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Reprint of: Dynamic efficiency in the English and Welsh water and sewerage industry

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ABSTRACT

The English and Welsh water and sewerage industry is characterised by indivisible capital which has a long service life. Previous studies of efficiency for the English and Welsh water and sewerage industry take a static framework, assuming all inputs can be adjusted instantaneously. This paper measures dynamic efficiency by incorporating intertemporal links of capital within the production function for the English and Welsh water and sewerage industry for the period 1997–2011. Dynamic Data Envelopment Analysis (DEA) considers capital as a quasi-fixed input and is modelled as a contemporaneous output into current production and an input from past production. The results show that the inadequate intertemporal allocation of quasi-fixed inputs is the largest contributor of inefficiency.

1. Introduction[1]

The English and Welsh water and sewerage sector is a long-life capital intensive industry, characterised by regional monopolies. The industry was privatised in 1989 and is regulated by Ofwat (Office of Water Services), the water service regulatory authority which acts as a proxy for a competitive market. Ofwat ensures that utility companies obtain a specified return on capital which is unique to the water sector whilst ensuring a competitive price for customers. To guarantee quality standards the industry is also regulated by the Drinking Water Inspectorate (DWI), National Resources Wales (NRW) and the Environment Agency (EA).

The aims of this paper are twofold: firstly to compare the conclusions from static and dynamic DEA highlighting the inefficiencies that arise out of a dynamic framework, and secondly to investigate the presence of a preference for capital expenditure known as the *capex bias*. The bias arises because of differing incentive rates between operating and capital expenditure, or due to the nature of the industry as much of the infrastructure is built in order to meet expected future demand. The presence of the bias drives to the heart of the brief set by regulators to guarantee consumer value.

Data Envelopment Analysis (DEA) is used to measure efficiency within a dynamic context by examining the presence of quasi-fixed capital. The English and Welsh water and sewerage industry is characterised by quasi-fixed inputs such as mains, sewers and treatment works which have a long service life and cannot be adjusted to their optimal level instantaneously. A dynamic perspective of the measurement of efficiency is required as decisions on quasi-fixed inputs not only influence current production, but also future production. Intertemporal effects are incorporated through the inclusion of capital as an output in the current period production as well as an input from the previous period's production. Firms therefore face a trade-off between increasing output today and producing capital to increase outputs in the future [21]. Dynamic DEA determines the optimal allocation of resources over the period by minimising dynamic costs given the technology. We allow for overall efficiency to be decomposed into a dynamic component and a static component. This approach determines the level of efficiency due to variable inputs and the inefficiency due to quasi-fixed inputs. We use a three stage approach by including environmental variables[2] within the dynamic framework to ensure firms are compared on a level playing field. Input slacks ratios are obtained from the dynamic DEA which are then regressed upon the environmental variables. The predicted slack ratios are used to adjust the input variables upwards for those firms

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[2] Fried et al. [19,20].

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operating in a relatively favourable environment. The DEA is repeated including the adjusted inputs to obtain adjusted efficiency scores accounting for differences in the operating environments.

The remainder of the paper is organised as follows: Section 2 describes the regulatory environment; Section 3 briefly reviews the extant literature; Section 4 outlines the methodology to measure dynamic efficiency; Section 5 outlines the sample data and variable definitions; Section 6 presents and discusses the results and Section 7 concludes the paper.

2. Regulation of the water industry

The English and Welsh water and sewerage industry in 1989 consisted of ten water and sewerage companies (WaSCs) and 29 water only companies (WoCs). Privatisation has seen a series of mergers and acquisitions resulting in ten WaSCs and nine WoCs within the industry. The companies are vertically integrated monopolies undertaking all activities of the value chain. WaSCs undertake both water and sewerage activities and WoCs only undertake water activities. Water services are provided by a single company that extracts, treates, distributes and retails the water whereas for sewerage activities a company collects, treats and disposes of the sewerage. WaSCs are considerably larger than WoCs undertaking 78% of water supply to the population and serve 85% of the total area of England and Wales [30].

The local provider of water and sewerage services is a monopoly; therefore Ofwat regulates prices through the use of price-cap regulation based on $RPI+K$ which allows companies to change prices according to the inflation rate (*RPI*, Retail Price Index) and a *K* factor determined by the regulator. The *K* factor has two components: a positive component which allows for price increases to accommodate large investment programmes and a negative component (X-efficiency) which reflects Ofwat's estimate of the scope for efficiency improvements. Ofwat's determination of the *K* factor is based on a building block approach to determine the “Required Revenue” which involves the individual assessment of utility operating costs, capital charges and return on capital. The first price-cap was set by the Government at the start of privatisation in 1989 and subsequent price reviews have been undertaken by Ofwat every 5 years in 1994, 1999, 2004 and 2009[3].

The allowed level of operating costs is determined through the use of yardstick competition and menu regulation. Ofwat analyses operating expenditure (*opex*) and capital expenditure (*capex*) separately. Operating expenditure is subject to an efficiency challenge which is decomposed into an industry efficiency challenge for continuing efficiency improvement (technical change) and a catch-up factor to the frontier company. The catch-up factor is determined through a suite of econometric and unit cost models which are used to calculate the company's relative efficiency. Based upon these efficiency scores firms are banded and given an efficiency challenge to catch-up 60% of the difference from the benchmark company[4]. Firms are further incentivised to improve efficiency between the five-year price reviews, if companies outperform their efficiency challenge the benefits can be kept for the five years. Capital expenditure was evaluated through the use of yardstick competition, using econometric models and unit costs. In the 2009 price review *capex* was analysed through the use of menu regulation which encourages firms to submit realistic and well evidenced capital planning schemes. Ofwat determines an independent baseline, and provides incentives for firms to outperform. The companies have the incentive to outperform their efficiency target through a symmetric efficiency incentive on the level of over and under spend. The incentive rate is based upon the ratio of Ofwat's baseline and the company's business plan. Opex is recovered within the period; however *capex* is added to the Regulatory Capital Value (RCV)[5] which earns a return based upon Ofwat's assumptions of the cost of capital. A fair return on capital is required to attract investment within the industry.

The 2014 price review to set prices for 2015–2020 is partly designed around eliminating the presence of the perceived *capex bias*. Ofwat [27] defines the *capex bias* as the view that companies within the industry have an inappropriate preference for expenditure on capital assets over day-to-day operational expenditure. [8] state that the bias is believed to exist for three reasons. Firstly, there are the different financial incentives created by examining *capex* and *opex* separately. Secondly, the presence of what is termed as the *Averch–Johnson effect*; which arises if the allowed rate of return is higher than the true cost of capital [3]. Thirdly, the culture of the sector is one that is focused on *capex* solutions and infrastructure to meet future demand.

3. Literature review

The privatisation and regulation of the water and sewerage industry in England and Wales has spawned a large literature on estimating productivity and cost efficiency. Ashton [2] analyses firm-specific cost efficiency conditions of WaSCs using a translog variable cost function over the period 1987–1997.The paper reports a moderate level of dispersion of inefficiency which may be due to the performance or the operating environment within the sector.

