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Regulation of Regional Water Companies and Spatial Dependence

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ABSTRACT

As water companies in England and Wales are monopolies, their costs and maximum prices are regulated. This involves the regulator (Ofwat) setting efficient base cost allowances for the companies. To calculate these allowances, Ofwat uses non-spatial cost models to benchmark the companies' cost efficiencies. There are parallels between companies' supply areas and the spatial dependence between neighbouring European NUTS regions. To account for the spatial dependence between neighbouring companies' costs, we augment Ofwat's models with spatially lagged independent variables. In some models a spatial variable is significant. We, therefore, suggest using a mix of spatial and non-spatial models to set the aforementioned allowances. This would change the financial environment some companies face in the next 5-year regulatory period (2025–30). Specifically, this would lead to increases (decreases) in the allowances of some companies and, other things unchanged and in turn, increases (decreases) in the maximum prices they can charge.

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1. Introduction

Realising scale economies is a key reason why the water companies in England and Wales are regional monopolists. Due to their monopolies, company costs and customer prices are regulated. In this paper, we focus on the regulation of the companies' base costs.

A number of studies have benchmarked the cost performance of the water companies in England and Wales (e.g. Portela et al. 2011, for water supply; Thanassoulis

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2002, for sewage collection and treatment; and Williams et al. 2020, for retail services).[1] This reflects the key role of cost performance benchmarking in the regulatory process, which involves the regulator (Ofwat) using cost models to estimate companies' cost efficiencies.[2] Crucially, Ofwat then uses these efficiencies to set the companies' efficient base cost allowances for the next 5-year regulatory period.

The regulatory framework is such that the companies have incentives to improve their cost performance. To illustrate, Ofwat sets a catch-up cost efficiency challenge for a company over the next 5-year regulatory period if its historical efficiency falls short of the benchmark. If a company is set a catch-up efficiency challenge, this is reflected by the downward adjustment for the next regulatory period of both its cost allowance and, other things unchanged, the maximum price Ofwat allows the company to charge for the relevant service. This is because the cost allowance has an important influence on the maximum price, so that customers do not pay a higher price due to company inefficiency. A company's historical cost efficiency, therefore, has a big influence on its financial environment in the next 5-year regulatory period.

This paper emerged from a project with one of the companies in the English and Welsh water industry, Severn Trent. Rather than Ofwat use the company efficiencies from only non-spatial cost models to compute the efficient base cost allowances, Severn Trent Water have suggested using a mix of Ofwat's non-spatial models and one or more spatial models from the project (Severn Trent Water 2023, 44–46). This Severn Trent document is wide-ranging and only summarises the spatial modelling. The first purpose of this paper, therefore, is to provide a full coverage of the spatial models. To fix ideas, the spatial models simply augment the set of explanatory variables in Ofwat's models with their spatial lags. For a particular company, the observations for these lagged variables are simply the weighted averages of the data for the companies it borders.

Ofwat dedicates a small part of a wide-ranging document to respond to Severn Trent's suggestion (Ofwat 2023a, 31–32). Whilst Ofwat acknowledges that the spatial lagged variables in the models Severn Trent submitted are statistically significant at marginal levels, Ofwat continues to prefer its non-spatial models. This is because Ofwat: (a) views the additional spatial lagged explanatory variables as being an added complexity that represents overfitting; and (b) points to a lack of clarity about the economic/engineering rationale to support the inclusion of the spatial lags. The second purpose of this paper, therefore, is to address (a) and (b). As (a) is simple to address, we take it up next.

Overfitting occurs when relative to the sample size there are too many regressors, leaving too few degrees of freedom to fit the model. For samples ranging from 110 to 187 observations, including the spatial lags increases the average number of regressors in a model from 5 to 7 (after rounding up), with the largest increase from 6 to 10 for one retail model estimated using 153 observations. Whilst the samples Ofwat use for the company cost models are never large, it is clear that we need not be concerned about the reduction in the number of degrees of freedom when the spatial lags are included.

(b) is addressed at different points throughout the paper. At the outset on (b), we note that there is a lot of academic literature that supports a spatial approach to our analysis. This is because the companies' supply areas resemble regional territories (e.g.

NUTS regions in Europe) and it is standard in the regional economics literature to account for the spatial dependence between neighbouring territories (e.g. and naming only a small selection, LeSage and Dominguez 2012; Zeilstra and Elhorst 2014; da Silva, Elhorst, and da Mota Silveira Neto 2017; Lo Cascio, Mazzola, and Epifanio 2019; Panzera, Cartone, and Postiglione 2022; Glass and Kenjegalieva 2024). To account for the spatial dependence between neighbouring companies in the English and Welsh water industry, we use spatial lags of the *x* regressors. As we will see in due course, the cost impacts of certain characteristics of neighbouring companies' corresponding business activities are not independent. A simple explanation for this is the long-standing yardstick cost competition between companies in the form of Ofwat's cost performance benchmarking.

Next, to contextualise our analysis, we provide some background on the companies. Water related activity and retail services are the two aggregate business activities of the water only companies (WOCs). Wastewater, which relates to sewage and bioresources, is a further aggregate activity of the water and sewerage companies (WASCs). All three aggregate activities are made up of sub-activities, which are discussed further at the beginning of Section 2. There are currently 6 WOCs and 11 WASCs and their regional supply areas are as shown in Figure 1.[3]

Whilst there is a large literature on efficiency modelling of energy utility companies using non-spatial models, Orea, Alvarez, and Jamasb (2018) is the only empirically focused spatial efficiency analysis. They analyse electric distribution companies in Norway, but our objective and approach are different. They use a single spatial lag of the dependent variable to collectively soak up the effects of various unobserved variables. Although we would expect the spatial lags of the independent variables we include to also account for unobserved factors, by including a number of spatial lags we obtain range of information about the nature of different spatial effects.

With regard to our research approach there were a few options. Data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are two well-known groups of

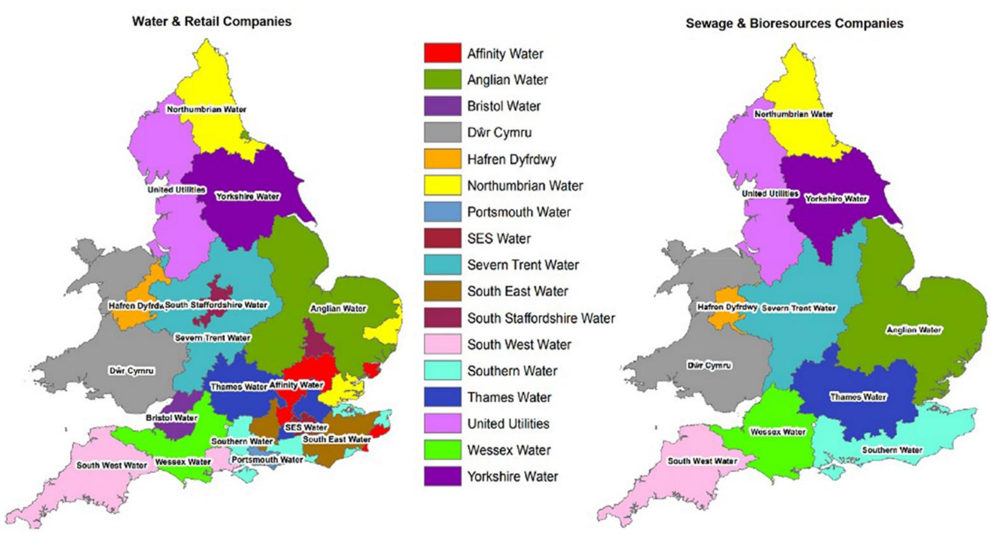

Figure 1. Company regional supply areas by business activity.

approaches that are specifically designed to estimate efficiency and have been applied to the activities of water companies in England and Wales and other countries. For discussion of the merits of DEA and SFA, see, for example, Wanke et al. (2020). Focusing on English and Welsh water studies, Thanassoulis (2000), Portela et al. (2011) and Pointon and Matthews (2016) are some examples that use DEA techniques to benchmark the performance of the companies' water and sewerage activities. Other studies have estimated the efficiencies of these companies using stochastic frontier models by making distributional assumptions about the error components, e.g. Molinos-Senante and Maziotis (2018, 2019).

Notwithstanding that the above methods have clear merits, we instead incorporate spatial regressors into the approach that Ofwat used to set the companies' modelled efficient base cost allowances at the 2019 price review (PR19) (Ofwat 2019). That is, the spatial cost models we estimate are the spatial counterparts of the non-spatial random effects models that Ofwat used for PR19. Ofwat then calculates sets of cost efficiencies for the companies (ratio of actual historical cost and the in-sample prediction of this cost from a model), where these efficiencies were used to determine the companies' modelled efficient base cost allowances for the 5-year period that PR19 covers (1 April 2020 – 31 March 2025). This was also the approach of the Competition and Markets Authority (CMA 2021) to redetermine these allowances for the four companies that appealed (Anglian, Bristol, Northumbrian and Yorkshire) against Ofwat's PR19 determination.

Ofwat (2023a) has used same approach at PR24 as it did at PR19 to determine the companies' modelled efficient base cost allowances for the next 5-year regulatory period (1 April 2025 – 31 March 2030). Given this is the well-established approach of Ofwat and the CMA, and we focus here on demonstrating how accounting for spatial dependence can have practical impacts on the levels of companies' modelled efficient base cost allowances, we pursue evolutionary development by incorporating spatial variables into the stakeholders' current models. As it stands, DEA and/or a stochastic frontier model would represent a transformative approach for the industry.

Summarising the key findings. First, in a good number (but not all) of the spatial models at least one spatially lagged independent variable is statistically significant. This finding is important as Ofwat and the companies dedicate a lot of resources to investigate the cost drivers in the models. We therefore suggest using a mix of non-spatial and spatial models to compute the modelled efficient base cost allowances for the companies.

Second, to different degrees, we find that using a mix of non-spatial and spatial models, as opposed to only non-spatial models, leads to increases in the modelled efficient base cost allowances for some companies, and decreases for others. While this in and of itself would represent changes in the financial environments of the companies, the relationship between these allowances and the maximum customer prices Ofwat sets for companies would further impact these environments. To see this, first recognise that, other things being equal, a lower (higher) allowance means that there is more (less) company cost inefficiency. To avoid customers paying for inefficiency, a lower (higher) allowance will, therefore, lead to Ofwat setting a lower (higher) maximum customer price for the relevant company service.

Third, we find that when we account for the spatial dependence, some of the biggest increases in the modelled efficient base cost allowances are for a number of companies that border Thames, which is by far the largest company in the industry. This finding is intuitive as we would expect bigger neighbours to have a bigger spatial influence.

