January 2019

Trust in water

Supplementary technical appendix: Econometric approach

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Cost assessment for PR19: our econometric models

About this document

This document sets out our approach and decisions regarding econometric modelling for PR19, including our final model specifications.

We consulted on econometric modelling for PR19 in March 2018.

Econometric analysis is key component of our cost assessment approach. Our wider approach to cost assessment is set out in Technical appendix 2: Securing cost efficiency.

Contents

1. Introduction

An important element of our approach to cost assessment is the development of econometric models. Our econometric models play an important role in setting efficient cost allowances in draft and final determinations.

The purpose of this document is to present and explain our decision on the econometric models we have used in the initial assessment of business plans. Our intention is to use the same models for the rest of the PR19 process (draft and final determinations), however we will make changes to our set of models if it is appropriate to do so in light of new data or evidence from company representations.

In PR19, we are setting up to six different price controls for the 17 largest water companies in England and Wales: water resources; water network plus; wastewater network plus; bioresources; residential retail; and business retail (where appropriate). We have developed econometric models as the primary tool for setting efficient cost allowances for all but the business retail controls.

During 2016 and 2017 we worked closely with stakeholders, through our cost assessment working groups, to develop and refine data and tools for cost assessment.

In March 2018, we issued Cost assessment for PR19: a consultation on econometric cost modelling (hereafter "our consultation"). We received 15 responses which are available on our website. Since the consultation, companies have submitted data for 2017/18, as well as business plans for the period 2020-21 to 2024-25. We have finalised our models based on consultation responses and the additional data received.

This document is structured as follows:

- **Chapter 2** provides an overview of our econometric approach;
- **Chapter 3** sets out the econometric models we use to benchmark costs of delivering wholesale water services;
- **Chapter 4** sets out the econometric models we use to benchmark costs of delivering wholesale wastewater services;
- **Chapter 5** sets out the econometric models we use to benchmark costs of delivering residential retail services.

2. Overview of our approach

The purpose of our econometric modelling is to inform the setting of efficient cost allowances for companies. Our emphasis is to develop models that are consistent with engineering, operational and economic understanding of cost drivers. We aim to develop models that are sensibly simple (without pursuing simplicity for its own sake) and capture the main cost drivers in each model.

We have explored a wide range of econometric models for PR19, applying the model development and assessment criteria set out in our consultation. We have drawn on lessons from PR14 and considered companies' responses. We have engaged with CEPA to support us in the development of econometric models for the wholesale water and wastewater controls, and with Vivid Economics to further develop our wholesale wastewater models in light of consultation responses. We have also received feedback from our academic advisors, Professor Andrew Smith and Dr Thijs Dekker of the University of Leeds, who have provided review and challenge throughout the process.

We recognise that there are practical limitations to the use of statistical modelling in cost assessment. All models are subject to error and a degree of bias. In many instances, it is not possible to identify a single "preferred" econometric model that clearly prevails over all others. To mitigate risks of error and bias we do not rely on a single model. Rather, we use a diverse set of models, with different drivers and different levels of aggregation, in triangulation. We also supplement our econometric work with further analysis and the cost adjustment claims process.[1]

In undertaking our econometric analysis, a number of key decisions are made regarding model specification. These are summarised below.

Enhancement costs are not included in our models

For wholesale water and wastewater, we use our econometric models to benchmark base costs only. That is, operating costs plus maintenance capital costs. Enhancement capital costs are not included. This is consistent with our PR19 methodology and reflects industry feedback and learnings from PR14, as well as the

[1] The cost adjustment claims process is discussed in Technical appendix 2: Securing cost efficiency

Competition and Markets Authority (CMA) determination on Bristol Water's PR14 price controls.

In our PR19 methodology we said that there are some areas of enhancement expenditure which we will consider including with our base econometric models. While we have not developed such models for PR19, we expect to revisit this approach in future price reviews.

In residential retail we include total costs in our models. That is, operating costs plus depreciation. There are no enhancement costs in retail.

In both wholesale and retail we exclude small elements of costs from our models, which we describe in the respective chapters.