Saal and Parker [30] estimate a cost function to evaluate the impact of privatisation and regulation on productivity. The impact of changes in quality regulations were taken into account through a quality-adjusted measure of output. The model highlights the importance of adjusting for changes in quality standards through the impact on the interaction term between water and sewerage activities, finding an improvement in the quality of one output may reduce the cost of producing the other. Productivity was examined over the period in which the null hypothesis of no productivity change was rejected. Individual parameter estimates reveal that the productivity change was led by improvements after the 1994 price review and were not due to privatisation. Saal et al [33] examine technical efficiency through an SFA (Stochastic Frontier Analysis) input distance function and find that productivity growth was not statistically different after privatisation and the 1994 price review. The impact of privatisation and regulation resulted in technological improvements rather than efficiency improvements. The average efficiency was lower in 2000 than at privatisation; however the price cap has influenced the relatively inefficient firms by substantially improving the minimum efficiency score.

Similarly, Bottasso and Conti [4] examine efficiency for water activities estimating an SFA translog cost function with quasi-fixed capital and confirm that operating inefficiency decreased for the period 1995–2001. Bottasso and Conti [5] examine economies of scale and technical change for the WoCs using a variable cost function for 1995–2005. Their results on total factor productivity indicate that the rate of technical change is much higher after the 1999 price review in comparison to the rate after the 1994 price review which was close to zero. Productivity improvements have been a result of labour saving technological progress.

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[3] The first price-cap in 1989 was set for 10 years with an opportunity for the regulator to hold an interim determination after five years, which the regulator implemented.

[4] Ofwat [26].

[5] The RCV is the value placed on companies 100 days after privatisation and is rolled forwards based on the amount of capital expenditure for each period less the level of depreciation.

Saal and Reid [34] analyse *opex* productivity growth of the WaSCs from 1993 to 2003 through the use of a quasi-fixed capital translog cost function. The paper examines the impact of the regulatory regime alongside the impact of significant levels of investment to improve drinking water quality on *opex* productivity growth. The results indicate a statistically significant improvement in *opex* productivity growth as a result of the price review in 1994 but find that the 1999 price review did not produce any additional productivity improvements.

DEA has been applied within the English and Welsh water and sewerage industry[6] to measure the operating expenditure efficiency for the water activities and water distribution respectively. These studies only examine operating expenditure and therefore do not take into account capital within their specification. Erbetta and Cave [15] consider a total cost model, for both water and sewerage activities for WaSCs using a four output model. Their results highlight that the majority of inefficiencies are due to the incorrect combination of inputs: the over-utilisation of labour and the under-utilisation of capital. Over the period 1993–2005 there was a positive trend for both technical and allocative efficiency. The results suggest that the 1999 price review stimulated technical efficiency progress of around 5% whereas the 1994 price review had no effect.

A common theme running throughout the literature of efficiency within the English and Welsh water and sewerage industry is the treatment of capital. Capital can be modelled either as part of a variable cost function or a long run cost function where the latter assumes that firms have the ability to adjust all inputs in the long run to their optimal level. Within the variable cost function, capital is incorporated as a quasi-fixed input, therefore capital is not considered as a control variable and cost minimisation is only related to variable inputs. Saal and Reid [34] model capital as a quasi-fixed factor as the technology used within the industry is indivisible and associated with a long service life and therefore invariant in the short-term. In addition, WaSCs face legal obligations to connect customers to the service as well as investment programmes agreed with the DWI and EA to meet increasing quality standards. Stone and Webster [39], and Bottasso and Conti [5] estimate a variable cost function for the English and Welsh water and sewerage industry and the coefficient on the quasi-fixed input implies a tendency of overcapitalisation which is a common finding in the literature of public utilities [9,12]. Bottasso and Conti [5] state that overcapitalisation can be interpreted as the Averch–Johnson effect due to the presence of rate of return regulation alongside the capital intensive nature of the industry and the presence of investment to meet future demand. Stone and Webster [39], and Bottasso and Conti [5] state that the presence of overcapitalisation could result in a misspecified total cost function where the assumption is that firms can instantaneously vary the level of capital. Saal and Parker [30] and Erbetta and Cave [15] consider a total cost function through the use of parametric and non-parametric specifications respectively. Erbetta and Cave [15] find an initial under-utilisation of capital and over-utilisation of labour which diminishes over the period. Saal and Parker [30] report capital-augmenting and labour-saving technological change over the period considered. This result is not surprising as one of the goals of privatisation was to expand capital investment in the industry. Indeed Saal and Parker [31] examine total factor productivity and find substantial capital growth in the post-privatisation period.

The pioneering work of Farrell [18] measures efficiency as the distance between an observation and an estimated ideal referred to as an efficient frontier. Cooper et al [11] defines DEA as a non-parametric technique which uses mathematical linear programming to create a piece wide surface or frontier over the data. Traditionally DEA is studied within a static context, therefore inputs and outputs were considered for a given period. However, developments in Network-DEA have expanded the simple black box of inputs and outputs into multiple stages of production and have been applied extensively in studying the banking industry (see for example [23,44]). But the static model implies that all inputs can be adjusted to their optimal level within the given period and there are no links between time periods. The Malmquist index allows for the evolution of efficiency over time to be measured[7] and is used to explain changes between two consecutive time periods. The Malmquist index allows for the decomposition of the intertemporal efficiency change into a catch-up and innovation (frontier-shift) effect.

The static model is based on the firm's ability to instantaneously adjust the factors of production and ignore the intertemporal linkage of production decisions [36]. However, Emrouznejad and Thanassoulis [14] make the case for the presence of an intertemporal relationship: 1) The existence of a stock of capital whose useful service life and the effects of investment extend over several periods; 2) The presence of lagged outputs which, in addition to contemporaneous effect of the inputs, depends on the inputs used in the previous periods and 3) The production of intermediate outputs.

Nemoto and Goto [25] argue that the assumption of static optimisation results in biased measurements of inefficiency if quasi-fixed inputs exist. They show that the allocative inefficiency in particular will be overstated to the extent that quasi-fixed inputs are not instantaneously adjusted to their optimal levels. The weakness of the static theory of production to describe how some inputs gradually adjust has led to the development of dynamic models.

Sengupta [35] was perhaps the first to introduce dynamics through the adjustment costs of quasi-fixed inputs. Fare and Grosskopf [16] introduce dynamics through the use of network DEA considering capital as an intermediate outputs. Nemoto and Goto [24,25] propose a model of dynamic DEA using a cost function which is closely related to adjustment-cost theory of investment and therefore provides a nonparametric alternative to the parametric Euler equation. The model augments the conventional DEA by treating quasi-fixed inputs at the end of one period as if they were outputs in the period and essentially inputs in the subsequent one. The firm therefore faces a trade-off, whether to myopically increase output or to increase quasi-fixed inputs to increase future production.

Geymuller (2009) extend Nemoto and Goto [25] by solely considering technical efficiency in the absence of input prices. [41] consider a slacks-based approach which considers both radial and non-radial efficiency. Their model allows for the inclusion of desirable, undesirable, discretionary (free) and non-discretionary (fixed) variables. The model however does not allow for the breakdown of overall efficiency to account for the inefficiencies relating to static and dynamic components[8]. Avkiran [1] applies a dynamic network slack based framework to examine yearly efficiency whilst incorporating intertemporal links and measuring the efficiency of sub divisions. [28] propose a dynamic DEA model which allows for the inclusion of quasi-fixed inputs when investment decisions are exogenous. Silva and Stefanou [37] develop a dynamic efficiency model which takes into account interdependence of production decisions whilst allowing for temporal efficiency measurements. Capital is treated as a quasi-fixed factor and is managed as an asset where rapid expansion or contraction of the stock of capital is accompanied by adjustment costs.