The remainder of this paper is organised as follows. Section 2 provides details of the industry structure and the companies' base costs. Section 3 sets out the research methodology. This covers: (i) the spatial cost models, which are for an aggregate business activity (top down view of modelled base costs), or a sub-activity (bottom up view); (ii) calculation of the associated cost efficiencies of the companies; (iii) triangulation of these efficiencies to obtain the overall efficiency of an aggregate business activity; and (iv) the approach to compute the modelled efficient base cost allowances. We present the empirical analysis in Section 4, where we compare the triangulated efficiencies from the non-spatial regressions with those from a mix of spatial and non-spatial models. Section 5 concludes and suggests further work.

2. Industry structure and base costs

We estimate models for the costs of the aggregate water service and its two sub-activities. The first of these sub-activities is abstraction, distribution and treatment of raw water, and the second is distribution of treated water. The wastewater cost models distinguish between three sub-activities: collection of sewage at source and its distribution to treatment works; treatment of sewage at the works and discharge of the liquid effluent; and the production of bioresources using sludge. The retail models are for the costs per household of the aggregate service and its two sub-activities. The first sub-activity is bad debt and bad debt management costs, and the second is other retail costs which include, for example, the cost of meter reading.

At a review of the price controls, Ofwat determines how much companies can charge their customers for each business service over the next 5-year regulatory period. To prevent customers covering company cost inefficiencies through higher bills and to ensure a base level of deliverability in terms of company investment, at a price review Ofwat also sets efficient base cost allowances. These allowances are also linked to the delivery of a base level of performance to achieve various environmental, social and economic welfare goals that relate to, for instance, supply interruptions, leakages and sewer flooding. For the WOCs, efficient base cost allowances are set for their water and retail business activities, while a further allowance is set for a WASC's wastewater business. Related to the additional wastewater business activity of the WASCs, it is evident from the sizes of the populations that the companies serve in Table 1 that many of the WASCs are larger than the WOCs.

The current WOCs are the result of some consolidation over a number of years. In contrast to the single area supply regions of the WASCs, takeovers of WOCs has resulted in some companies that previously supplied just one area serving two or more. For example, while South West Water has always been responsible for supplying the area in Figure 1 that borders only Wessex Water, South West acquired Bournemouth Water in 2015. Following the integration of this WOC, a further area was added to South West's region, which in Figure 1 is the area that borders Wessex,

Table 1. Populations of the companies' supply areas in 2021/22.

Company (code)	Company type	Watersupplyarea population (000s)	Wastewatersupply areapopulation (000s)
Anglian Water (ANH)	WASC	4,909.539	6,397.033
Hafren Dyfrdwy (HDD)[a]	WASC	210.158	–
Northumbrian Water (NES)	WASC	4,772.948	2,745.627
United Utilities (NWT)	WASC	7,338.219	7,390.698
Southern Water (SRN)	WASC	2,632.356	4,590.329
Severn Trent England (SVE)[a]	WASC	8,765.040	–
South West Water (SWB)	WASC	2,265.135	1,647.649
Thames Water (TMS)	WASC	10,384.385	15,543.119
Dŵr Cymru (Welsh Water, WSH)	WASC	3,104.753	3,107.907
Wessex Water (WSX)	WASC	1,364.139	2,851.971
Yorkshire Water (YKY)	WASC	5,409.807	5,244.666
Affinity Water (AFW)	WOC	3,921.772	–
Bristol Water (BRL)	WOC	1,239.061	–
Portsmouth Water (PRT)	WOC	747.031	–
SES Water (SES)	WOC	745.894	–
South East Water (SEW)	WOC	2,277.599	–
South Staffordshire (SSC)	WOC	1,716.183	–
Severn Trent England and Hafren Dyfrdwy (SVH = SVE+HDD)[a]	–	–	9, 334.491*

[a]When a former company, Severn Trent (SVT), acquired Dee Valley Water (DWW) in 2017, there were some adjustments to the companies' supply areas due to some minor concerns from the CMA. As such, two new companies were formed in 2018 – Severn Trent England (SVE) and Hafren Dyfrdwy (HDD). This resulted in HDD becoming the WASC for all former SVT and DWW customers in Wales. Although ultimately separate efficient base wastewater cost allowances are set for SVE and HDD, in Ofwat's wastewater modelling for PR24, and also in our models, the two companies are combined. *Source*: Ofwat (2023b).

Portsmouth and Southern. Additionally, in 2022 South West acquired Bristol Water. The subsequent integration of this WOC has resulted in South West serving a third area. More generally, the takeover of a smaller WOC by a larger WASC is supported by the findings of Bottasso and Conti (2009). They conclude that, on average, such a takeover would provide the opportunity to take advantage of a number of different unexploited economies to realise moderate cost savings.

The efficient base cost allowances that Ofwat sets for the companies is Ofwat's independent prediction of what companies' costs are expected to be over a 5-year regulatory period. These allowances account for companies' unique operating circumstances and represent how much companies can recover from their customers. The efficient base cost allowances that Ofwat sets for companies primarily consist of expenditure that relates to the routine year-on-year costs that companies incur to sustain a base level of service to customers and the environment. This service includes base levels of performance that companies should deliver in relation to, for instance, supply interruptions, leakages and sewer flooding. Base costs also include some additional components, such as some asset enhancement costs.

To sustain base levels of water and wastewater services, three common types of expenditure for both these activities are operating expenditure (opex), capital maintenance and network reinforcement (Ofwat 2023a, 13, table 2.2). Opex for a WOC or WASC refers to payments for the day-to-day operations of the business, such as operating and maintaining the network and treatment works and paying staff and energy bills (Thames Water 2022). Enhancement expenditure to address low water pressure and reduce the risk of sewer flooding are examples of other components of the base costs of water and wastewater services, respectively. For completeness as we provided insights to retail costs above, base retail costs comprise bad debt, debt management costs and other opex (including customer service, meter reading, and depreciation). The efficient base cost allowances are further split into modelled and unmodelled base costs. The focus in this paper is solely on modelled base costs which account for approximately 80% of companies' total expenditure (Ofwat 2022).

3. Research design

3.1. General form of the local spatial cost models

The general form of the local spatial cost models we estimate using Generalised Least Squares (GLS) is given in Equation 1, where the variables are logged. This type of model is referred to as the SLX model (Halleck Vega and Elhorst 2015), which is a model where the set of explanatory variables include the usual non-spatial x regressors and also their spatial lags.[4]

$$c_{it} = \alpha + \beta' x_{it} + \gamma' \sum_{j=1}^{N} w_{ijt} z_{jt} + \theta_i + \varepsilon_{it}. \tag{1}$$

The different empirical specifications of Equation 1 that we estimate are for aggregate and disaggregated water, retail and wastewater services. The annual panel datasets to estimate the empirical specifications are publicly available from Ofwat and are for the non-spatial PR19 model specifications, but for the updated historical periods that PR24 covers. The datasets for water, sewerage and bioresources are for $2011/12 - 2021/22$, while the datasets for retail services are for $2013/14 - 2021/22$ (see 4.1 for more details of the data).

To ensure the statistical inference is valid and to guard against omitted variable bias, when there is a statistical rationale we augment the PR19 model specifications with spatially lagged independent variables. That is, we include a spatial lag when at least one of the following is the case: the spatial lag is significant; including the lag leads to a notable improvement in model fit; its inclusion markedly improves the significance of at least one other variable. In the empirical analysis intuitive geo-economic rationales for the inclusion of such lags are discussed. The panel datasets for sewerage and bioresources are balanced and comprise 10 companies, while the water and retail datasets are unbalanced and comprise 19 distinct companies.[5] For each dataset the time periods are indexed $t \in 1, \ldots, T$ and the companies are indexed $i, j \in 1, \ldots, N$ for $i \neq j$.

In Equation 1, c_{it} is the observation of a measure of a company's cost of undertaking an aggregate or disaggregated service in period t; α is the common intercept; x_{it} is the $(1 \times K)$ vector of observations of the company's explanatory variables that are outside the control of its management (see 3.2); β' is the associated $(K \times 1)$ vector of coefficients to be estimated; and ε_{it} is noise. Following Ofwat's approach to estimate the non-spatial cost models for PR19 (Ofwat 2019) and PR24 (Ofwat 2023a), θ_i is a random effect to account for unobserved heterogeneity.

By including spatially lagged independent variables we account for the impact on a company's cost of the weighted observations of only its first order neighbours. In a local spatial model, the spatial lags of all the x variables are often included. A spatial lag of an x variable is, therefore, often included when at least one of the following is the case. (a) The spatial lag is not statistically significant; (b) it does not materially improve the significance of one or more other regressors; (c) it does not lead to a notable improvement in model fit; and (d) there is no geo-economic rationale for its inclusion. Such an approach would have big implications for the modelled efficient base cost allowances for the WOCs and WASCs. Moreover, as it stands in the industry, (a)-(d) would not be acceptable to Ofwat and the CMA. In contrast to many local spatial models in the literature, we would expect to omit one or more spatially lagged x variables for at least one of the reasons in (a)–(d). Hence, in Equation 1$\sum_{j=1}^{N} w_{ij}z_{jt}$ is the $(1 \times L)$ vector of spatial lags and γ' is the associated $(L \times 1)$ vector of coefficients to be estimated, where $\sum_{j=1}^{N} w_{ij}z_{jt} \subset \sum_{j=1}^{N} w_{ij}x_{jt}$ so $K > L$.

The w_{ijt}'s in Equation 1 are the exogenous, row-normalised, non-negative elements of the spatial weights matrix W_t, where this matrix is specified prior to the estimation of the model. In the sewerage and bioresource models, W_t is fixed and $(N \times N)$ over all the time periods as the panel datasets are balanced. We could therefore drop the subscript t here, but retain it so that the notation also applies to the water and retail services models. That is, in the water and retail modelling, although the dimension of W_t is fixed because the number of companies remains the same over the sample, the panels are unbalanced and so the companies that feature in W_t are not the same in each time period. These small changes to the companies in the cross-sections also involves some changes to company supply areas and thus the lengths of the borders that some companies share. As a result, some of the w_{ijt}'s change over the time periods.

The specification of W_t represents (i) which companies neighbour one another; and (ii) the strength of the spatial links between neighbouring companies. As is standard, we set all the weights on the main diagonal of W_t to zero, as a company cannot be its own neighbour. Moreover, as a result of the specification of the off-diagonal elements of W_t, the spatially lagged variables are weighted averages. Each off-diagonal weight is the length of the border between the ith and jth companies as a proportion of the total border length between the ith company and its neighbours.[6] In other words, for the ith company, the longer the $ij-$th border relative to the ith company's total border length, the greater the weight attached to the jth neighbouring company's observations. This is intuitive as, everything else equal, it reflects the greater relative scope for spatial dependence along a relatively longer border.