Key cost drivers for the delivery of wholesale service

A key consideration for our econometric modelling is the choice of cost drivers. For wholesale water and wastewater, we find four key categories of cost drivers to be consistently important:

- **Scale** variables, to measure the size of the network and/or level of output. This is the primary cost driver in all our models;
- **Complexity** variables, to capture the complexity of required treatment or the complexity of the network;
- **Topography** variables, to capture energy requirements for transporting or pumping water or wastewater; and
- **Density** variables, to capture economies of scale at the treatment level and costs resulting from operating in highly dense areas.

Retail costs are also driven by scale, but otherwise are associated with very different cost drivers to those of wholesale water and wastewater. Retail is discussed in chapter 5.

Consideration of functional form

In PR14 we used a **translog** (or "variable elasticity") cost model. The translog is a relatively complex "non-linear" functional form that allows for varying scale or density effects between companies.

At PR19 our starting point is the **Cobb-Douglas** (or “constant elasticity”) model. This model assumes that scale or density effects are constant. That is, a percentage change in the explanatory variable (for example scale or density) results in the same percentage change in costs for all companies. Starting with the Cobb-Douglas specification, we would add non-linear or cross-product terms only when there is a clear economic or engineering rationale for doing so and statistical tests show such non-linear effects to be important.

Our final models include non-linear terms only for models in wholesale water activities.

The majority of companies agreed with this approach. Some companies expressed concerns about the use of translog cost functions due to instability over different modelling specifications, multicollinearity and difficulty over interpretation.

While the translog has appealing properties in that estimated elasticities[2] vary with company size, in practice we find that individual company elasticities can have a counter-intuitive sign, that some translog terms are highly insignificant and (individually) unstable, and that the specification takes up degrees of freedom that could be dispensed with more relevant cost drivers.

Consideration of estimation method

Our underlying data for modelling is a “panel” data. Panel data is two dimensional – in our case, water companies and time, as we have data for a set of companies over a number of years.

We tested models using two methods, ordinary least squares (OLS) and random effects. In our consultation we presented models estimated with the OLS method. We noted at the time that we found that the two methods produced similar results and that we would revisit the choice of estimation method later in the process.

We use the random effects method to estimate all our models. The random effects method is specifically designed for panel data. We use random effects models as it reflects the panel structure of the data and performs better statistically. Overall, the coefficients are more statistically significant than when using OLS, and the Breusch-

[2] The elasticity is the responsiveness of cost to a change in the value of a cost driver.

Pagan tests consistently provide results supporting use of the random effects method over the OLS.

Triangulation

In most circumstances, our development and assessment criteria have led to the selection of multiple models across different levels of aggregation.

We use a ‘triangulation’ process to combine different models in order to arrive at our view of costs at different levels of aggregation (for example, at the level of the PR19 controls, or at the wholesale water/wholesale wastewater levels, which we used in the IAP).

Triangulation involves assigning a weight to each model. We do not consider that a statistical approach would be appropriate to determining triangulation weights, given the importance we place on the economic and engineering rationale of the model. Our standard approach is to apply equal weights to all models at any given level of aggregation. We would need a strong argument to justify deviating from this position.

The specific triangulation process for each area of modelling is set out in its respective chapter.

3. Cost models for wholesale water activities

In this chapter we present the econometric models we have used to assess wholesale water costs in the IAP. The chapter is structured as follows:

- Our econometric models for wholesale water activities;
- Data;
- Our choice of dependent variables;
- Our choice of cost drivers;
- Triangulation and setting allowances.

3.1 Our econometric models for wholesale water activities

Table 1 presents the five econometric models we use to benchmark base costs of wholesale water activities.

Table 1: Econometric models for wholesale water

Model name	WRP1	WRP2	TWD1	WW1	WW2
Dependent variable (log)	Water resources + Raw water distribution + Water treatment		Treated water distribution	Wholesale water total	
Connected properties (log)	1.014***	1.014***		0.993***	0.984***
Lengths of main (log)			1.013***		
Water treated at works of complexity levels 3 to 6 (%)	0.008***			0.003***	
Weighted average treatment complexity (log)		0.443***			0.371***
Number of booster pumping stations per lengths of main (log)			0.465***	0.515***	0.517***
Weighted average density (log)	-1.360**	-0.701 (0.2)	-3.068***	-1.711***	-1.473***
Squared term of log of weighted average density	0.083**	0.036 (0.372)	0.245***	0.126***	0.109***
Constant term	-5.316***	-7.605***	5.777***	-1.273	-2.267**
Overall R-Squared	0.93	0.92	0.97	0.98	0.98
Number of observations	124	124	124	124	124

Notes: The dependent variable is modelled base costs in 2017/18 prices, using the CPIH adjustment. P values expressed in parentheses are based on clustered standard errors at the company level. *, ** and *** denote significance at 10, 5 and 1 percent respectively.