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[6] Cubbin and Tzanidakis [13] and Thanassoulis [42,43].

[7] See Fare et al. [17].

[8] This is partly rectified in Tone and Tsutsi [40], where they extract the dynamic change in efficiency and the dynamic change in divisional efficiency.

The model of Nemoto and Goto [25] is applied to the English and Welsh water and sewerage industry to incorporate the intertemporal nature of capital. Firstly, the capital within the industry has a long asset life and span over several periods. Secondly, the firms face a trade-off between the performance in the current period and investing in capital to meet future demand and to improve the quality of outputs and productivity.

4. Methodology

This section outlines the dynamic DEA model by Nemoto and Goto [25] which will be applied to the English and Welsh water and sewerage industry. Let us have N DMUs ($n=1,\ldots,N$), J variable inputs ($j=1,\ldots,J$), S quasi-fixed inputs ($s=1,\ldots,S$) producing R outputs ($r=1,\ldots,R$). The DEA model is shown in Eq. (1.1) where γ^t is a constant discount factor$x_t$denotes the variable inputs used in period t, and k_t denotes the quasi-fixed at the end of period t .w_t, v_t are price vectors of variable inputs and quasi-fixed inputs in period t respectively. y_t denotes the outputs produced in period t and i is a $N\times 1$ vector of ones to impose the convexity constraint under Variable Returns to Scale (VRS). VRS specification is examined to obtain a pure measure of managerial inefficiency excluding any scale inefficiencies as WaSCs do not have control over their operating size, unless the regulator permits mergers (Thanassoulis, 2000a). Overall efficiency (OE) examines the cost minimising level of quasi-fixed and variable inputs given prices whilst incorporating the quasi-fixed inputs as an intertemporal factor of production.

$$\begin{aligned}
&\hat{C}\left(\bar{k}_0\right)=\min_{\{x_t,\,k_t,\,\lambda_t\}_{t=1}^{T}}\sum_{t=1}^{T}\gamma^t(w_t'x_t+v_t'k_{t-1})\\
&s.t.\quad X_t\lambda_t\le x_t\,,\quad t=1,2,\ldots,T\\
&\quad K_{t-1}\lambda_t\le k_{t-1}\,,\quad t=1,2,\ldots,T\\
&\quad K_t\lambda_t\ge k_t\,,\quad t=1,2,\ldots,T-1\;N\times 1\\
&\quad Y_t\lambda_t\ge y_t,\quad t=1,2,\ldots,T\\
&\quad i'\lambda_t=1,\quad t=1,2,\ldots,T\\
&\quad k_0=\bar{k}_0,\quad x_t\ge 0,k_t\ge 0,\ \lambda_t\ge 0,t=1,2,\ldots,T
\end{aligned}\qquad 1.1$$

The bar over the variables represents fixed levels of variables. The difference between this DEA model and the static model is the inclusion of the capital stock at time t as an output. Nemoto and Goto [25] highlight that overall efficiency is calculated by:

$$OE=\hat{C}\left(\bar{k}_0\right)/C \tag{1.2}$$

Here C is the discounted sum of actual costs over the period considered. Overall efficiency can be decomposed into dynamic and static efficiency; static efficiency can then be decomposed into technical efficiency and allocative efficiency. Static efficiency is calculated holding the quasi-fixed inputs fixed and examining the optimal level of variable inputs given input prices. The difference between overall efficiency and static efficiency is dynamic efficiency. Static efficiency can be written formally as the linear programming problem in the following equation:

$$\begin{aligned}
&C_{SE}=\min_{\{x_t,\ \lambda_t\}_{t=1}^{T}}\sum_{t=1}^{T}\gamma^t\left(w_t'x_t+v_t'\bar{k}_{t-1}\right)\\
&\quad s.t.\,X_t\lambda_t\le x_t,\quad t=1,2,\ldots,T\\
&\quad K_{t-1}\lambda_t\le\bar{k}_{t-1}\,,\quad t=1,2,\ldots,T\\
&\quad K_t\lambda_t\ge\bar{k}_t\,,\quad t=1,2,\ldots,T-1\\
&\quad Y_t\lambda_t\ge y_t,\quad t=1,2,\ldots,T\\
&\quad i'\lambda_t=1,\quad t=1,2,\ldots,T\\
&\quad x_t\ge 0\,,\quad \lambda_t\ge 0\,,\quad t=1,2,\ldots,T
\end{aligned}\tag{1.3}$$

Static efficiency (SE) and dynamic efficiency (DE) are then calculated by Eqs. (1.4) and (1.5). Dynamic efficiency measures the impact on costs of not using the optimal path of quasi-fixed inputs.

$$SE=C_{SE}/C \tag{1.4}$$

$$DE=\hat{C}\left(\bar{k}_0\right)/C_{SE} \tag{1.5}$$

Nemoto and Goto [25] highlight that dynamic efficiency includes forecast errors for input prices and demands for outputs in the future.

Static efficiency can be broken down into allocative and technical efficiency. Technical efficiency is obtained by examining the radial contraction of variable inputs by solving the following linear programming problem:

$$\begin{aligned}
&C_{TE}=\min_{\{\theta_t,\ \lambda_t\}_{t=1}^{T}}\sum_{t=1}^{T}\gamma^t\left(\theta_t w_t'\bar{x}_t+v_t'\bar{k}_{t-1}\right)\\
&\quad s.t.\,X_t\lambda_t\le\theta_t\bar{x}_t\,,\quad t=1,2,\ldots,T\\
&\quad K_{t-1}\lambda_t\le\bar{k}_{t-1}\,,\quad t=1,2,\ldots,T\\
&\quad K_t\,\lambda_t\ge\bar{k}_t\,,\quad t=1,2,\ldots,T-1\\
&\quad Y_t\lambda_t\ge y_t\,,\quad t=1,2,\ldots,T\\
&\quad i'\lambda_t=1\,,\quad t=1,2,\ldots,T\\
&\quad \theta_t\ge 0\,,\ \lambda_t\ge 0\,,\ t=1,2,\ldots,T
\end{aligned}\tag{1.6}$$

The radial contraction θ_t is allowed to vary over the periods. Since the quasi-fixed inputs are exogenously given at the actual levels there are no restrictions across the periods. Therefore the LP programme can be reduced to T single period problems that are independent of one another. Technical efficiency (TE) is measured as

$$TE=\ C_{TE}/C$$

Allocative efficiency (AE) can be calculated as

$$AE=C_{SE}/C_{TE}$$

AE reflects the costs that could be saved if variable inputs were adjusted to the optimal level along the short-run isoquant. The relationship for overall efficiency can be decomposed as

$$OE=TE.AE.DE$$

The dual of problem (1.1) is:

$$\begin{aligned}
&J_T\left(\bar{k}_0\right)=\max_{\{\alpha_t,\beta_t,\mu_t,\phi_t,\epsilon_t\}_{t=1}^{T}}\ \gamma v_1'\bar{k}_0-\beta_1\bar{k}_0+\sum_{t=1}^{T}\mu_t'y_t+\sum_{t=1}^{T}\epsilon_t\\
&\quad s.t.\ \alpha_t'\le\gamma^t w_t'\quad t=1,2,\ldots,T\\
&\quad -\alpha_t'X_t-\beta_t'K_{t-1}+\phi_t'K_t+\mu_t'Y_t+i'\epsilon_t\le 0\quad t=1,2,\ldots,T\\
&\quad \beta_t'-\phi_{t-1}'\le\gamma^t v_t'\quad t=1,2,\ldots,T\\
&\quad \alpha_t\ge 0,\ \beta_t\ge 0,\ \mu_t\ge 0\quad t=1,2,\ldots,T\\
&\quad \phi_t>0,\ t=1,2,\ldots,T-1,\ \phi_T=0\quad t=1,2,\ldots,T
\end{aligned}\tag{1.7}$$