3.2. Company efficiencies and the modelled efficient base cost allowances

At a price review, Ofwat uses its independent view of the companies' modelled base costs to set their efficient cost allowances for the next 5− year regulatory period. This begins with econometric modelling of the companies' historical expenditures, where Ofwat has used the same type of modelling approach for PR19 and PR24. This involves Ofwat estimating specifications of the non-spatial counterpart of Equation 1 for the base costs of aggregate and/or disaggregated water, retail and wastewater services. We contribute by also estimating the corresponding spatial models and find that there is a statistical case for some (but not all) of the spatial regressions. In light of this, using only non-spatial regressions and a mix of the preferred spatial and non-spatial models, we compare the modelled efficient base cost allowances. Next, we turn to how Ofwat and we use the fitted models to obtain these allowances.

Each of the fitted models are used to estimate the companies' historical in-sample efficiencies, while taking into account the unique characteristics of operating regions that are outside management control (i.e. exogenous factors). Examples of these characteristics are company scale, population density and the complexities of water and sewage treatment. As the models are specified to account for exogenous factors, any remaining variation in base costs across the companies is attributed to differences in their historical efficiencies. *A company's historical in-sample cost efficiency is estimated as the ratio of its actual historical base cost to the prediction of this historical cost from the fitted model.If a company's historical cost efficiency score is less than (greater than) 1, this indicates that its costs are lower (higher) than the expected costs from the model.* As will be evident in the below discussion of the procedure to set the modelled efficient base cost allowances, the historical in-sample efficiencies are used to benchmark the companies' base costs and thus establish which companies need to catch-up to the cost efficiency benchmark.

Following Ofwat for PR19 and PR24, we use a three-step procedure to set the modelled efficient base cost allowances. In the first step, the fitted aggregate and/or disaggregated water, wastewater and retail cost models are used to obtain post-sample cost forecasts for the next 5−year regulatory period. This involves plugging in post-sample predictions of the independent variables into the fitted models. The majority of the predicted observations for the independent variables are Office of National Statistics (ONS) projections, linear trends and averages over recent years. In the second step, we triangulate the post-sample cost forecasts and historical in-sample cost efficiencies. We do so by calculating weighted averages of these forecasts and efficiencies across the aggregate and disaggregated water, wastewater and retail services to obtain an overall forecast and efficiency for each of the three aggregate activities.

In Figure 2, for aggregate and disaggregated water services, we present the Ofwat PR19 process we follow to triangulate the historical in-sample cost efficiencies and post-sample forecasts for the next 5− year regulatory period. In the note under Figure 2 we describe the triangulation procedure for water services. The difference between Figure 2 and the corresponding one in Ofwat (2019) is that in our figure we incorporate spatial models (see the note under Figure 2 for details). We also provide flow charts of the Ofwat PR19 processes we follow to triangulate the historical in-sample cost efficiencies and post-sample cost forecasts for aggregate and/or disaggregated retail and wastewater services. The flow charts for retail and wastewater services are presented in Appendix A in Figures A1 and A2, respectively. In the notes under each of these figures we again describe the corresponding triangulation procedure.

The third step of the procedure to set the companies' modelled efficient base cost allowances for the next 5-year regulatory period comprises (a) the setting of the catch-up cost efficiency challenge for a company that falls short of the overall efficiency benchmark; (b) the setting of the expected cost performance improvement that is not catch-up; and (c) adjustment of the aforementioned allowances for real price effects (RPEs).

a. *Catch-up cost efficiency challenge*. We follow Ofwat's approach at PR19 and set the overall cost efficiency benchmark at the 4th company for water and retail, and

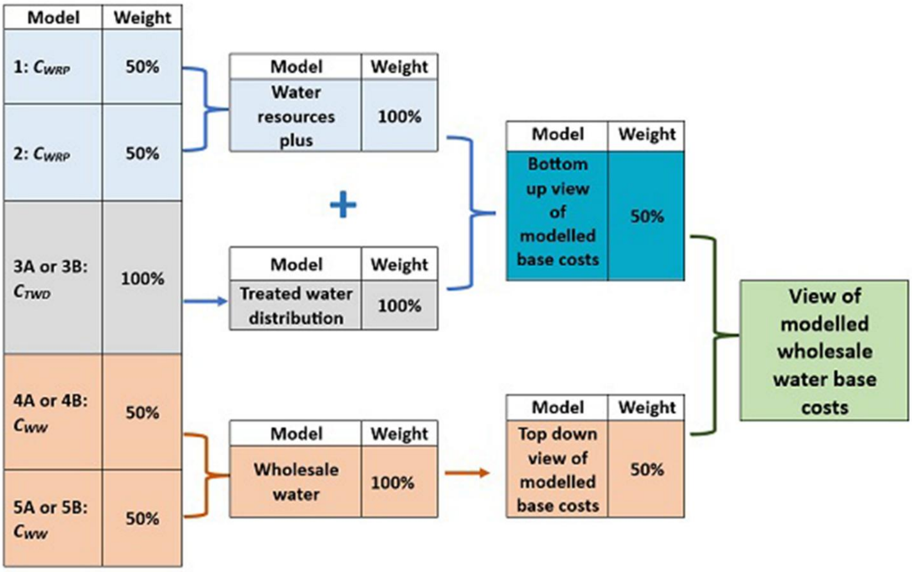

Figure note – Description of the triangulation of the post-sample forecasts of a company's modelled base costs and its historical in-sample cost efficiencies from the aggregate and disaggregated models for water services.

The objective of the triangulation is to obtain weighted averages of the above post-sample forecasts and historical in-sample efficiencies. Figure 2 presents the triangulation procedure for water services to obtain these weighted averages. This procedure begins by making a distinction between the five non-spatial water models (labelled 1, 2, 3A, 4A and 5A in the above figure) and three spatial models (labelled 3B, 4B and 5B) that are used in the **two triangulations** for water services. The dependent variables for these models are provided in the above figure and are the aggregate (or, in other words, wholesale) cost of water services (C_{WW}) and the disaggregated costs of its two sub-activities, water resources plus (C_{WRP}) and treated water distribution (C_{TWD}).

The **first triangulation** involves using the post-sample forecasts and historical in-sample efficiencies from the above five non-spatial model specifications that Ofwat use, where the weights in figure 2 that are attached to the post-sample forecasts and historical in-sample efficiencies are those that Ofwat used for PR19. The + sign in figure 2 indicates that the unweighted average of the post-sample cost forecasts from models 1 and 2 and the corresponding forecast from model 3A are summed. This + sign also indicates that the historical cost efficiency across these three models is the actual historical C_{WRP}+C_{TWD} divided by the sum of the unweighted average of the predictions of historical C_{WRP} from models 1 and 2 and the prediction of C_{TWD} from model 3A. As we move from left-to-right across figure 2, the colour of the shaded boxes remains unchanged if the models used in that part of the triangulation have the same dependent variable (e.g., C_{WRP} is the dependent variable in models 1 and 2). A change of colour indicates when this is not the case.

The **second triangulation** uses the same approach as the first, but uses the predictions of the historical in-sample costs, historical in-sample cost efficiencies and post-sample cost forecasts from a mix of non-spatial and spatial models. This involves retaining two non-spatial models (1 and 2) from the first triangulation and replacing the other three (3A, 4A and 5A) with the preferred spatial counterparts (3B, 4B and 5B). See the empirical analysis on how we determine whether a non-spatial model is preferred to its spatial counterpart and vice-versa.

Figure 2. Triangulation of the post-sample base cost forecasts and historical in-sample cost efficiencies for water services.

the 3rd company for wastewater. If a company's overall cost efficiency falls short of the benchmark, it is set a catch-up efficiency challenge over the next 5– year regulatory period. This means that the company's modelled base cost allowances will be reduced by an amount that equates to its shortfall from the overall cost efficiency benchmark. This is because as Ofwat sets the maximum prices that companies can charge their customers based on the modelled base cost allowances, Ofwat needs to remove any shortfall from the benchmark from these allowances, otherwise a company's shortfall would be passed on to its customers in the form of higher prices, i.e. customers pay for company cost inefficiency.

b. *Expected cost performance challenge that is not catch-up*. A company whose overall cost efficiency for a business activity falls short of the benchmark will face a cost performance challenge that has two components - the catch-up in (a) and a further improvement that is referred to as the frontier shift. Hence, if a company's overall efficiency for a business activity is on the benchmark, or outperforms it, the frontier shift will be the company's only cost performance challenge. The frontier shift is a common annual rate for all companies, which Ofwat sets using data from sources such as EU KLEMS on the productivity gains that comparator sectors have achieved (e.g. construction; manufacturing; transport and storage; chemicals; machinery and equipment). The adjustment for RPEs, which we discuss next, is subtracted from the frontier shift to obtain a net shift. In our calculations of the modelled efficient base cost allowances, we use Ofwat's PR19 rates for the frontier shift and adjustment for RPEs.

c. *Adjustment for RPEs*. Key factor inputs in the water industry are energy, chemicals, materials and labour, while the Consumer Price Index (CPIH) is based on a basket of goods for an average household. There will, therefore, be differences between the input price inflation that impacts companies' costs and the CPIH Ofwat uses to set the customer price controls. Such differences are accounted for via an adjustment of the modelled efficient base cost allowances for RPEs.

4. Empirical analysis

4.1. Datasets and variables

The datasets for sewerage and bioresources are balanced panels comprising annual observations for the 10 companies in Figure 1 over an 11−year period (2011/12 – 2021/22). The water and retail panel datasets are also annual, comprise 19 distinct companies and cover 2011/12 – 2021/22 and 2013/14 – 2021/22, respectively. Due to a small amount of takeover activity, we have observations for 17 companies for every year in the water and retail samples, so these panels are unbalanced. For the companies in the final year of the sample (see Figure 1) and for the 5-year post-sample period that PR24 covers (2025/26 – 2029/30), we use our estimated models to calculate three sets of modelled efficient base cost allowances. Two sets are for water and retail for the WOCs and WASCs, and for the WASCs the other set is for wastewater, where the latter are combined allowances for sewerage and bioresources.