3.2 Data

For wholesale water, we use a panel data of 124 observations. The panel data has seven years of historical data. The first five years, from 2011-12 to 2015-16, include data on 18 water companies (as during this period South West Water and Bournemouth Water were separate entities). The last two years, from 2016-17 to 2017-18, include data on 17 companies (when the two companies merged). The data is sourced from business plan data tables.

3.3 Our choice of dependent variables

The dependent variable is constructed from business table WS1 as the sum of operating costs and maintenance capex (lines 11-13), excluding the following lines:

- Abstraction charges (WS1, line 3) for water resources only;
- Business rates (WS1, line 8);
- Third party services (WS1, line 10);
- Costs associated with Traffic Management Act (WS5, line 5);
- Statutory water softening (WS5, line 9).

Levels of aggregation

Table 2 presents the levels of cost aggregation that we tested for econometric modelling, and whether a model at that level was adopted:

Table 2: levels of aggregation of the dependent variable in wholesale water

Granularity	Dependent variable	Adopted?
Granular	Water resources costs	×
	Raw water distribution costs	×
	Water treatment costs	×
	Treated water distribution costs	✓
Mid-level	Water resources costs + Raw water distribution costs + Water treatment costs (“water resources plus”)	✓
	Raw water distribution costs + Water treatment costs + Treated water distribution costs (“network plus water”)	×
Aggregated	Wholesale water costs	✓

Of the granular levels of aggregation we considered, we only use models for treated water distribution.

We tested models at the granular levels of water resources, raw water distribution and water treatment. Models at these levels often produced too wide a range of efficiencies (ie wide variation of the residuals). We considered that our models at the aggregate level of water resources plus provided a better basis for our assessment.

For water resources, we developed a model with a single driver, the number of connected customers. While the model appears to have reasonable statistical properties, we considered the range of efficiency scores to be too wide and that using models at different levels of aggregation provided a more satisfactory basis of assessment. Additional variables that we tested, such as the number of sources per property and the proportion of water from impounding reservoirs, did not generate expected results.

We also considered water resources models proposed by companies for our consultation. Some models were well fitted but lacked an engineering rationale. For example, we expect costs associated with sourcing water from impounding reservoirs to be relatively low compared with other sources (eg pumped storage reservoirs, rivers and boreholes), however some company models showed the opposite effect. Severn Trent Water was unable to identify an equivalent set of primary cost drivers that look to sufficiently reflect the main factors which might be expected to influence water resources costs. Additionally, South West Water suggested that “modelling the water resource part of the value chain in isolation is problematic due to ignoring the trade-offs with water treatment and the wide efficiency score that result from the modelling”.

The water resources plus level of aggregation that we adopted captures the interaction between different services of the value chain and allows for a comparison of costs that internalise inherent choices and trade-offs across the value chain. Moreover, these models produce robust results which are consistent with economic and engineering judgement about the sign and size of the impact of cost drivers on costs. This view was echoed in responses to our consultation.

3.4 Our choice of cost drivers

As we set out in chapter 2, the key factors driving costs for wholesale water activities are **scale**; treatment **complexity**; **topography**, and **Density**. We discuss each below.

Scale

Scale is a key driver of costs. Larger operations deliver more output and incur greater costs.

For water resources plus (WRP), we use the number of households as a measure of company scale. We considered the total volume of water treated as an alternative scale driver. We ruled it out on the basis that companies can influence the volume of water through leakage reduction and water efficiency schemes, which we wish to incentivise. The same view was expressed by a few companies in response to our consultation, and the number of households was generally the favoured driver for WRP.