The measurement of inefficiency in the period t for variable inputs τ_t^x, for quasi-fixed inputs τ_t^k and for net investment in quasi-fixed inputs τ_t^h follows as:

$$\begin{aligned}
&\tau_t^x=\gamma^t w_t'(x_t-\ x_t^*)/C\quad t=1,2,\ldots,T;\\
&\tau_t^k=\gamma^t v_t'(k_{t-1}-\ k_{t-1}^*)/C\quad t=2,3,\ldots,T;\\
&\tau_t^h=\left\{\left(\phi_t^{*'}k_t-\phi_{t-1}^{*'}k_{t-1}\right)-\left(\phi_t^{*'}k_t^*-\phi_{t-1}^{*'}k_{t-1}^*\right)\right\}/C\ t=2,3,\ldots,T-1
\end{aligned}\tag{1.8}$$

where x_t and k_t are evaluated at the observed values, k_t^* and x_t^* are the optimal values of capital and variable inputs at time t. ϕ_t^* is the marginal adjustment cost at time t derived from the dual in Eq. (1.7). C is the discounted sum of actual total costs over the planning period. Positive (negative) values of τ_t^x, τ_t^k and τ_t^h indicate excess (short) usage of inputs or excess (short) net investment. The equations measure the inefficiencies according to the normalised deviations of observations along from the optimal input usage.

Table 1
Summary of linear programmes.

Dynamic efficiency model	Variable factor	Exogenous factors	Action
Dynamic overall	– Labour – Other inputs – Capital		Intertemporal readjustment
Dynamic Static efficiency	– Labour – Other inputs	– Capital	Realignment of input mix
Dynamic technical efficiency	– Labour – Other inputs	– capital	Radial contraction
Static efficiency model			
Static overall efficiency	– Labour – Other inputs – Capital		Realignment of input mix
Static technical efficiency	– Labour – Other inputs – Capital		Radial contraction

Dynamic DEA is compared to static DEA where all inputs are considered as variable therefore implying that they can be instantaneously adjusted to their optimal level. Static cost efficiency $\left(CE^S\right)$ is obtained by the following linear programme:

$$\begin{aligned}
CE^S = & \min_{x_t,k_t,\lambda_t} \sum_{t=1}^{T} \gamma^t (w_t' x_t + v_t' k_{t-1}) \\
& s.t.\ X_t\lambda_t \le x_t, \quad t=1,2,..,T \\
& K_{t-1}\lambda_t \le k_{t-1}, \quad t=1,2,..,T \\
& Y_t\lambda_t \ge y_t, \quad t=1,2,..,T \\
& i'\lambda_t = 1, \quad t=1,2,\dots,T \\
& \lambda_t \ge 0,\ x_t \ge 0,\ k_t \ge 0, \quad t=1,2,..,T
\end{aligned} \tag{1.9}$$

$$OE^S = CE^S / C \tag{1.10}$$

Cost efficiency can be decomposed into allocative and technical efficiency by Eq. (1.12). Static technical efficiency $\left(TE^S\right)$ is measured through the following linear programme:

$$\begin{aligned}
TE^S = & \min_{\theta_t,\lambda_t} \sum_{t=1}^{T} \gamma^t \theta_t (w_t' x_t + v_t' k_{t-1}) \\
& s.t.\ X_t\lambda_t \le \theta_t x_t, \quad t=1,2,..,T \\
& K_{t-1}\lambda_t \le \theta_t k_{t-1}, \quad t=1,2,..,T \\
& Y_t\lambda_t \ge y_t, \quad t=1,2,..,T \\
& i'\lambda_t = 1, \quad t=1,2,\dots,T \\
& \theta_t \ge 0,\ \lambda_t \ge 0, \quad t=1,2,..,T
\end{aligned} \tag{1.11}$$

Static allocative efficiency (AE^S) is defined as

$$AE^S = OE^S / TE^S \tag{1.12}$$

A summary of the linear programmes for both dynamic and static DEA are reported in Table 1 which denotes which factors of production are variable, which are exogenous and the action required by the linear programme.

DEA makes the implicit assumption of homogeneity [22], implying that firms operate within a similar environment. WaSCs operate under different operating characteristics which are outside of managerial control, known as non-discretionary or environmental variables. Non-discretionary variables can influence the production function, increasing or decreasing the maximum attainable output level if the environmental variables are favourable or unfavourable respectively. The second part of this paper incorporates environmental variables within the dynamic DEA framework through the use of the three stage approach based upon Fried et al [19]. The first stage generates the efficiency scores and the input slacks. The second stage accounts for the effect of the environmental impact upon the slacks through a second stage regression. The third stage adjusts inputs variables to create a level playing field before repeating the DEA analysis. Input variables are adjusted upwards for those firms that operate under relatively favourable environments.

The firms with a relatively unfavourable operating environment have their inputs adjusted by a relatively small amount, while those with favourable operating environments are adjusted upwards by a relatively large amount. Adjusting the inputs upwards provides a performance target managers can reach regardless of their operating environment [19].

Fried et al [19,20] consider the impact of environmental variables on technical efficiency while Blank and Valdmanis [7] extend their work to consider the impact of environmental variables on cost efficiency through cost efficiency slacks for each firm and time period. The cost slack ratio is the ratio of the optimal input x^*_{jnt} for the jth variable input, n^{th} DMU and t^{th} time period and the actual variable input defined by Eq. (1.13). The cost slack ratio for quasi-fixed inputs is defined in Eq. (1.14) for the sth quasi fixed input, nth DMU and tth time period. The cost slack ratios are greater than, less than or equal to 1[9]. A value greater than 1 implies an over-utilisation of input, a value less than 1 implies an underutilisation of inputs and a value equal to 1 implies an efficient use of inputs.

$$S_{jnt} = \frac{x_{jnt}}{x^*_{jnt}} \tag{1.13}$$

$$SK_{snt} = \frac{k_{snt}}{k^*_{snt}} \tag{1.14}$$

To determine the impact of environmental variables the input slack ratios are regressed on the environmental variables. The slack ratios are centred on their means and do not have a mass of observations at one point meaning that this approach avoids the censoring problem when using efficiency scores within the second stage regression. To ensure that the predicted slack ratios take positive values only a log

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[9] Fried et al. [19,20] consider both the radial and non-radial slacks whereas this approach only considers radial slacks.