The datasets for the dependent and non-spatial independent variables are available from Ofwat's website and are version 3 of the data for PR24 (Ofwat 2023b). These datasets comprise the observations Ofwat used for PR19 plus more recent observations Ofwat has since added. All the monetary variables are at 2017/18 prices and, as discussed in 3.1, when there is a statistical rationale, we augment these non-spatial model specifications with spatial lagged independent variables.[7] We construct the spatial lagged variables by pre-multiplying the non-spatial variables by W_t (see 3.1 for details of the specifications of W_t). On this, note that in the wastewater (sewerage and bioresources) modelling, W_t is (10×10) in every time period as the panels are balanced. In the water and retail modelling, although the dimension of W_t is (17×17) in every time period, the 17 companies that feature in W_t are not the same over all the time periods due to the panels being unbalanced. The end goal is to compare how including the spatial lagged independent variables changes the companies' modelled efficient base cost allowances for $2025/26 - 2029/30$.

In Table 2, we describe the measures of the dependent and non-spatial independent variables, introduce our notation for the variables, and, for the data in levels, provide summary statistics. We can see from this table that a number of the cost measures are for sub-activities, e.g. two wastewater sub-activities are sewage collection and sewage treatment. The PR19 approach represents our suite of baseline non-spatial model specifications. That is, following PR19 we use the same measures of the dependent variables and the same subsets of non-spatial independent variables from the full list in Table 2. We then augment these baseline models with spatial lags of the independent variables. The precise model specifications will become clear in the presentation of the estimation results in the next subsection.

For some variables in Table 2, further description is warranted. The measure of *SewageLoad* in a company's supply area is the Biochemical Oxygen Demand (BOD) 5 measure, which is an adjusted measure of load for the levels of pollution in sewage.[8] In some of the C_{SWT} models and all the models of the combined costs of bioresources and sewage treatment (C_{BRP}), one of the determinants is the percentage of sewage load treated with an ammonia permit limit ≤ 3 mg/litre ($\%Ammonia \leq 3$). This regressor is included to account for the complexity of a company's sewage treatment. This is because meeting tighter ammonia discharge permit limits tends to involve more, and/or larger, treatment processing and thus higher raw materials (energy and chemicals) costs (Ofwat 2023a).

In the retail models when the dependent variable is $\frac{BadDebt}{No.Households}$ or $\frac{TotRetailCost}{No.Households}$, one of the determinants is a proxy for the probability that customers will default on paying their water bills. Two alternative proxy measures are used for this propensity: the percentage of households in a company's supply area that are income deprived ($\%IncDeprived$); or the percentage of households in a company's area where at least one person in the house has a payment default on his/her credit record ($\%Default$) (PwC 2022).

Due to space constraints, we could not report in Table 2 the skewness and kurtosis of the variables. For these descriptive statistics see Table B1 in Appendix B. For the water variables, we can see that, to different degrees, the cost measures C_{WRP}, C_{TWD} and C_{WW} are positively skewed, indicating a concentration of lower values and a relatively small number of high values. Non-spatial regressors such as $\%Water3-6$ and *PopDensity* have non-negligible skewness and high kurtosis, suggesting notable variation in water treatment complexity and population density.

For the retail variables, the cost measures have slight positive skewness with nearly normal kurtosis. $\%Metered$ is also one of two non-spatial determinants that is slightly

Table 2. Variables and summary statistics.

	Notation	Min	Max	Mean	St. Dev.
Water variables					
Cost measures					
1a. Water Resources Plus Botex (million 2017/18 £s) = water resources Botex + raw water distribution Botex + water treatment Botex, where Botex is a measure of base expenditure = operating and capital maintenance expenditure	C_{WRP}	5.245	245.110	81.534	64.743
1b. Treated Water Distribution Botex+ (million 2017/18 £s), where Botex + is a measure of base expenditure = operating expenditure + capital maintenance expenditure + certain growth and enhancement expenditure	C_{TWD}	6.013	503.385	113.693	101.798
1c. Wholesale Water Botex+ (million 2017/18 £s)	C_{WW}	11.971	719.770	195.227	161.028
Non-spatial determinants					
Number of connected properties in a company's supply area	*Properties*	1.054×10^5	4.003×10^6	1.516×10^6	1.144×10^6
% of water treated at works in complexity levels 3–6	$\%Water3-6$	17.019	100	86.276	17.224
Weighted average of treatment complexity levels 1–7, where the weights are volume of water treated at each level	*Complexity*	2.120	5.790	4.795	0.695
Weighted average of the population density of middle layer super output areas (MSOAs) in a company region, where the weights are MSOA populations	*PopDensity*	1006.015	8502.561	2975.768	1542.178
Company mains length (kms)	*MainsLength*	1969.800	47634.100	20182.487	13814.016
Number of booster pumping stations per mains length km	$\frac{No.BPSs}{MainsLength}$	0.009	0.037	0.016	0.005
Retail variables					
Cost measures					
2a. Bad debt and bad debt management costs per household (million 2017/18 £s)	$\frac{BadDebt}{No.Households}$	0.000487	0.031	0.012	0.006
2b. Other retail costs (total retail cost minus 2a) per household with smoothed depreciation (million 2017/18 £s)	$\frac{OtherRetailCost}{No.Households}$	0.011	0.028	0.017	0.004
2c. Total retail costs per household with smoothed depreciation (million 2017/18 £s)	$\frac{TotRetailCost}{No.Households}$	0.013	0.050	0.029	0.008
Non-spatial determinants					
Percentage of households with dual service (water and wastewater services from one company)	*%DualService*	0	96.174	41.155	36.029
Percentage of households with a water meter	*%Metered*	23.398	90.076	54.977	15.330
Number of household connections (thousands)	*No.Connections*	94.755	5648.682	1691.658	1404.382
Average household bill size (2017/18 £s)	*AverageBill*	94.997	499.393	280.020	105.420
Equifax based measure of the % of households in a company's area with payment default	*%Default*	17.920	29.936	24.100	3.213
Income score from the index of multiple deprivation (IMD): % of households in a company's supply region that are income deprived	*%IncDeprived*	8.232	17.398	13.126	2.530
Total bidirectional domestic and international migration for the company region as a % of the region's population	*%Migration*	6.831	19.322	12.150	2.500
Wastewater (sewage and bioresources) variables					
Cost measures					
3a. Sewage collection Botex+ (million 2017/18 £s)	C_{SWC}	48.245	343.438	134.965	69.703

(*continued*)

Table 2. Continued.

	Notation	Min	Max	Mean	St. Dev.
3b. Sewage treatment Botex+ (million 2017/18 £s)	C_{SWT}	50.424	329.927	138.579	67.803
4a. Bioresources Botex (million 2017/18 £s)	C_{BR}	11.450	211.906	63.311	39.726
4b. Bioresources Plus Botex+ (million 2017/18 £s) = Bioresources Botex (4a) + Sewage treatment Botex+ (3b)	C_{BRP}	78.528	480.305	201.891	101.333
Non-spatial determinants					
Company sewer length (kms)	$SewerLength$	22495.000	1.093×10^5	57161.147	28367.251
Company pumping capacity per sewer length km	$\frac{PumpCapacity}{SewerLength}$	1.072	3.427	1.611	0.564
Number of properties (in thousands) in a company supply area per sewer length km	$\frac{No.Properties}{SewerLength}$	31.237	55.684	41.865	6.156
*PopDensity*above but for the WASCs	$PopDensWASC$	1570.014	6839.729	2879.357	1333.034
Total sewage load in a company supply region (pollution adjusted kgs per day)	$SewageLoad$	99953.602	3.819×10^5	3.892×10^5	2.432×10^5
% of load treated at small sewage plants (size bands 1–3)	$\%Bands1-3$	0.653	10.757	3.866	2.740
% of load treated at the largest sewage plants (size band 6)	$\%Band6$	57.499	94.591	78.186	10.441
% of load treated with an ammonia permit limit ≤3 milligrammes/litre	$\%Ammonia \leq 3$	0.621	86.724	23.293	24.538
Total sludge a company produces in the sewage treatment process (tonnes of dry solid)	$TonnesSludge$	37.900	391.963	146.687	96.554
Number of sewage works divided by number of properties in a company supply region	$\frac{No.SewageWorks}{No.Properties}$	0.0000580	0.0009034	0.0003467	0.0002234

skewed (the other being $\%Migration$), indicating some variability across operating regions in the share of properties with water meters. The skewness statistics for $\%DualService$, $AverageBill$, $\%Default$ and $\%IncDeprived$ suggest that their distributions are nearly symmetrical.

For the wastewater variables, the cost measures C_{SWC} and C_{BR} are positively skewed with moderate kurtosis, indicating the presence of some relatively high values. The non-spatial determinants $\frac{PumpCapacity}{SewerLength}$ and $PopDensWASC$ have non-negligible skewness and high kurtosis, suggesting marked variability in pumping capacity and population density.

4.2. Estimated cost models and discussion

In Tables 3–5, we present the estimated non-spatial cost model specifications that Ofwat and the CMA used for PR19, but for the updated longer PR24 samples that include two or three further years. With the exception of the independent variables denoted by a %, the variables are logged. There was a statistical rationale to augment a good number (but not all) of the non-spatialmodels with spatially lagged regressors. For these cases we report in the same tables the estimated spatial cost models. Following Ofwat's PR19 and PR24 approach we use clustered standard errors, where the clustering is by company (Ofwat 2019, 2023a). The significant spatial lags in Tables 3–5, along with the finding that including spatial lags can lead to changes in the signs, magnitudes and significance of non-spatial parameters, provides support for our spatial model specifications.

Table 3. Estimated water cost models.

	Non-Spatial (NSp) and Spatial (Sp) Water Model Specifications: Logged Dependent Variable							
	Model 1 NSp: C_{WRP}	Model 2 NSp: C_{WRP}	Model 3A NSp: C_{TWD}	Model 3B Sp: C_{TWD}	Model 4A NSp: C_{WW}	Model 4B Sp: C_{WW}	Model 5A NSp: C_{WW}	Model 5B Sp: C_{WW}
Properties	1.054*** (0.000)	1.057*** (0.000)			1.052*** (0.000)	1.086*** (0.000)	1.046*** (0.000)	1.077*** (0.000)
MainsLength			1.026*** (0.000)	1.060*** (0.000)				
PopDensity	−4.986** (0.017)	−5.048** (0.034)	−5.562*** (0.000)	−7.213*** (0.000)	−4.684*** (0.001)	−6.132*** (0.000)	−4.308*** (0.002)	−5.695*** (0.000)
$PopDensity^2$	0.303** (0.017)	0.306** (0.033)	0.393*** (0.000)	0.495*** (0.000)	0.301*** (0.000)	0.390*** (0.000)	0.276*** (0.001)	0.361*** (0.000)
$\frac{No.BPSs}{MainsLength}$			0.433*** (0.001)	0.481*** (0.000)	0.509*** (0.003)	0.551*** (0.000)	0.486*** (0.003)	0.527*** (0.000)
$\%Water3-6$	0.004*** (0.009)				0.003** (0.011)	0.002** (0.028)		
Complexity		0.315 (0.234)					0.323** (0.030)	0.278* (0.076)
$W_tPopDensity$				−7.318*** (0.004)		−5.941** (0.027)		−5.763* (0.062)
$W_tPopDensity^2$				0.476*** (0.003)		0.388** (0.024)		0.375* (0.055)
Constant	9.415 (0.226)	9.591 (0.226)	15.643*** (0.002)	50.175*** (0.001)	10.300* (0.056)	38.569*** (0.003)	8.675 (0.108)	36.121** (0.016)
Adj. R^2	0.901	0.896	0.952	0.958	0.963	0.968	0.965	0.971
No. of Obs.	187	187	187	187	187	187	187	187

Notes: *p*-values are in parentheses and ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

To fix ideas, we note that our baseline Ofwat results comprise multiple non-spatial models to explain the same dependent variable. This is because for robustness and sensitivity reasons, Ofwat use multiple measures to capture the same type of relationship, e.g. $\%Water3-6$ and *Complexity* in the two models in Table 3 for C_{WRP}. We adopt a general-to-specific approach to the spatial modelling by first including the spatial lags of all the regressors in the corresponding baseline non-spatial model. In the modelling for price reviews, unless there is a strong economic/engineering rationale to retain a regressor that is not significant, it will typically be omitted as retaining it will influence the companies' modelled efficient base cost allowances for the next 5−year regulatory period. We therefore only retain spatial lagged determinants if there is a statistical rationale to do so.