Treated water distribution (TWD) costs are associated with running a distribution network consisting mainly of water mains. We use the length of mains as the scale cost driver for TWD costs. The length of mains is the most intuitive driver of network costs. A number of companies advocated using this driver and the same driver was used in our PR14 distribution network models. While companies have a degree of control over the length of mains, we consider that it remains substantially determined by exogenous factors, and the benefit it brings in terms of providing a good proxy of scale outweighs any concerns around endogeneity.

For the aggregated wholesale water model, we use the number of households as the scale cost driver. It has a slightly better statistical fit than length of mains, it is a more intuitive cost driver of wholesale services (length of mains is not an intuitive cost driver to use for water resources and treatment), and it is more exogenous (ie it is not in management control).

The estimated coefficients of the scale cost drivers are close to one across all models. This value is as expected. It implies that doubling the number of properties, or the length of mains, results in a doubling of costs (known as ‘constant returns to scale’).

Complexity

The complexity of treatment reflects both the quality of the raw water source supplying the treatment process and the treated output quality requirements. Where complexity is higher, costs are expected to increase due to the challenge of maintaining and operating multiple stages of treatment that utilise significant amounts of consumables, such as power and chemicals.

Water companies report the volume of water treated at treatment works of different complexity levels, ranging from zero to six.

We have selected two measures to control for treatment complexity: the percentage of water treated at water treatment works with complexity level 3 or higher and the weighted average complexity.

In discussion with our engineers and based on statistical evidence, we consider that there is a step change in treatment costs between works of complexity level 2 or less and works at higher levels of complexity. Levels 0, 1 and 2 include relatively simple works, such as those treating good quality groundwater sources, while level 3 will introduce works with multiple treatment stages treating lower quality sources. In response to our consultation a few companies concurred with this view and some companies proposed to use level 4 as the cut-off.

The weighted average treatment complexity is calculated as the weighted average of the numbers one to seven, each corresponds to a treatment complexity level as defined in our business plan data tables, where the weight for each level of complexity is the proportion of water treated at that level.

Other measures of complexity are also considered (eg the percentage of water coming from boreholes). However, these are not taken forward since they do not provide as direct a measure of treatment complexity, (for example, due to the significant variation in raw water quality between different groundwater sources) and perform less well statistically.

We find that the coefficients for the complexity variables are positive and statistically significant across different specifications.

Topography

Topography and the distribution of demand centres across the region can influence a company's distribution costs through greater requirements to pump and transport water to customers.

We use the number of booster pumping stations per length of mains as a measure of topography in our treated water distribution and wholesale water models. The variable is consistently significant with significant explanatory power across our models.

Companies supported the inclusion of a driver that accounts for pumping requirements. Some companies proposed using average pumping head to account for this. However, this driver was not statistically significant across a number of different specifications we tested and was therefore excluded.

Density

The density of an area could have two opposing effects on costs. On the one hand, the density variable captures the potential for a water treatment business to treat water using larger and fewer treatment works incurring lower unit costs. On the other hand, dense areas may be associated with higher property, rental and access costs.

We considered a range of different density measures. We concluded that the weighted average density was the most advantageous. Unlike other density measures such as the average number of households per length of main (as used in PR14), the weighted average density is beyond company control and it better reflects relative densities within regions. This measure is calculated as follows:

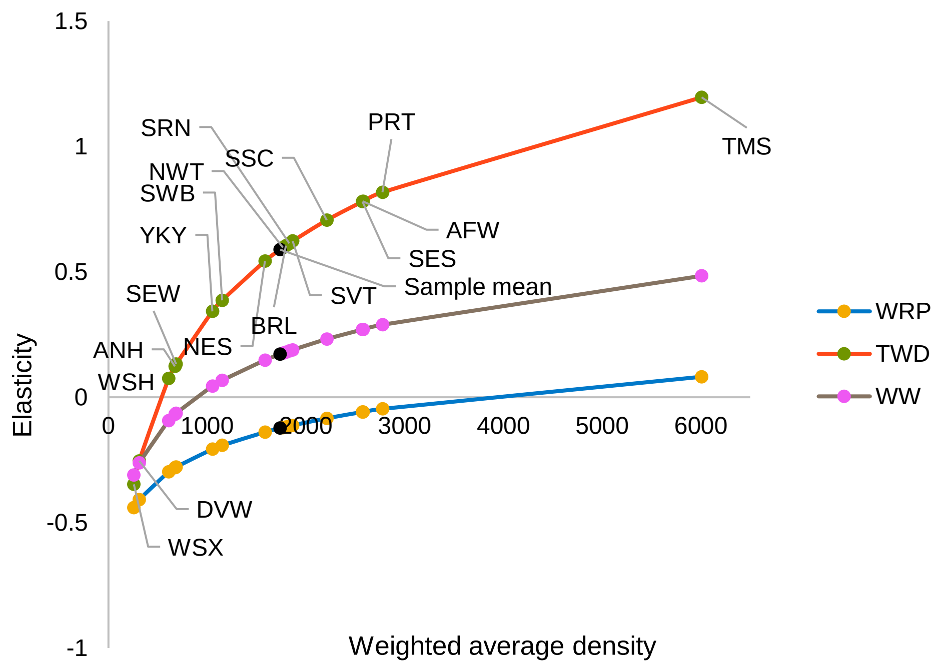
- **Densities:** We calculate the population density per each local authority district (LAD) as population per squared km.