transformation of the dependent variable is taken. The data for each time period is pooled and regressed upon M environmental variables $Q_{nt} = [Q_{1nt,\ldots,}\, Q_{Mnt}]$, $n=1,..,N$, $t=1,,,.,T$ separately for each input slack[10]. Simar and Wilson [38] highlight the presence of serial correlation amongst the efficiency scores generated by DEA which leads to incorrect inference within the second stage regression. To correct for the presence of serial correlation, Simar and Wilson [38] propose two algorithms. Algorithm 1 is a bootstrapped truncated regression to provide correct inference. Algorithm 2 is an extension to incorporate for the potential bias in non-parametric estimators. By using Monte-Carlo experiments, the authors conclude that Algorithm 1 overcomes Algorithm 2 in small samples [38, pp. 50–51]. To correct for the presence of serial correlation, a bootstrap regression is applied to the second stage regression of the environmental variables on the input slacks in the following equation[11]:

$$\log\left(S_{jnt}\right) = f^j\left(Q_{nt};\beta^j\right) + u_{jnt} \quad (j=1,\ldots,J \quad t=1,\ldots,T \quad n=1,\ldots,N) \tag{1.15}$$

$$\log\left(SK_{snt}\right) = f^s\left(Q_{nt};\beta^s\right) + u_{snt} \quad (s=1,\ldots,S \quad t=1,\ldots,T-1 \quad n=1,\ldots,N)$$

where $f^j\left(Q_{nt};\beta^j\right)$ and $f^s\left(Q_{nt};\beta^s\right)$ are deterministic feasible slack frontiers, parameter vectors β^j and β^s are to be estimated. The interpretation of the coefficients depends upon whether the resource is under or over-utilised. If the resource is over-utilised and takes a value greater than 1, a negative coefficient will imply moving to the optimal level of resources. However, if the input is under-utilised a negative coefficient will imply that the environmental variable is unfavourable, moving away from the optimal utilisation of inputs.

The predicted slacks are obtained and the inputs are adjusted using the methodology of Blank and Valdmanis [7] for each WaSC and time period[12]. The inputs are adjusted upwards using Eq. (1.16) in which the least favourable set of environmental conditions are used as a base[13].

$$x^{adj}_{jnt} = x^{nt}_j\left(\frac{max^{nt}\left(\hat{S}_{jnt}\right)}{\hat{S}_{jnt}}\right) \; j=1,..,J;\; t=1,\ldots,T;\; n=1,..,N \tag{1.16}$$

$$k^{adj}_{snt} = k^{nt}_s\left(\frac{max^{nt}\left(\widehat{SK}_{snt}\right)}{\widehat{SK}_{snt}}\right) \; s=1,..,S;\; t=0,\ldots,T;\; n=1,..,N$$

where $\hat{S}_{jnt}$ are the predicted slacks of resource j for firm n at time t and $max^{nt}\left(\hat{S}_{jnt}\right)$ represents the firm with the most unfavourable conditions. Firms operating within a favourable environment have their inputs adjusted upwards by a relatively higher amount whereas those with unfavourable environment have their inputs adjusted upwards by a relatively lower amount. The final stage reruns the dynamic DEA programme using the adjusted inputs to control for environmental differences.

5. Data

This section describes the data used within the paper and the definitions of the variables considered. The data is available for the period 1996/97–2010/11 for the ten WaSCs. WaSCs are only considered within the analysis as Saal and Parker [32] and Bottasso et al [6] highlight that it may be misleading to pool the data for WaSCs and WoCs as they exhibit different technologies. Within the panel there were three mergers of WaSCs with the smaller WoCs[14].

5.1. Definition of variables

For the application of this methodology for the English and Welsh water and sewerage industry, two physical outputs will be considered for water and sewerage activities: water delivered and the equivalent population served. To take into account changes in quality within the industry the output measures are adjusted by a quality index following Saal and Parker [30]. Water output is measured as $(Y_1) = Water\ Delivered \times Q_w$ where Q_w is the measure of water quality. Water quality is defined as the ratio of the average percentage of each WaSC's water supply zones that are compliant with key water quality indicators as defined by the DWI[15]. Sewerage output is measured as $(Y_2) = Equivalent\ Popuation \times Q_s$, where Q_s is a measure of sewerage quality. Sewerage quality is accounted for by calculating the proportion of the total load receiving secondary treatment. Bottasso and Conti [4] highlight the estimation gains for including not only the physical quantity of outputs but also the number of properties served for water and sewerage[16]. However, due to the limited number of firms within the dataset, only two outputs have been considered[17].

Three inputs are considered within the model: labour, capital and other. Staff costs and the number of full time employees are obtained from companies' statutory accounts. The price of labour is calculated as the total labour costs divided by the number for full time equivalent employees[18].

The value of the capital stock is measured by the MEA (Modern Equivalent Asset) value. The MEA value is the estimation of the replacement cost of tangible fixed assets reported for water and sewerage services. The frequent revaluations of the MEA value results in arbitrary jumps in the measure of capital over time and therefore many authors[19] have adjusted the MEA value in order to smooth out the series for the revaluations.

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[10] Fried et al. [20] highlight that as the slacks are obtained from the first stage DEA model when considering separate equations, the error components are probably not independently and identically distributed (i.i.d). It would be preferable to stack the regressions and estimate via SUR allowing the error terms to be correlated across inputs. Due to the timing difference within the dynamic DEA this has not be considered here.

[11] Simar and Wilson [38] apply a bootstrap truncated regression as the inverse of the Farrell efficiency scores are bounded at 1. A bootstrap regression is applied as the cost slack ratios take a value greater than, less than or equal to 1.

[12] Regression for capital slacks is run for the period 1997–2010 as the linear programme does not return an optimal value of the capital stock for the end of 1996 and 2011. Using the coefficients obtained, predicted slacks are obtained for the end of 1997 and 2011 and capital is adjusted using the same methodology.

[13] The reciprocal of the ratio from Blank and Valdmanis [7] is used so the maximum slack, considered as the most unfavourable environment is the highest over-utilisation of inputs. Inputs are adjusted upwards by the amount in which firms operate under a favourable environment.

[14] Mergers occurred in April 2000 between Hartlepool Water and Anglian Water, Northumbrian Water and Essex and Suffolk Water and finally the merger between Yorkshire Water and York Waterworks. As capital from the merged entity is incorporated over time, to avoid the acquisition of capital being treated as investment, the data for the pre-merged companies has been aggregated.

[15] The average of several key indicators is considered: taste, odour, nitrate, aluminium, iron, lead and pesticides.

[16] The physical measure of output is applied following Bottasso and Conti (2011). This approaches allows for the incorporation of a quality adjusted measure of the physical output.

[17] The physical output of water is used instead of the water properties to take into account the different demand for water by different customers. Equivalent population served is calculated assuming that one person is equivalent to 60 g of biochemical demand. Equivalent population served is used instead of sewerage properties to incorporate the difference in strengths and volume of sewage.

[18] Following Saal and Parker [30] and Saal et al. [29] this methodology allows for the price of labour to vary over time and company. Data from the ASHE (Annual Survey of Hours and Earnings) could be considered but due to the lack of regional data, this would mean applying the same price index for all companies. Staff costs were obtained from the statutory accounts rather than the June Return [15] as those reported within the June Return only relate to direct labour. This is not a perfect measure as the statutory accounts relate to the group activities. Following Stone and Webster [39] capitalised staff costs were not excluded due to a lack of consistency in the company's reports.

[19] Saal and Parker [30,31], Saal and Reid [34], Stone and Webster [39] and Erbetta and Cave [15].