In the five non-spatial cost models for water services in Table 3 (models 1, 2 and 3 A−5 A), the coefficients on the variables have the expected signs and these signs match those in the corresponding PR19 model for a shorter study period (Ofwat 2019). With one exception, the coefficients on the variables in our non-spatial water models and the PR19 water models are significant at marginal levels. The exception is the positive $PopDensity^2$ parameter, which is significant in our model 2, but not significant in the corresponding PR19 model. We can see from Table 3 that we include $W_tPopDensity$ and $W_tPopDensity^2$ in the three spatial models (3B−5 B). We find that the signs of the coefficients on these variables and their significance at marginal levels is robust across the three models. The signs of the coefficients on the non-spatial

Table 4. Estimated retail cost models.

	Non-spatial (NSp) and spatial (Sp) retail cost model specifications: logged dependent variable						
	Model 6	Model 7A	Model 7B	Model 8A	Model 8B	Model 9A	Model 9B
	NSp : $\frac{\text{BadDebt}}{\text{No.Households}}$	NSp : $\frac{\text{BadDebt}}{\text{No.Households}}$	Sp : $\frac{\text{BadDebt}}{\text{No.Households}}$	NSp : $\frac{\text{OtherRetailCost}}{\text{No.Households}}$	NSp : $\frac{\text{OtherRetailCost}}{\text{No.Households}}$	NSp : $\frac{\text{OtherRetailCost}}{\text{No.Households}}$	Sp : $\frac{\text{OtherRetailCost}}{\text{No.Households}}$
AverageBill	1.188*** (0.000)	1.164*** (0.000)	1.213*** (0.000)				
%Default	0.024 (0.209)						
%IncDeprived		0.021 (0.392)	−0.008 (0.642)				
%Migration		−0.015 (0.515)	0.050* (0.052)				
%DualService				0.002** (0.025)	0.002** (0.019)	0.003*** (0.000)	0.005*** (0.000)
%Metered				4.371×10^{-4} (0.809)	0.003 (0.155)	4.050×10^{-4} (0.834)	0.003 (0.250)
No.Connections						−0.049 (0.117)	−0.124*** (0.006)
W_t*AverageBill*			0.771 (0.125)				
W_t*%Migration*			−0.126*** (0.002)				
W_t*%Metered*					−0.005 (0.141)		−0.005 (0.184)
W_t*%DualService*							−0.009*** (0.001)
W_t*No.Connections*							0.161*** (0.009)
Constant	−11.807*** (0.000)	−11.201*** (0.000)	−14.697*** (0.000)	−4.190*** (0.000)	−4.078*** (0.000)	−3.892*** (0.000)	−4.049*** (0.000)
Adj. R^2 (No. Obs)	0.615(153)	0.605(153)	0.619(153)	0.127(153)	0.134(153)	0.138(153)	0.324(153)

Non-spatial (NSp) and spatial (Sp) retail cost model specifications: logged dependent variable					
	Model 10	Model 11A	Model 11B	Model 12A	Model 12B
	NSp: $\frac{\text{TotRetailCost}}{\text{No.Households}}$	NSp: $\frac{\text{TotRetailCost}}{\text{No.Households}}$	Sp: $\frac{\text{TotRetailCost}}{\text{No.Households}}$	NSp: $\frac{\text{TotRetailCost}}{\text{No.Households}}$	Sp: $\frac{\text{TotRetailCost}}{\text{No.Households}}$
AverageBill	0.519^{***}	0.621^{***}	0.768^{***}	0.657^{***}	0.803^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
%Default	0.011	0.020	0.053^{***}		
	(0.415)	(0.141)	(0.000)		
%IncDeprived				−0.002	0.035^{**}
				(0.854)	(0.033)
%Migration				0.004	0.027^{*}
				(0.733)	(0.067)
%Metered	0.001	0.003	0.002	-2.412×10^{-4}	−0.002
	(0.668)	(0.348)	(0.242)	(0.923)	(0.340)
No.Connections		-0.081^{***}	-0.200^{***}	-0.068^{**}	-0.175^{***}
		(0.005)	(0.000)	(0.044)	(0.000)
W_t*AverageBill*			-0.675^{***}		-0.620^{***}
			(0.000)		(0.000)
W_t*%Migration*					−0.028
					(0.105)
W_t*No.Connections*					0.146^{**}
					(0.022)
W_t*%Default*			-0.019^{*}		
			(0.053)		
W_t*%IncDeprived*					-0.031^{*}
					(0.080)
Constant	-6.807^{***}	-7.122^{***}	-3.520^{***}	-6.777^{***}	-4.331^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R^2 (No. Obs)	0.613(153)	0.636(153)	0.783(153)	0.602(153)	0.754(153)

Notes: *p*-values are in parentheses and ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5. Estimated wastewater cost models.

	Non-spatial (NSp) and spatial (Sp) wastewater cost model specifications: logged dependent variable						
	Model 13A NSp: C_{SWC}	Model 13B Sp: C_{SWC}	Model 14 NSp: C_{SWC}	Model 15A NSp: C_{SWT}	Model 15B Sp: C_{SWT}	Model 16A NSp: C_{SWT}	Model 16B Sp: C_{SWT}
SewerLength	0.804*** (0.000)	0.840*** (0.000)	0.852*** (0.000)				
$\frac{PumpCapacity}{SewerLength}$	0.345** (0.012)	0.432*** (0.003)	0.555*** (0.000)				
$\frac{No.Properties}{SewerLength}$	1.043*** (0.000)	1.106*** (0.000)					
SewageLoad				0.651*** (0.000)	0.652*** (0.000)	0.682*** (0.000)	0.675*** (0.000)
$\%Bands1-3$				0.028 (0.225)	0.033 (0.160)		
$\%Band6$						−0.011* (0.053)	−0.012* (0.084)
$\%Ammonia \leq 3$				0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)
PopDensWASC			−5.043* (0.060)				
$PopDensWASC^2$			0.335** (0.039)				
$W_t \frac{No.Properties}{SewerLength}$		−0.468*** (0.004)					
$W_t\%Ammonia<3$					0.004** (0.017)		0.004** (0.030)
Constant	−7.957*** (0.000)	−6.859*** (0.000)	14.208 (0.196)	−3.708*** (0.003)	−3.850*** (0.001)	−3.137*** (0.000)	−3.113*** (0.000)
Adj. R^2 (No. Obs)	0.917 (110)	0.922 (110)	0.895 (110)	0.854 (110)	0.882 (110)	0.855 (110)	0.870 (110)

	Non-spatial (NSp) and spatial (Sp) bioresources cost model specifications: logged dependent variable					
	Model 17 NSp: C_{BR}	Model 18 NSp: C_{BR}	Model 19A NSp: C_{BRP}	Model 19B Sp: C_{BRP}	Model 20A NSp: C_{BRP}	Model 20B Sp: C_{BRP}
SewageLoad			0.761*** (0.000)	0.763*** (0.000)	0.793*** (0.000)	0.760*** (0.000)
$\%Bands1-3$	0.065*** (0.007)		0.033* (0.081)	0.042** (0.037)		
$\%Band6$					−0.013** (0.010)	−0.013** (0.015)
$\%Ammonia \leq 3$			0.005*** (0.000)	0.005*** (0.000)	0.005*** (0.000)	0.005*** (0.000)
PopDensWASC	−0.138 (0.464)					
TonnesSludge	1.125*** (0.000)	1.140*** (0.000)				
$\frac{No.SewageWorks}{Properties}$		0.317* (0.091)				
$W_t\%Bands1-3$				−0.059*** (0.004)		
$W_t\%Band6$						0.013** (0.024)
Constant	−0.586 (0.636)	1.095 (0.128)	−4.706*** (0.001)	−4.607*** (0.002)	−3.998*** (0.000)	−4.572*** (0.000)
Adj. R^2 (No. Obs)	0.818 (110)	0.791 (110)	0.911 (110)	0.928 (110)	0.917 (110)	0.930 (110)

Notes: *p*-values are in parentheses and ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

variables and their significance at marginal levels is also robust to the inclusion of these spatial lags.

Turning to the geo-economic rationale for the inclusion of these spatial lags in models 3B −5 B. The same type of rationale can also be used to support the inclusion of the spatial lag of another density measure, $W_t \frac{No.Properties}{SewerLength}$, in model 13B for the cost of sewage collection (see Table 5). Compared to using a uniform population density across a company's region, we include $W_tPopDensity$ and $W_tPopDensity^2$ to provide a more complete picture. To illustrate, consider the supply region of the largest company in the sample, Thames Water, where there are similar types of examples for other companies in the industry.

Thames' region is viewed as very urban due its high population density. This is because the London part of Thames' region, which is situated well away from some of the company's borders, has a very high population density that dominates the lower densities in other parts of its region. Omitting $W_tPopDensity$ and $W_tPopDensity^2$ in models 3 A −5 A assumes that population density across the Thames region is high and uniform. This does not though reflect the vast areas of the Thames region that are very rural, e.g. the majority of the Cotswolds district which is in the west and north west of the Thames region (Severn Trent Water 2023, 46). By including $W_tPopDensity$ and $W_tPopDensity^2$ we include an extra layer of density information that proxies for more rural areas close to the borders of the Thames region.