- **Weights:** the weight assigned to the density of each LAD is the population in the LAD, which resides within the company's service area, divided by the total population in the companies' service area.

We also include a quadratic term of density to allow for potential opposing effects on costs as described above. As shown in table 1, the density terms in our models suggest that, at lower levels of density, scale economies are strong and therefore increasing density reduces costs. However, the positive effect of the quadratic term suggests that as density rises its negative impact on costs decreases, ultimately becoming positive at high values of density.

Figure 1 shows how the elasticity of costs for different levels of aggregation varies with respect to density across companies. The elasticity of TWD costs with respect to density is higher than that of WRP. This may be because scale economies might be weaker for TWD compared to WRP, where the inclusion of scale effects in treatment works tends to lower costs as density increases. Furthermore, the additional access and property costs associated with higher density are more pronounced in TWD than in WRP. This latter observation explains why the elasticity for TWD is above for Thames Water, the company with the highest density.

Figure 1: The distribution of weighted average density elasticities in different models



Other cost drivers

We have paid careful attention to companies' view on cost drivers. Companies proposed various drivers, including regional wages, asset age and the proportion of lengths of main renewed and relined.

We considered the role of regional labour costs in explaining variation in cost across companies. We have consistently found that the regional wage level is not a robust cost driver. In many specification the variable has very low predictive power, and sometimes it showed a counter-intuitive negative sign (albeit statistically insignificant). CEPA came to the same conclusion in its report.[3] Thames Water has submitted models with regional wage as driver for our consultation. The driver was not statistically significant in any of the models and its predictive power was poor. We recognise that variation in labour cost can have an impact on costs although companies can exercise control to mitigate this impact. We consider also that the

[3] The report was published alongside our consultation: CPR19 Econometric Benchmarking Models, CEPA March 2018.

inclusion of a density variable, and a square of density, in our models, capture the effect of regional wage as the two are correlated.

In the models presented in our consultation we included asset age and maintenance related variables to capture the effect of older networks and workload on costs. In response to our consultation, a number of companies raised concerns that these variables are under management control and that data quality for asset age is poor. We decided not to include these variables in our final models for the IAP.

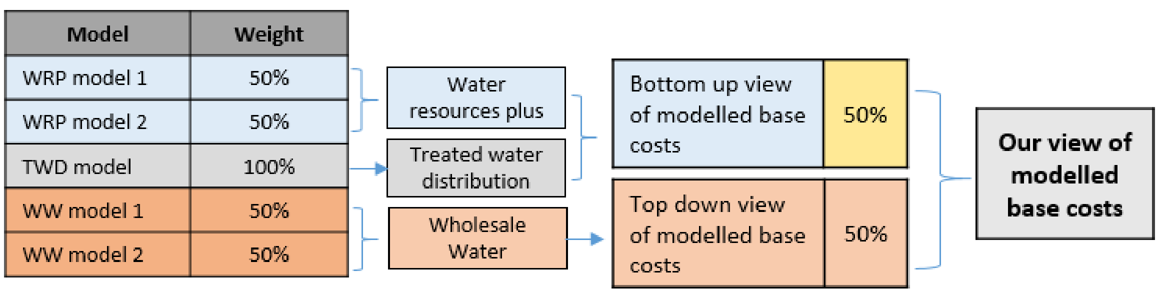
We also considered including a time trend or time dummy variables for individual years, however such variables did not have a stable or significant effect on the model.

