0.433	0.401	0.583
NES	0.734	0.697	0.608	0.764	0.716	0.571	0.626	0.564	0.495	0.466	0.619
SRN	0.771	0.563		0.607	0.529	0.509	0.478	0.437	0.368		0.526
SVE	0.722	0.631	0.533	0.604	0.621	0.552	0.518	0.529	0.465	0.417	0.570
SWB	0.861	0.840	0.720	0.720	0.534	0.515	0.648		0.481		0.637
TMS	0.757	0.700	0.632	0.751		0.612	0.590	0.551	0.530	0.355	0.582
UU	0.775	0.595	0.647	0.658	0.622	0.532	0.518	0.457	0.464	0.382	0.558
WSH	0.813			0.636	0.675	0.536	0.481	0.468	0.423	0.299	0.524
WSX	0.755	0.578	0.698	0.607	0.618	0.557	0.587	0.390	0.501	0.318	0.575
YKY	0.711	0.637	0.603	0.553	0.504		0.454	0.478	0.444	0.369	0.537
All E&W	0.751	0.650	0.622	0.654	0.606	0.545	0.529	0.485	0.459	0.381	0.569

Company Ranks based on Average Predicted Unit Costs

Company											
ANH	4	6	6	2	9	5	6	4	3	6	8
NES	3	7	3	10	8	8	9	9	8	8	9
SRN	7	1	#N/A	4	2	1	2	2	1	#N/A	2
SVE	2	4	1	3	5	6	5	7	6	7	5
SWB	10	9	8	8	3	2	10	#N/A	7	#N/A	10
TMS	6	8	4	9	#N/A	9	8	8	10	3	7
UU	8	3	5	7	6	3	4	3	5	5	4
WSH	9	#N/A	#N/A	6	7	4	3	5	2	1	1
WSX	5	2	7	5	4	7	7	1	9	2	6
YKY	1	5	2	1	1	#N/A	1	6	4	4	3

Table A3: Annual Cost Change by Company and Plant Size Decile

Company	1	2	3	4	5	6	7	8	9	10	Total
ANH	0.028	0.026	0.029	0.026	0.030	0.022	0.015	0.008	0.016	0.008	0.021
NES	0.048	0.040	0.040	0.031	0.024	0.033	0.033	0.021	0.018	0.012	0.033
SRN	0.043	0.045		0.029	0.019	0.024	0.010	0.026	0.004		0.024
SVE	0.041	0.039	0.038	0.031	0.022	0.029	0.023	0.019	0.024	0.011	0.028
SWB	0.050	0.035	0.032	0.037	0.029	0.034	0.034		0.025		0.033
TMS	0.038	0.043	0.035	0.034		0.019	0.021	0.019	0.016	0.003	0.023
UU	0.051	0.046	0.044	0.042	0.031	0.029	0.027	0.026	0.030	-0.001	0.032
WSH	0.051			0.038	0.045	0.033	0.024	0.031	0.031	0.020	0.034
WSX	0.051	0.039	0.031	0.032	0.031	0.021	0.032	0.002	0.017	0.006	0.029
YKY	0.036	0.038	0.034	0.029	0.032		0.020	0.023	0.031	0.017	0.029
All E&W	0.041	0.038	0.035	0.034	0.029	0.027	0.023	0.019	0.022	0.007	0.028

Company Ranks Based on Average Annual Cost Change

Company											
ANH	1	1	1	1	5	3	2	2	3	4	1
NES	6	6	7	4	3	7	9	5	5	6	8
SRN	5	8	#N/A	2	1	4	1	7	1	#N/A	3
SVE	4	5	6	5	2	5	5	3	6	5	4
SWB	7	2	3	8	4	9	10	#N/A	7	#N/A	9
TMS	3	7	5	7	#N/A	1	4	4	2	2	2
UU	10	9	8	10	7	6	7	8	8	1	7
WSH	9	#N/A	#N/A	9	9	8	6	9	10	8	10
WSX	8	4	2	6	6	2	8	1	4	3	5
YKY	2	3	4	3	8	#N/A	3	6	9	7	6

Table A4: Overall Cost Efficiency by Company and Plant Size Decile

Company	1	2	3	4	5	6	7	8	9	10	Total
ANH	0.838	0.824	0.854	0.843	0.826	0.944	0.855	0.811	0.801	0.805	0.831
NES	0.822	0.716	0.817	0.783	0.652	0.776	0.790	0.838	0.775	0.607	0.765
SRN	0.694	0.659		0.737	0.755	0.680	0.656	0.681	0.751		0.701
SVE	0.919	0.932	0.940	0.922	0.897	0.908	0.905	0.907	0.888	0.902	0.913
SWB	0.770	0.796	0.801	0.816	0.695	0.822	0.811		0.839		0.781
TMS	0.654	0.634	0.631	0.631		0.644	0.617	0.668	0.572	0.685	0.643
UU	0.706	0.698	0.709	0.773	0.736	0.712	0.724	0.746	0.792	0.752	0.736
WSH	0.703			0.861	0.816	0.864	0.877	0.771	0.801	0.803	0.815
WSX	0.577	0.614	0.669	0.637	0.669	0.611	0.624	0.592	0.662	0.651	0.636
YKY	0.736	0.760	0.767	0.770	0.710		0.711	0.718	0.730	0.717	0.739
All E&W	0.784	0.744	0.785	0.776	0.760	0.751	0.748	0.761	0.765	0.749	0.762

Company Ranks Based on Average Overall Cost Efficiency

Company											
ANH	2	2	2	3	2	1	3	3	3	2	2
NES	3	5	3	5	9	5	5	2	6	8	5
SRN	8	7	#N/A	8	4	7	8	7	7	#N/A	8
SVE	1	1	1	1	1	2	1	1	1	1	1
SWB	4	3	4	4	7	4	4	#N/A	2	#N/A	4
TMS	9	8	8	10	#N/A	8	10	8	10	6	9
UU	6	6	6	6	5	6	6	5	5	4	7
WSH	7	#N/A	#N/A	2	3	3	2	4	4	3	3
WSX	10	9	7	9	8	9	9	9	9	7	10
YKY	5	4	5	7	6	#N/A	7	6	8	5	6

Table A5: Company Benchmarking with Overall Cost Efficiency and Ofwat Deltas

	Overall Cost Efficiency		Ofwat Delta		
Company	Average	Weighted Avg.	Average	Weighted Avg.	Aggregate
ANH	0.831	0.818	-0.035	0.021	0.003
NES	0.765	0.706	0.037	0.179	0.171
SRN	0.701	0.706	0.234	0.241	0.255
SVE	0.913	0.904	-0.155	-0.179	-0.169
SWB	0.781	0.791	0.056	0.004	0.005
TMS	0.643	0.658	0.260	0.199	0.207
UU	0.736	0.752	0.122	0.066	0.056
WSH	0.815	0.810	-0.050	-0.079	-0.055
WSX	0.636	0.643	0.247	0.229	0.229
YKY	0.739	0.730	0.111	0.147	0.145
All E&W	**0.762**	**0.761**	**0.076**	**0.069**	**0.069**

	Rank – Overall Cost Efficiency		Rank – Ofwat Delta		
	Average	Weighted Avg.	Average	Weighted Avg.	Aggregate
ANH	2	2	3	4	3
NES	5	8	4	7	7
SRN	8	7	8	10	10
SVE	1	1	1	1	1
SWB	4	4	5	3	4
TMS	9	9	10	8	8
UU	7	5	7	5	5
WSH	3	3	2	2	2
WSX	10	10	9	9	9
YKY	6	6	6	6	6