Whilst it is well-established that cost modelling plays a key role in Ofwat's determination of the companies' base cost allowances for water and wastewater, PR19 was the first time Ofwat used cost models to inform the setting of the base cost allowances for retail. The evolution of the retail cost modelling is therefore at an earlier stage than the water and wastewater cost modelling. This is in line with our finding that some corresponding non-spatial retail models for the PR19 and PR24 study periods are less robust than the corresponding non-spatial water and wastewater models. This is primarily due to some coefficients in our non-spatial retail models for the longer PR24 study period being insignificant, but with the same sign as in the corresponding non-spatial model for the PR19 study period (Ofwat 2019). As will become evident from the following discussion of the fitted retail cost models, an overall finding is that when spatial lags are included, the results for the non-spatial explanatory variables are more robust to the length of the study period.

We make two observations about the fitted retail cost models in Table 4. First, with a few exceptions, an estimated coefficient from the non-spatial models has the same sign as that in the corresponding PR19 model for a shorter study period. The exceptions in Table 4 are the negative and insignificant impact of $\%Migration$ in model 7 A, as we would expect this coefficient to be positive; and the negative and insignificant impacts of $\%IncDeprived$ and $\%Metered$ in model 12 A, as we would expect positive parameters for these variables.

Second, in the non-spatial and spatial models we include the same non-spatial regressors as the aforementioned PR19 models. This is so we can see how the spatial variables improve the model specifications. As is the case in the PR19 models, this involves including some non-spatial variables that are some way from being significant at marginal levels due to the economic/operational rationales that support their inclusion. However, as the spatial variables do not directly relate to a company's supply area, our criteria to include a spatial lag is stricter. As we discuss further below for particular spatial variables, we include a spatial lag if it is significant at a marginal level, or, alternatively, if its inclusion leads to more intuitive results for a non-spatial coefficient (i.e. an improvement in significance and also possibly an intuitive change in the sign of the coefficient).[9]

Some significant spatial lags at marginal levels include $W_t No.Connections$ in models 9B and 12B and $W_t AverageBill$ in model 11B. The negative and significant coefficients on the non-spatial *No.Connections* variable in models 9B and 12B are consistent with scale economies leading to lower unit retail costs. As a spatial lag is able to capture a different type of relationship to that which its non-spatial counterpart picks up, and the value of a spatial lag increases with the border length that companies share, we suggest $W_t No.Connections$ in these two models is a proxy for the absolute size of the impact associated with features of the housing stock in a company's region that increase its retail cost. We suggest that one such cost is that associated with metered properties, as $\%$*Metered* is a share, so does not account for the absolute size effect. Also, $\%$*Metered* does not perform well because, although in a number of retail models its coefficient has the expected positive sign, its impact is always small and insignificant. In models 9B and 12B, the negligible and insignificant $\%$*Metered* parameter is negative, but in the calculation of the modelled efficient base cost allowances for retail in 4.3, this effect is comfortably more than offset by the non-negligible, significant, positive impact of $W_t No.Connections$.

In model 11B, the *AverageBill* and $W_t AverageBill$ parameters are significant at the 1% level and are positive and negative, respectively. Once again these findings highlight the different relationships that a spatial lag and its non-spatial counterpart can capture. The results for *AverageBill* in models 6, 7 A and 7B $\left(\frac{BadDebt}{No.Households}\right)$ suggest that its correctly signed positive coefficient in model 11B $\left(\frac{TotRetailCost}{No.Households}\right)$ (and also models 10, 11 A, 12 A and 12B) is because an increase in *AverageBill* is associated with a rise in the unit bad debt portion of unit retail cost. Given the relationship in the regulatory framework between the benchmarking of the companies' cost efficiencies and the price controls Ofwat sets, we suggest that the negative $W_t AverageBill$ parameter in model 11B reflects the yardstick cost pressure on a company from its neighbours.

As we touched on above, for the retail models, the inclusion of significant spatial lags at marginal levels can lead to an improvement in the results for a non-spatial variable. To illustrate, in line with our priors the $\%$*Default* parameter is positive in models 11 A and 11B, but is insignificant in the former and significant in the latter. A further case is the $\%$*IncDeprived* parameter in models 12 A and 12B, which is insignificant with a counterintuitive negative sign in the former and positive and significant in the latter.

Next, we elaborate on how including a spatial lag that is not significant at marginal levels in a retail model can lead to more intuitive results for a non-spatial variable. Whereas in model 7 A the $\%$*Migration* parameter has a counterintuitive negative sign, augmenting this model with only the spatial lag of this variable yields the expected positive coefficient on $\%$*Migration*. By also including $W_t AverageBill$ (p-value $= 12.5\%$, see model 7B in Table 4), the p-value for $\%Migration$ in this spatial model goes from 19.5% to 5.2%. We suggest that the significant positive $\%Migration$ and negative $W_t\%Migration$ parameters in model 7B are intuitive as they are consistent with the bi-directional nature of migration.

As expected in model 7 A, the $\%IncDeprived$ parameter is positive and in the corresponding spatial model 7B, this effect remains small and insignificant but becomes negative. The effect of $\%IncDeprived$ in model 7B, therefore, has only a negligible impact on our calculation of the companies' modelled efficient base cost allowances for retail. In the calculation of these allowances, it follows that this negligible impact will be comfortably more than offset by the positive and non-negligible effect of $W_tAverageBill$ in model 7B. We therefore suggest that in model 7B, this spatial lag is a better proxy than $\%IncDeprived$ for customers' propensities to default on their water bills. This is because income deprivation extends across regional borders and, unlike $\%IncDeprived$, $W_tAverageBill$ (i.e. the weighted average of the observations of all the ith company's neighbours) specifically relates to the water industry, while also being outside the control of company i's management. Additionally, including $W_t\%Metered$ in models 8B and 9B (p-values of 14.1% and 18.4%) and $W_t\%Migration$ in model 12B (p-value $=$ 10.5%), markedly reduces the p-values of the corresponding non-spatial variables. The latter results in the expected positive coefficient on $\%Migration$ becoming significant at a marginal level (p-value $=$ 6.7%).

Finally, on the estimated models, we turn to the results for wastewater. In the non-spatial cost models in Table 5 for sewage, bioresources, and bioresources and sewage treatment combined (models 13 A; 14; 15 A; 16 A; 17; 18; 19 A; 20 A), the coefficients have the same signs as those in the CMA's PR19 models (CMA 2021). In addition to including in model 13B the significant spatially lagged density variable, $W_t \frac{No.Properties}{SewerLength}$, where we discussed above the geo-economic rationale for the inclusion of this variable when we considered the water models, four further spatial models in Table 5 include a single significant spatial lag. These significant lags are $W_t\%Ammonia{<}3$ in models 15B and 16B, $W_t\%Bands1-3$ in model 19B, and $W_t\%Band6$ in model 20B.

Ahead of the below discussion of the geo-economic rationales for the inclusion of the above significant spatial lags in the relevant wastewater cost models, we note that $\%Ammonia{<}3$ is included in the models for C_{SWT} to account for the higher cost associated with more complex treatment. As expected, the estimated coefficients on $\%Ammonia{<}\ 3$ are exclusively positive and significant. The geo-economic rationale for the inclusion of the spatial lag of this complexity variable is to proxy for a number of geographical topography/topology characteristics that are challenging to measure and are thus unobserved. This spatial lag proxies for these omitted factors as areas close to and across company borders are more likely to have similar such characteristics. $\%Ammonia < 3$ only captures the average of this particular characteristic for a company's region, with its spatial lag providing another layer of topography/topology information for areas close to borders (Severn Trent Water 2023, 46).

Interestingly, in the two spatial models for C_{BRP} (19B and 20B), the significant negative $W_t\%Bands1-3$ and positive $W_t\%Band6$ parameters have the opposite sign to the corresponding significant non-spatial variable. On the results for these non-spatial variables, in model 20B, for example, the negative and significant coefficient on $\%Band6$

is consistent with the scale economies in sewage treatment at the largest plants. Note that we follow Ofwat (2019) and the CMA (2021) by ensuring $\%Bands1-3$ and $\%Band6$ are not included in the same model for reasons of collinearity. In model 20B, we therefore suggest that to some degree (and hence without there being the same collinearity issue) $W_t\%Band6$ is proxying for the positive cost impact of the omitted $\%Bands1-3$ variable.

4.3. Cost efficiencies and the modelled efficient base cost allowances

In Table 6, we report two sets of in-sample triangulated overall company efficiencies (and their ranks) for water, retail and wastewater services. The first is the baseline set and is obtained using only the non-spatial models in Tables 3–5. The second set is obtained using the preferred models, which are a mix of the reported non-spatial and spatial models. All the spatial models in Tables 3–5 are preferred to the non-spatial counterpart, which unless otherwise stated in 4.2 is because at least one spatially lagged variable is significant at a marginal level. The triangulated efficiency is the ratio of a company's triangulated actual historical base cost to the modelled in-sample prediction of this triangulated cost. Hence, a company with a triangulated efficiency score less than (greater than) 1 has actual costs that are lower (higher) than the modelling predicts. The ranks provide important insights as it is a company's ranking that determines whether it will be set a catch-up efficiency challenge.

When we compare the two sets of reported efficiencies for each business activity, we find that, although the two sample average efficiencies are the same or similar, there are some notable rises and declines in the efficiencies and ranks for a number of companies. Compared to the baseline results, when the mix of non-spatial and spatial models are used, the biggest declines in efficiency and rank in Table 6 are for water services for Bristol and Northumbrian, respectively (−0.12 and −6). From the same comparison, we note that the three biggest rises in efficiency when spatial dependence is accounted for are also for water services: SES (0.26), Affinity (0.14) and South East (0.11). This comparison also reveals that when spatial dependence is accounted for this efficiency rise for South East represents the biggest rise up the efficiency rankings in Table 6 (+8).

Interestingly, South East, SES and Affinity border by far the largest company in the industry, Thames, and are considerably smaller as they are WOCs (see Figure 1 and Table 1). The higher triangulated water efficiencies for these three WOCs when we account for spatial dependence may be because this approach takes into account that Thames is much larger, and, as a result, it is more likely that the effects of some of its cost drivers will straddle supply regions and impact these three smaller neighbours. Relatedly, compared to the baseline triangulated efficiencies, when we use spatial models the biggest rises in triangulated wastewater efficiency in Table 6 are for Southern and Anglian (0.06 and 0.05, respectively). Both these companies also border Thames and are noticeably smaller. We therefore suggest that the reason for these higher efficiencies for Southern and Anglian is same as we gave above for South East, SES and Affinity.

Table 6. Triangulated cost efficiencies and the efficient base cost allowancess from the modelling.