3.5 Triangulation and setting allowances

Figure 2 illustrates our triangulation approach. We assign weights to the five models in wholesale water to estimate a view of wholesale modelled base costs. In the first step, the results of the two water resources plus models are averaged and added to the treated water distribution model to form our 'bottom up' view. The two wholesale modes are averaged to form our 'top down view'. We then average the bottom up and top down views to arrive at our view of modelled base costs in wholesale water.

Our choice of level of aggregation provides us with estimates of efficient costs at a different level of aggregation than needed for our price controls. To determine control level cost allowances, we apply the proportions of business plan base costs relating to water resources and network plus to our efficient wholesale modelled base costs.

Figure 2: Triangulation of wholesale water models



4. Cost models for wholesale wastewater activities

In this chapter we present the econometric models we have used to assess wholesale wastewater costs in the IAP. The chapter is structured as follows:

- Our econometric models for wholesale wastewater activities;
- Data;
- Our choice of dependent variables;
- Our choice of cost drivers;
- Triangulation and setting allowances.

4.1 Our econometric models for wholesale wastewater activities

Table 3 presents the eight econometric models we use to benchmark costs of wholesale wastewater services.

Table 3: Econometric models for wholesale wastewater

Model name	SWC1	SWC2	SWT1	SWT2	BR1	BR2	BRP1	BRP2
Dependent variable (log)	Sewage collection		Sewage treatment		Bioresources		Bioresources + Sewage treatment	
Sewer length (log)	0.739***	0.714***						
Load (log)			0.795***	0.779***			0.788***	0.770***
Sludge produced (log)					1.058***	1.183***		
Load treated in size bands 1-3 (%)			0.045**				0.039**	
Load treated in size band 6 (%)				-0.012*				-0.010**
Pumping capacity per sewer length (log)	0.170**	0.346**						
Load with ammonia consent below 3mg/l (%)			0.004***	0.004***			0.005***	0.005***
Number of properties per sewer	1.471***							
Weighted average density (log)		0.256**			-0.280 (0.121)			
Sewage treatment works per number of properties						0.320*		
Constant term	-8.907***	-5.037***	-5.498***	-4.203***	0.749	0.746	-5.107***	-3.944***
Overall R-Squared	0.91	0.82	0.87	0.85	0.80	0.80	0.92	0.92
Number of observations	70	70	70	70	70	70	70	70

Notes: Dependent variable is modelled base costs in 2017/18 prices, using the CPIH adjustment for each level of aggregation. P values expressed in parentheses are based on clustered standard errors at the company level. *, ** and *** denote significance level at 10, 5 and 1 per cent respectively.

4.2 Data

For wholesale wastewater we use panel data of 70 observations. The panel data includes information on the 10 wastewater companies in operation over seven years, from 2011-12 to 2017-18. The data is sourced from business plan data tables.

In AMP7 there will be 11 wastewater companies (the additional company is HDD, which has been supplying wastewater services from 1 July 2018). In Appendix 1 we set out how we determine allowances for the 11 wastewater companies with the models we estimated using historical data for the 10 companies in the sample.

4.3 Our choice of dependent variables

The dependent variable is constructed from business tables and is the sum of operating costs, maintenance capex (lines 11-13 in table WWS1) and transferred private sewers and pumping stations costs (WWS2, line 78), excluding the following lines:

- Business rates (WWS1, line 8);
- Third party services (WWS1, line 10);
- Costs associated with Traffic Management Act (WWS5, line 5);
- Costs associated with Industrial Emissions Directorate (WWS5, line 9).

Following feedback to our consultation and advice from Vivid Economics, we include ‘income treated as negative expenditure’ for bioresources (BR). As income generation is a significant contributor to bioresources activities, such income should be netted from base costs to correct for revenue generation opportunities in bioresources. Not including this line in base costs would disincentive income generation and available efficiency opportunities would not be achieved.

We include costs associated with transferred private sewers and pumping stations. Those assets have been transferred to the ownership of the water companies. Any remaining costs is considered part of base costs. Our allowance for these costs is made through our econometric models rather than as a separate assessment.