The methodology for adjusting the capital stock follows that of Saal and Parker [31], Saal and Reid [34], Stone and Webster [39], and Erbetta and Cave [15]. The MEA capital stock value for the year ending 2009 is used as a starting point and the MEA values are rolled forwards and backwards with net investment for each year valued at 2009 prices. Net investment is the sum of disposals, additions, investment and depreciation. Following Stone and Webster [39], and others[20] the series is deflated with the Construction Output Price Index (COPI).

Capital costs are calculated as the sum of depreciation (including IRC[21]) and the opportunity cost of capital. The opportunity cost of capital is calculated as the Weighted Average Cost of Capital (WACC) applying assumptions made by Ofwat at each price review multiplied by the company's Regulatory Capital Value (RCV). The RCV is an accepted measure of the capital stock by Ofwat. The RCV is the value placed on companies 100 days after privatisation and is rolled forwards based on the amount of capital expenditure in each period less depreciation charges. The capital price is calculated as the capital cost divided by the capital stock.

Total costs are calculated as the sum of capital costs and operating expenditure net of third party services, exceptional items, doubtful debts, service charges and local authority rates[22]. Other costs are therefore calculated as total operating costs less labour costs and capital costs. Other costs comprise of a composite of other goods and therefore, following Saal et al. [29], the price of other goods has been proxied by the price index relating to the price of inputs for the distribution and purification of water collected by the ONS. A measure for the physical amount of other inputs is calculated as other costs divided by the price of other costs. Following Erbetta and Cave [15] all costs apart from power costs are deflated using RPI to 2009 prices and power is deflated by an energy price index for the industrial sector derived from the Department for Trade and Industry (DTI).

The model is a 2 variable input, 1 quasi-fixed input and 2 output model for 10 DMUs per period[23].

5.2. *Quality variables*

Environmental variables are incorporated to control for differences in the operating environments faced by the WaSCs and WoCs which allow for those companies that operate under a relatively unfavourable (high cost) environment to be analysed on a level playing field. The first environmental variable is the proportion of distribution input abstracted from rivers to take into account the differences in the resources and treatment (Z1). This allows for cost differentials between the different sources (boreholes, river abstraction and reservoirs). Abstraction from rivers requires higher treatment costs but fewer abstraction costs. The density of a company's water operations is calculated as the total water population divided by the length of mains (Z2). Similarly, sewerage density is calculated by the total sewerage population divided by the length of sewers (Z3). It is expected that serving more dense areas would be less costly than in rural areas due to additional treatment costs with having additional works and serving a sparsely populated density. The level of leakage is controlled by calculating the proportion of leakage relative to distribution input (Z4). Erbetta and Cave [15] state that leakage can be a proxy for the quality of the network, therefore the higher the proportion of leakage the more critical the condition of the assets. Cherchye et al [10] however state that a higher proportion of leakage might be as a result of a lack of maintenance expenditure. Finally, the proportion of trade effluent (Z5) is calculated as the volume of trade effluent divided by the volume of waste water returned. A higher proportion of trade effluent is likely to incur higher costs, especially with regards to treatment and energy costs. Table 2 presents a snapshot of the data used in this study.

6. Results

In the first instance, the results are considered for the implication of modelling dynamic versus static DEA. The results from the dynamic DEA allows for the decomposition of efficiency into dynamic, static, technical and allocative inefficiencies. The optimality conditions and trends for the average efficiency are considered over the period. Secondly, the implication of firms operating environments is examined. The results from the second stage regression allow for the assessment of whether differing operating characteristics are favourable or unfavourable for the firms. Finally, the static and dynamic DEA will be re-estimated and the results compared against the original DEA to examine the impact on firms' efficiency scores when taking into account their operating environment.

The planning period within the model covers the period 1996/97–2010/11, thus $\bar{k}_0$ corresponds to the initial capital stock at the beginning of 1997 and k_T is the terminal capital stock at the end of 2011. Table 3 reports the efficiency scores for the whole period calculated under variable returns to scale for both the dynamic and static efficiency model. The application of a cost function implies input orientation; firms reduce their inputs given the amount of outputs. Input-orientation is the assumption mostly considered within the literature (Thanassoulis, 2000; [13,15]) as the demand level faced by suppliers is exogenous. Overall efficiency (OE) for dynamic DEA can be decomposed into static efficiency (SE), technical efficiency (TE), allocative efficiency (AE) and dynamic efficiency (DE). The results for the OE reports the efficiency score when firms can adjust both variable and quasi-fixed capital whilst taking into account the intertemporal nature of capital. Static efficiency within the dynamic context considers the efficiency when firms can only consider the reduction of variable inputs and capital is held fixed. OE scores range from 77.8% to 100%. The results for the SE are higher than those for OE, which indicates that given the level of quasi-fixed inputs firms are between 91.6% and 100% efficient. Dynamic efficiency is calculated as the ratio of OE and SE. Dynamic inefficiency ranges from 0% to 22.3% and these results imply that firms are relatively efficient with regards to the variable inputs and that the quasi-fixed inputs are the major source of overall inefficiency.

The static model allows for the contraction of both variable and quasi-fixed inputs without taking into account the intertemporal nature of quasi-fixed inputs. Overall efficiency OE^S indicates that firms are between 73.9% and 100% efficient. These results are all less than or equal to OE but of a similar magnitude with the differences ranging between 0 and 5.4%. The overall efficiency OE^S is decomposed into TE^S and AE^S, the results show that within the static model the main source of inefficiency is due to the wrong factor mix (AE^S). The relative magnitude of the overall efficiency scores under dynamic and static DEA are of a similar magnitude

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[20] Bottasso and Conti [5] and Erbetta and Cave [15].

[21] IRC is the Infrastructure Renewal Charge. This is a charge on infrastructure assets which acts as a depreciation.

[22] These costs are deemed as non-controllable costs by Ofwat and are not incorporated within their assessment of efficiency. Exceptional items are by definition atypical. Third party services relate to costs incurred for output produced by other companies. Local authority rates and doubtful debts are considered as non-controllable. High levels of doubtful debts are due to the legal and regulatory decision of prohibiting the shutting off of water and sewerage activities when bills are not paid. Service charges are charges by the Environment Agency for water abstraction.

[23] The model suffers from a dimensionality issue, therefore the efficiency scores are biased upwards, although the relative positions stay the same. The paper seeks to examine the relative differences of the inefficiencies between variable and capital inputs and the comparison of static and dynamic DEA.

Table 2
Sample descriptive statistics.

Variable		Mean	Std.dev	Min	Max
Outputs					
Water delivered	Ml/day	11014.6	551.9	284.2	2179.4
Equivalent population	(thousands)	6179.8	3704.1	1118.4	14271.9
Water properties	(thousands)	1870.4	979.2	492.9	3538.8
Sewerage properties	(thousands)	2198.0	1331.0	586.7	5426.5
Input quantities					
Capital stock	£m	23299.9	13400.8	7030.2	49129.9
Employees		2943.3	1401.7	1157.0	5894.0
Other		184.4	111.4	15.3	491.2
Input prices					
Capital price	£	0.019	0.004	0.010	0.030
Labour price	£m	0.035	0.004	0.024	0.045
Other cost deflator		0.782	0.140	0.651	1.052
Operating characteristics					
Water density		150.893	45.114	100.648	283.411
Sewerage density		172.001	18.675	131.798	225.861
% DI from rivers		0.393	0.203	0.000	0.781
Trade effluent		0.074	0.035	0.025	0.175
Proportion of leakage		0.227	0.049	0.147	0.379
Water quality		0.967	0.026	0.836	0.995
Sewerage quality		0.904	0.152	0.302	1

150 Observations. Costs and input prices are expressed in real terms in 2009 prices.

Table 3
Dynamic and static efficiency score.