Company	Triangulated water cost efficiency for in-sample period (2011/12-2021/22)		Triangulated retail cost efficiency for in-sample period (2013/14-2021/22)		Triangulated wastewater cost efficiency for in-sample period (2011/12-2011/22)	
	Non-spatial (Rank)	Mixed non-spatial and spatial (Rank)	Non-spatial (Rank)	Mixed non-spatial and spatial (Rank)	Non-spatial (Rank)	Mixed non-spatial and spatial (Rank)
Affinity (AFW)	0.99 (4)	0.85 (2)	0.98 (8)	0.99 (8)		
Anglian (ANH)	1.13 (14)	1.09 (11)	0.86 (3)	0.88 (2)	1.01 (6)	0.96 (3)
Bristol (BRL)	1.12 (13)	1.24 (12)	1.00 (9)	1.00 (10)		
Hafren Dyfrdwy (HDD)	1.08 (10)	1.08 (10)	1.09 (12)	1.09 (14)		
Northumbrian (NES)	1.04 (6)	1.10 (12)	1.01 (10)	1.03 (11)	0.92 (1)	0.91 (1)
United Utilities (NWT)	1.02 (5)	1.08 (9)	1.03 (11)	0.99 (9)	1.07 (7)	1.08 (7)
Portsmouth (PRT)	0.72 (1)	0.78 (1)	0.97 (7)	0.97 (5)		
SES Water (SES)	1.49 (17)	1.23 (15)	1.28 (16)	1.23 (17)		
South East (SEW)	1.08 (11)	0.97 (3)	0.85 (2)	0.90 (3)		
Southern (SRN)	1.22 (15)	1.23 (16)	1.31 (17)	1.23 (16)	1.15 (10)	1.09 (8)
South Staffordshire (SSC)	0.94 (2)	1.02 (6)	1.09 (13)	1.07 (13)		
Severn Trent England (SVE)	1.04 (7)	1.01 (4)	0.93 (5)	0.95 (4)		
Severn Trent and Hafren (SVH)					0.94 (4)	0.97 (4)
South West (SWB)	0.96 (3)	1.02 (5)	0.80 (1)	0.82 (1)	1.00 (5)	1.02 (6)
Thames (TMS)	1.05 (8)	1.05 (7)	1.18 (15)	1.11 (15)	0.94 (3)	0.97 (5)
Dŵr Cymru (WSH)	1.11 (12)	1.06 (8)	1.12 (14)	1.03 (12)	1.12 (8)	1.09 (9)
Wessex (WSX)	1.28 (16)	1.19 (14)	0.92 (4)	0.99 (7)	0.93 (2)	0.96 (2)
Yorkshire (YKY)	1.06 (9)	1.12 (13)	0.94 (6)	0.98 (6)	1.14 (9)	1.12 (10)
Sample average efficiency	1.08	1.07	1.02	1.01	1.02	1.02

Company	Out-of-sample 5-year (2025/26-2029/30) efficient water base cost allowance from the modelling		Out-of-sample 5-year (2025/26-2029/30) efficient retail base cost allowance from the modelling		Out-of-sample 5-year (2025/26-2029/30) efficient wastewater base cost allowance from the modelling	
	Non-spatial, 17/18 million £s	Mixed non-spatial and spatial, 17/18million £s (%change)	Non-spatial, 17/18million £s	Mixed non-spatial and spatial, 17/18million £s (%change)	Non-spatial, 17/18million £s	Mixed non-spatial and spatial, 17/18million £s (%change)
Affinity (AFW)	1,014	1,244 (22.67)	136.3	135.3 (−0.74)		
Anglian (ANH)	1,379	1,479 (7.22)	417.5	413.4 (−0.98)	1,953	2,134 (9.24)
Bristol (BRL)	367	339 (−7.40)	51.2	52.9 (3.36)		
Hafren Dyfrdwy (HDD)	107	110 (2.48)	10.2	9.9 (−2.92)	22.38	22.53 (0.69)
Northumbrian (NES)	1,156	1,131 (−2.12)	239.5	234.4 (−2.11)	754	786 (4.31)
United Utilities (NWT)	2,018	1,984 (−1.68)	519.2	549.5 (5.83)	2,062	2,098 (1.74)
Portsmouth (PRT)	166	160 (−3.90)	23.1	23.7 (2.75)		
SES Water (SES)	166	209 (25.90)	28.4	29.8 (5.00)		
South East (SEW)	641	745 (16.21)	103.9	102.6 (−1.30)		
Southern (SRN)	788	813 (3.06)	255.7	269.8 (5.52)	1,542	1,686 (9.32)
South Staffordshire (SSC)	395	374 (−5.52)	62.9	64.6 (2.65)		
Severn Trent England (SVE)	2,330	2,482 (6.54)	548.4	547.2 (−0.22)	2,323	2,346 (0.99)
South West (SWB)	653	628 (−3.87)	162.7	167.2 (2.75)	679	684 (0.76)
Thames (TMS)	3,648	3,834 (5.09)	745.7	793.1 (6.35)	4,258	4,244 (−0.33)
Dŵr Cymru (WSH)	1,060	1,140 (7.57)	232.8	258.3 (10.95)	1,065	1,116 (4.75)
Wessex (WSX)	437	491 (12.31)	158.4	149.7 (−5.53)	935	938 (0.39)
Yorkshire (YKY)	1,426	1,401 (−1.76)	359.6	354.2 (−1.51)	1,628	1,698 (4.27)
Industry	17,751	18,562 (4.57)	4,055.6	4,155.5 (2.46)	17,222	17,752 (3.08)

We also report in Table 6 two sets of triangulated modelled efficient base cost allowances for water, retail and wastewater services. These allowances are in 2017/18 prices and are for the out-of-sample period that corresponds to the 5− year regulatory period that PR24 covers (1 April 2025 – 31 March 2030). Even though both the non-spatial and spatial models are random effects specifications estimated using the same GLS approach, and the spatial models include only a small number of additional spatial lagged variables, when compared to the baseline allowances, we can see that when we account for spatial dependence there are rises in the allowances for some companies and decreases for others. To illustrate, when we use the spatial models, there is an increase in the water and retail allowances for 59% and 53% of companies, respectively. Interestingly, and as we discuss further below, accounting for spatial dependence leads to a rise in the wastewater allowance for all but one company.

Consistent with the relationship between the efficiencies and modelled efficient base cost allowances, when we account for spatial dependence the three companies with the biggest rises in their water cost efficiencies (SES, Affinity and South East) have the biggest percentage increases in their allowances. The company with the next biggest percentage increase in its water allowance when we account for spatial dependence is Wessex, which also borders Thames. Along similar lines, when we model spatial dependence the two companies with the biggest increases in their wastewater cost efficiencies (Southern and Anglian) are the companies with the biggest percentage rises in their allowances. Interestingly, when spatial models are used the only company with a lower wastewater allowance is Thames, which may reflect some allowance redistribution to Southern and Anglian.

When we account for spatial dependence in the retail modelling, the biggest rise in efficiency and biggest percentage increase in the cost allowance are for Welsh Water (Dŵr Cymru). This is possibly due to the spatial factors accounting for additional costs associated with retail services that cover diverse rural and urban areas. Omitting these spatial factors in the baseline non-spatial retail modelling is consistent with these costs reducing Welsh Water's efficiency.

Other things unchanged, a higher triangulated modelled efficient base cost allowance for a company will lead to an increase in the maximum price it can charge its customers for the relevant service. This is because a higher allowance reflects a rise in cost efficiency and a smaller (or no) catch-up efficiency challenge. The regulator accounts for by allowing the company to raise its maximum price and thus increase its remuneration.

5. Summary and concluding remarks

As the English and Welsh WOCs and WASCs have regional supply areas, parallels can be drawn between these areas and other regional territories, such as the NUTS regions in Europe. Given spatial dependence between neighbouring NUTS regions (and various other neighbouring territories, such as U.S. states) is well-documented, this study was motivated by the hypothesis that there is also spatial dependence between the impacts of the cost characteristics of neighbouring WOCs and WACs.

As the water companies are regional monopoly operators, their costs and maximum prices are regulated. This involves the regulator (Ofwat) setting modelled efficient base cost allowances for the companies for the next 5− year regulatory period. To do so, Ofwat uses non-spatial cost models to benchmark the companies' historical cost efficiencies. The companies have incentives to improve their cost performance as Ofwat sets a catch-up cost efficiency challenge for a company over the next regulatory period if its historical efficiency falls short of the benchmark. If a company is set a catch-up efficiency challenge, this is reflected by the downward adjustment for the next regulatory period of both its cost allowance and, other things unchanged, the maximum price it is allowed to charge for the relevant service. This is because the cost allowance has a big influence on the maximum price, so that customers do not pay a higher price due to company cost inefficiency. To avoid companies facing distorted financial environments in the next regulatory period, appropriately specified cost models and the unbiased historical cost efficiencies that follow are key.

Our investigation into the specifications of the cost models reveals that in a good number (but not all) of our spatial models at least one spatially lagged independent variable is significant. This is important because based on this, we suggest using a mix of spatial and non-spatial models to set the companies' modelled efficient base cost allowances for the next regulatory period (1 April 2025 – 31 March 2030). When we use a mix of spatial and non-spatial models, rather than only the latter, there are increases (decreases) in these allowances for some companies. Other things unchanged, this will lead to the regulatory cap on the maximum price a company can charge its customers for a particular service being raised (lowered) for the next regulatory period. When we account for the spatial dependence, we find that some of the biggest increases in these allowances are for a number of companies that border Thames. This type of effect is intuitive because Thames is by far the biggest company in the industry and we would expect bigger neighbours to have a bigger spatial influence.

Our findings suggest that it would be worthwhile investigating if there is spatial dependence between the regulated variables of public utility companies in other industries and countries, and that our approach could be applied to account for this dependence. As we present a simple evolution of current cost modelling practice in the English and Welsh water industry, our approach may be of interest to companies and policy makers in other public utility industries.

Notes

1. See further in this section and section 2 for more details about the business activities of the companies.
2. There has also been a number of studies on the cost efficiencies of water companies in other countries. Examples include water supply in Portugal (Carvalho and Marques 2011), Italy (Guerrini, Romano, and Campedelli 2013), Slovenia (Filippini, Hrovatin, and Zorić 2008) and Denmark (Guerrini et al. 2015); wastewater services in Portugal (Carvalho and Marques, 2011), Denmark (Guerrini et al. 2015) and Chile (Molinos-Senante and Maziotis 2021); and retail services in Portugal (Marques and De Witte 2011, and Carvalho and Marques 2014).
3. We thank the GIS team at Severn Trent Water for creating these maps.

4. First, we construct the spatially lagged independent variables. As these additional spatial regressors are exogenous, we can follow the well-known practice (e.g. Baltagi and Levin 1986; Halleck Vega and Elhorst 2015) and estimate the SLX model using a standard non-spatial procedure. For this we use Stata as Ofwat also use this software to estimate its non-spatial random effects models (see Ofwat's website for the Stata do-files to estimate its models). As we use a standard non-spatial panel data estimator, one could also estimate Equation 1 using other econometrics packages (LIMDEP and EViews).
5. There are 17 companies in each year of the water and retail datasets, but the data is unbalanced due to a small amount of takeover activity. This includes the takeovers by South West of Bournemouth Water in 2015 and Bristol Water in 2022. In Ofwat's water and retail modelling for PR24, and also our modelling, Bournemouth and South West are treated as a single entity. In contrast and in line with Ofwat's current approach for PR24, Bristol and South West are separate entities in our water and retail samples.
6. We thank the GIS team at Severn Trent Water for providing the border lengths.
7. Nominal monetary variables are deflated using the CPIH.
8. When there is more pollution in sewage, there is higher demand for dissolved oxygen to breakdown organic matter. BOD5 is a standard measure that adjusts for the extent of the pollution in sewage by adjusting for the levels and concentration fluctuations of dissolved oxygen in the effluent. Specifically, the BOD5 measure is the sewage load adjusted for demand for dissolved oxygen over a 5-day period.
9. We exercise some flexibility when exploring whether including spatial lags leads to an intuitive improvement in the findings for the non-spatial variables. This involves considering spatial lags that are significant at less than 20%. This criterion is based on a similar approach to the PR19 retail cost modelling to support the inclusion of an economically / operationally important non-spatial explanatory variable that is insignificant at marginal levels (Economic Insight 2018; Williams et al. 2020).

Disclosure statement

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Appendix A

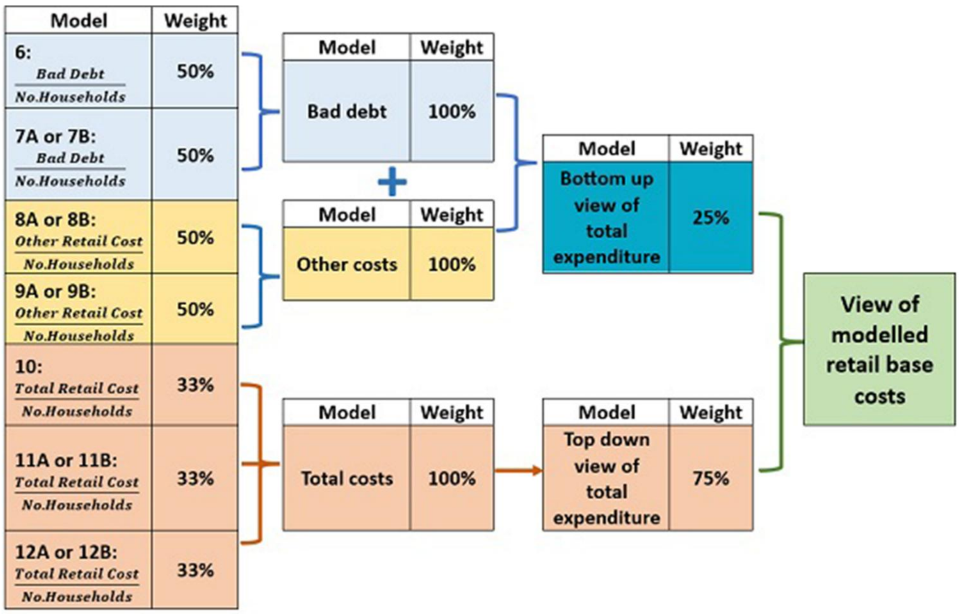

Figure note – Description of the triangulation of the post-sample forecasts of a company's modelled base costs and its historical in-sample cost efficiencies from the aggregate and disaggregated models for retail services.

Figure A1 presents the triangulation procedure for retail services, where this procedure is of the same type and has the same objective as the triangulation for water services. This procedure begins by making a distinction between the seven non-spatial retail models (labelled 6, 7A, 8A, 9A, 10, 11A and 12A in the above figure) and five spatial models (labelled 7B, 8B, 9B, 11B and 12B) that are used in the **two triangulations** for retail services. The cost measures that are the dependent variables in these retail models are provided in the above figure and are an aggregate measure (Total retail cost ÷ No. of households) and two disaggregated measures for the two subactivities (Bad debt ÷ No. of households and Other retail costs ÷ No. of households).

The **first triangulation** involves using the post-sample forecasts and historical in-sample efficiencies from the above seven non-spatial model specifications that Ofwat use, where the weights in figure A1 that are attached to the post-sample forecasts and historical in-sample efficiencies are those that Ofwat used for PR19. The **second triangulation** uses the same approach as the first, but uses the predictions of the historical in-sample costs, historical in-sample cost efficiencies and post-sample cost forecasts from a mix of non-spatial and spatial models. This involves retaining two non-spatial models (6 and 10) from the first triangulation and replacing the other five (7A, 8A, 9A, 11A and 12A) with the preferred spatial counterparts (7B, 8B, 9B, 11B and 12B).

Figure A1. Triangulation of the post-sample base cost forecasts and historical in-sample cost efficiencies for retail services.

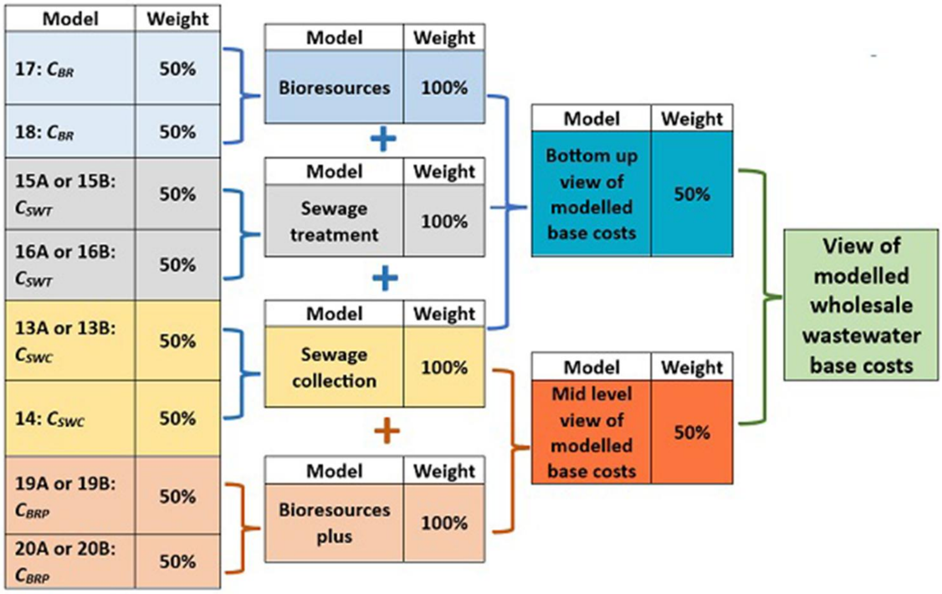

Figure note – Description of the triangulation of the post-sample forecasts of a company's modelled base costs and its historical in-sample cost efficiencies from the disaggregated models for wastewater services.

Figure A2 presents the triangulation procedure for wastewater services, where this procedure is of the same type and has the same objective as the triangulations for water and retail services. This procedure begins by making a distinction between the eight non-spatial wastewater models (labelled 13A, 14, 15A, 16A, 17, 18, 19A and 20A in the above figure) and five spatial models (labelled 13B, 15B, 16B, 19B and 20B) that are used in the **two triangulations** for wastewater services. The dependent variables for these wastewater models are provided in the above figure and are the costs of four disaggregated activities: sewage collection (C_{SWC}); sewage treatment (C_{SWT}); bioresources (C_{BR}); and bioresources plus (C_{BRP}).

The **first triangulation** involves using the post-sample forecasts and historical in-sample efficiencies from the above eight non-spatial model specifications that Ofwat use, where the weights in figure A2 that are attached to the post-sample forecasts and historical in-sample efficiencies are those that Ofwat used for PR19. The **second triangulation** uses the same approach as the first, but uses the predictions of the historical in-sample costs, historical in-sample cost efficiencies and post-sample cost forecasts from a mix of non-spatial and spatial models. This involves retaining three non-spatial models (14, 17 and 18) from the first triangulation and replacing the other five (13A, 15A, 16A, 19A and 20A) with the preferred spatial counterparts (13B, 15B, 16B, 19B and 20B). We can see from figure A2 that in the first and second triangulations, the results for the C_{SWC} models are used to calculate both the mid level and bottom up views of modelled base wastewater costs.

Figure A2. Triangulation of the post-sample base cost forecasts and historical in-sample cost efficiencies for wastewater services.

Appendix B

Table B1. Skewness and kurtosis of the variables.

Water variables			Retail variables			Wastewater (sewageand bioresources)variables		
Notation	Skewness	Kurtosis	Notation	Skewness	Kurtosis	Notation	Skewness	Kurtosis
C_{WRP}	0.823	−0.361	$\frac{BadDebt}{No.Households}$	0.677	0.005	C_{SWC}	1.155	1.114
C_{TWD}	1.759	3.535	$\frac{OtherRetailCost}{No.Households}$	0.589	−0.075	C_{SWT}	0.506	−0.575
C_{WW}	1.255	1.329	$\frac{TotRetailCost}{No.Households}$	0.692	−0.079	C_{BR}	1.216	1.634
$Properties$	0.754	−0.623	$\%DualService$	−0.015	−1.613	C_{BRP}	0.581	−0.311
$\%Water3-6$	−2.009	3.977	$\%Metered$	0.473	−0.552	$SewerLength$	0.514	−1.161
$Complexity$	−1.432	2.620	$No.Connections$	1.195	0.896	$\frac{PumpCapacity}{SewerLength}$	2.184	3.879
$PopDensity$	2.029	5.009	$AverageBill$	−0.045	−1.215	$\frac{No.Properties}{SewerLength}$	0.335	−0.549
$MainsLength$	0.426	−1.020	$\%Default$	−0.100	−1.001	$PopDensWASC$	1.980	3.350
$\frac{No.BPSs}{MainsLength}$	1.812	5.284	$\%IncDeprived$	0.006	−1.001	$SewageLoad$	1.050	0.358
			$\%Migration$	0.603	0.291	$\%Bands1-3$	1.187	0.687
						$\%Band6$	−0.318	−0.818
						$\%Ammonia \leq 3$	1.150	0.561
						$TonnesSludge$	1.128	0.477
						$\frac{No.SewageWorks}{No.Properties}$	1.187	0.830