	Dynamic					**Static**		
	OE	**SE**	**TE**	**AE**	**DE**	**OE^s**	**TE^s**	**AE^s**
WASC1	0.894	0.932	0.938	0.994	0.959	0.870	0.956	0.910
WASC2	0.778	0.916	1	0.916	0.849	0.739	0.992	0.746
WASC3	1	1	1	1	1	1	1	1
WASC4	1	1	1	1	1	1	1	1
WASC5	1	1	1	1	1	1	1	1
WASC6	0.859	0.965	0.985	0.979	0.890	0.804	0.959	0.838
WASC7	1	1	1	1	1	1	1	1
WASC8	0.779	0.998	1	0.998	0.781	0.761	0.993	0.767
WASC9	1	1	1	1	1	1	1	1
WASC10	0.932	0.997	1	0.997	0.935	0.917	0.995	0.922

and the ranks between the firms do not alter. The dynamic DEA allows for an extension of the static DEA to incorporate capital over time and to examine the overall efficiency and efficiency holding capital fixed. The results indicate that the firms are relatively efficient with regards to variable inputs and the majority of the inefficiencies are due to the over-utilisation of capital inputs.

Fig. 1(a)–(f) demonstrates the deviations over time of the dynamic overall inefficiency measured by deviations from the optimality condition τ_t^x and τ_t^k in Eq. (1.8). Five of the firms are showed below; the remaining five are efficient over the whole period and therefore do not have deviations from optimality.

A common finding is the over-utilisation of capital inputs. The deviations in variable inputs from the optimal seem more volatile over the period, whereas quasi-fixed inputs are persistently overused. For companies WaSC1 and WaSC2 it can be seen that there has been a considerable improvement in the efficiency of variable inputs over the period considered, whereas quasi-fixed remain persistently overused.

The inefficiencies evaluated by τ_t^h are concerned with the allocation of net investment over the planning period. Nemoto and Goto [25] highlight that the distribution over time of net investment negatively impacts efficiency depending on the adjustment cost of capital. To examine the relationship between the deviation from optimal investment and inefficiency, the absolute value of the excess or short investment τ_t^h) (are plotted against the level of inefficiency (θ_t) in Fig. 2 for $t = 2, \ldots, T-1$. The figure shows a positive association between the deviation from optimal investment and level of inefficiency. The absolute deviation of investment from its optimal level and the inefficiency score has a correlation coefficient of 0.3889 which is significant at the 1% level.

We now turn to the incorporation of environmental variables within the dynamic DEA. Slacks are obtained from the dynamic cost function and the static cost function and are regressed upon a number of environmental variables to take into account the impact of operating conditions on efficiency. Five environmental variables are considered within the analysis, namely water and sewerage density, the proportion of trade effluent, proportion of leakage and the proportion of DI from boreholes. Table 4 shows the coefficients and standard errors of the regressions:

All companies over-utilise the capital inputs but the interpretation of the coefficients for labour and other inputs is more complex as some companies over-utilise these inputs whilst others under-utilise them. The coefficient for the proportion of DI obtained from rivers for capital inputs have a positive coefficient. Capital is over-utilised by firms; the positive value would therefore imply that those with a higher proportion of DI from rivers operate under a relatively more unfavourable operating condition. Rivers require more power with regards to treatment than the other sources of abstraction. The coefficient for water density for capital is negative which implies a higher density is favourable; however this result is statistically insignificant. On the other hand, the coefficient for sewerage density for capital is positive; therefore it implies that operating in an urban environment is unfavourable. WaSCs with a higher proportion of trade effluent operate within an unfavourable operating environment, which is indicated through the positive coefficient for capital. This result is intuitive as trade effluent may require a higher level of treatment, therefore imposing higher costs upon the companies. Leakage has a negative coefficient for capital slacks, which indicates that utilities with higher leakage operate under a favourable environment; this may be due to a lack of capital maintenance expenditure.

The predicted efficiency scores are generated from the regressions and the actual variables are adjusted upwards by the amount in which

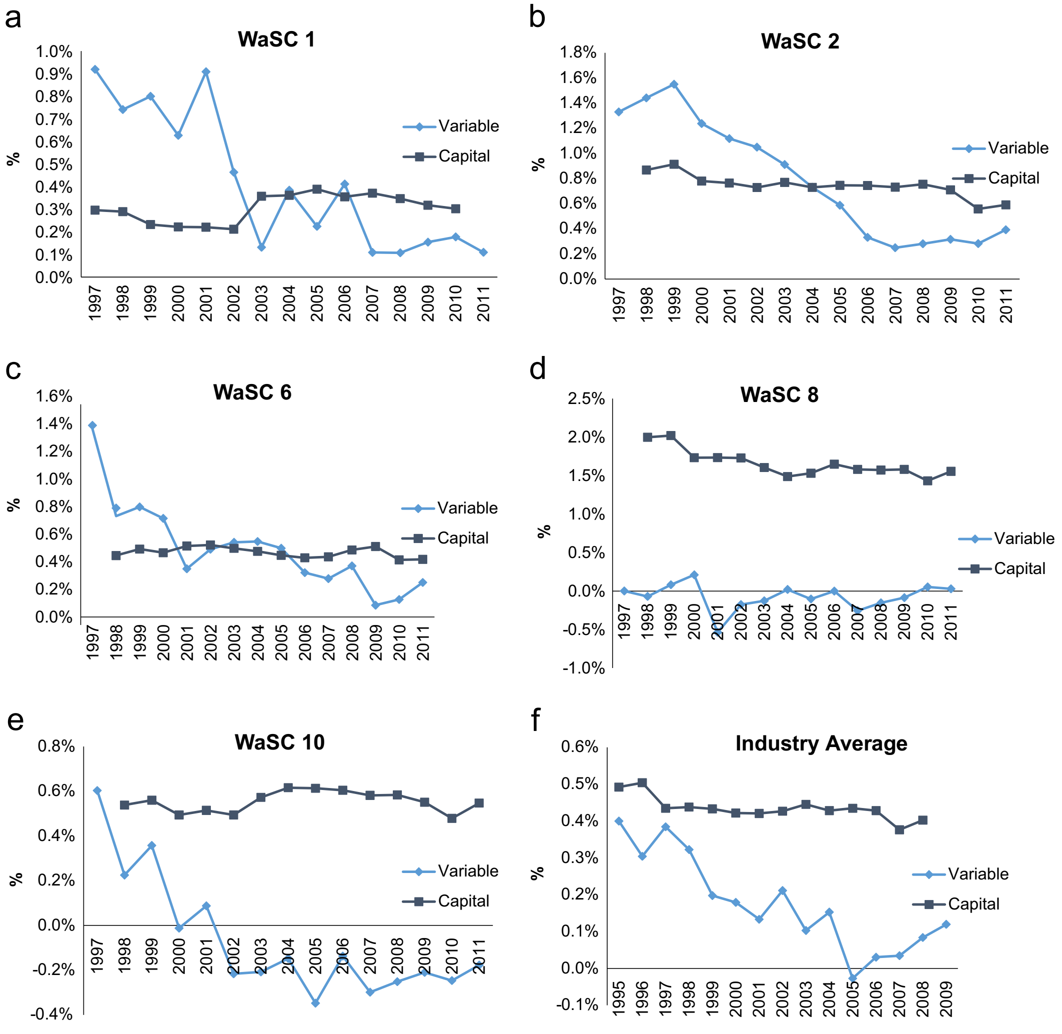

Fig. 1. Inefficiency of variable and capital inputs.

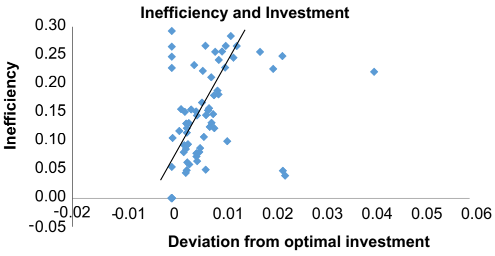

Fig. 2. Inefficiency and investment.

they operate under a favourable environment relative to the most unfavourable using Eq. (1.16). Summary statistics are reported in Table 5 for the inputs before and after adjustments for environmental factors. The results indicate a higher mean for all input variables and the standard deviation between inputs increases when taking into account the differing operating environments.

The DEA efficiency scores are recalculated with the adjusted data and the dynamic and static efficiency results are shown in Table 6 below.

As with the unadjusted results, the DEA scores highlight the finding that most of the inefficiencies are due to dynamic efficiency. The majority of the efficiency scores increase when taking into account differences in the operating environment. The incorporation of environmental variables increases the average overall efficiency score by 2.4 percentage points and the maximum increase is 9.5 percentage points.

The largest increase in efficiency scores relates to the dynamic component. This implies that the environmental variables have the largest effect in equalising the playing field for quasi-fixed inputs. This is to be expected as a proportion of the differences in companies capital will be explained through the differences in the exogenous operating conditions. When accounting for the environmental variables there are no changes in the firms' rankings. However the dispersion of efficiency is reduced with the range falling from 22% to 14%.

Overall the results indicate that when taking into account intertemporal relationships the main contributor to overall inefficiency is the dynamic efficiency. The optimality conditions highlight the persistent over-use of quasi-fixed inputs. These results are consistent with those of Stone and Webster [39], and Bottasso and Conti [5] who also find a presence of over capitalisation within the industry. According to Bottasso and Conti [5] our findings can be interpreted as the result of an *Averch–Johnson effect*. This is due to the presence of rate of return regulation, as well as the nature of the industry where infrastructure is built to meet future demand.

When examining the trends of inefficiencies over the period there appears to be an improvement of the efficiency of variable inputs, whereas the inefficiencies of capital are more persistent. This could be as a result of the differing incentive rates between *opex* and *capex* and rate of return regulation, which overall indicate a presence of a *capex*

Table 4
Slack regression. Standard errors in parenthesis.

Independent variable	Dependent variables		
	Labour slack	Other slack	Capital slack
Intercept	−0.6333 (0.1645)	−0.6840*** (0.2308)	−0.4360*** (0.0779)
Water density	0.0001 (0.0003)	−0.0028*** (0.0005)	−0.0002 (0.0001)
Sewerage density	0.0009 (0.0008)	0.0063*** (0.0013)	0.0022*** (0.0004)
Prop of DI from rivers	0.0302 (0.0788)	0.0365 (0.1190)	0.0032 (0.0388)
Prop of leakage	−0.6475* (0.3425)	0.6177 (0.4549)	−0.0605 (0.1763)
Trade effluent	−0.5368* (0.3196)	0.3462 (0.5041)	2.4011*** (0.2882)

* Indicates significance at the 10%; total number of iterations = 2000.
** Indicates significance at the 5%.
*** Indicates significance at the 1%.

Table 5
Environmental adjusted data description.

	Initial resources				**Adjusted resources**			
	Mean	Std.dev	Min	Max	Mean	Std.dev	Min	Max
Employees	2943.3	1401.7	1157.0	5894.0	3268.0	1586.7	1241.6	6812.3
Other input	184.4	111.4	15.3	491.2	237.8	173.9	17.8	877.8
Capital	23229.9	13400.3	7030.2	49129.9	27344.0	16130.7	9408.2	83262.7

Table 6
Environmental adjusted dynamic and static DEA efficiency scores.

	Dynamic					**Static**		
	OE	**SE**	**TE**	**AE**	**DE**	**OE^s**	**TE^s**	**AE^s**
WASC1	0.889	0.948	0.958	0.990	0.937	0.875	0.960	0.911
WASC2	0.859	0.958	0.989	0.969	0.897	0.828	0.984	0.841
WASC3	1	1	1	1	1	1	1	1
WASC4	1	1	1	1	1	1	1	1
WASC5	1	1	1	1	1	1	1	1
WASC6	0.883	0.977	0.991	0.986	0.904	0.844	0.981	0.860
WASC7	1	1	1	1	1	1	1	1
WASC8	0.874	0.998	1	0.998	0.876	0.863	0.997	0.866
WASC9	1	1	1	1	1	1	1	1
WASC10	0.976	0.997	0.997	1	0.979	0.969	0.998	0.971

bias. The inclusion of environmental variables allows firms to be considered when taking into account differences in the operating environment. The inclusion of environmental variables increases the majority of efficiency scores; however the ranks do not change amongst firms. The inclusion of environmental variables dampens the magnitude of the perceived *capex bias*.

7. Conclusion

This paper has evaluated the effect of dynamic DEA in the English and Welsh water and sewerage industry. A two output model has been constructed for the ten WaSCs within the industry for the period 1996/97–2010/11. Environmental variables have been considered within the analysis in order to account for those firms that operate under relatively favourable or unfavourable environments.

The estimates show that the main estimated inefficiencies are due to the quasi-fixed inputs. The overall first stage inefficiencies within the industry range from 0 to 22.2%. The optimality conditions show the persistent over-utilisation of quasi-fixed inputs. Our results indicate that the inefficiencies from variable inputs have improved over the period, whereas those from capital stock remain persistent. These results are consistent may be due to the different incentive rates between *opex* and *capex* and the *Averch–Johnson* effect created by the presence of rate of return regulation. Overall the results infer the presence of a *capex bias* within the industry.

The incorporation of environmental variables allows for firms to be considered on a level playing field. The effect of adjusting the input slacks for those operating in unfavourable conditions improves the efficiency scores of the majority of firms. The environmental variables impact significantly upon capital differences within the industry, thereby reducing the magnitude of any *capex bias*. The implication for policy is that the presence of a *capex bias* leads to intergeneration distortions. A pound (£) spent on *opex* is fully recovered in the year in which it is spent whereas for a pound spent on *capex* only a proportion is recovered as capex is added to the RCV and only the rate of return and an element for depreciation charge is recovered from customers annually for the life of the asset. An inappropriate preference for *capex* reduces costs to be recovered and hence lowers consumer costs in the short term at the expense of higher ones for future generations. Within the 2014 price review Ofwat aims to eliminate the *capex* by equalising the incentives rate for *opex* and *capex* and by earning a rate of return based on a proportion of the total expenditure instead of capital expenditure alone.

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