Levels of aggregation

Table 4 presents the dependent variables that we explored to benchmark using econometric models per each level of aggregation.

Table 4: Levels of aggregation of the dependent variable in wholesale wastewater

Granularity	Dependent variable	Adopted?
Granular	Sewage collection costs	✓
	Sewage treatment costs	✓
	Bioresources costs	✓
Mid-level	Bioresources costs + Sewage treatment costs (“Bioresources plus”)	✓
	Sewage collection costs + Sewage treatment costs (“Network plus wastewater”)	✗
Aggregated	Wholesale wastewater costs	✗

As can be seen in the table above, we did not adopt models at the network plus and wholesale levels. We consider that the models we selected, at the granular and bioresources plus (BRP) levels, provide a more robust set with which to obtain a baseline for efficiency assessment.

The models we have selected include costs drivers that mirror engineering and operational considerations, with a plausible sign and size for the estimated parameters. Our decision to use these levels of aggregation is in line with findings from our consultants, Vivid Economics.

We found a number of issues with models at the network plus and wholesale level. In both cases, factors that capture economies of scale in treatment (see below) often lack statistical significance and/or fluctuate in sign and size between different possible model specifications. Such a finding is likely due to scale having different effects in different parts of the value chain. The effect of density is also ambiguous across different parts of the value chain (for example, in sewage collection (SWC) and sewage treatment models (SWT) – see section 4) and may also contribute to the statistical performance of these models.

4.4 Our choice of cost drivers

The key factors driving costs for wholesale wastewater activities are:

- **Scale/output/volume** – larger scale/output/volume drives higher total costs;
- **Size of treatment works** – larger size allows lower unit cost due to economies of scale at the treatment level;
- The **topography** of a company's geographical area;
- Treatment **complexity** – higher complexity drives higher costs; and
- The **density** of the network and/or the population served.

We discuss these factors below.

Scale

Scale is a key driver of costs. Larger operations deliver more output and incur greater costs.

For our sewage collection models, we use the length of sewers as a measure of scale. For our sewage treatment and bioresources plus models, we use the organic load received at sewage treatment works, and for our bioresources models, we use the volume of sludge produced. These scale drivers were widely supported by companies in our consultation. The drivers have a strong and consistent statistical performance in our models and a strong narrative as cost drivers for the respective value chain. Consistent with expectations, the estimated coefficients are positive and relatively close to one.

We considered a number of alternative scale drivers. For example, for our collection models we considered the volume of wastewater received at treatment works, and the lengths of sewer replaced or renewed. The narrative and statistical performance of our selected driver, the length of sewers, was stronger than that of the alternative measures.

We also consider data quality issues. For example, a couple of companies have raised data quality concerns with the measure of load received at treatment works. We have tested an alternative scale variable in our models, the number of connected properties, which produced very similar results. However, we found that load could explain more variation in the cost data and has a stronger engineering link with costs. Therefore, we maintain the load variable in our models.

We find the variation in scale across companies explains a large proportion of the variation in costs. The value of the estimated coefficients varies from 0.71 to 1.18, which is a plausible range. The high end of the range is in the bioresources models, where we expect costs to be more responsive to scale due to a lower proportion of long-lived assets, and therefore fixed costs.

While in theory we would expect the coefficient to be below one (but not a lot below one), indicating, on average, economies of scale (namely, a one percent increase in scale leads to a less than one percent increase in cost), in practice the variable could deviate from the expected range (eg due to inaccuracies related to a small sample, data quality and an “omitted variable bias”, where the coefficient “compensates” for the effect of an omitted factor). We do not consider that our model selection should be influenced by whether the estimated coefficient is slightly above one, despite the difference in theoretical interpretation of the coefficient on either side of unity.

Size of treatment works

We expect large treatment works to have a lower unit cost of treatment than small treatment works.

We use two measures in our sewage treatment and bioresources plus models (as both of these contain treatment costs). One variable is the proportion of load treated at small works (bands 1-3), measuring any diseconomies of scale from operating small works. The other variable is the proportion of load treated at the largest category of works (band 6), to capture economies of scale at very large treatment works. We have tested models with both variables included but rejected them due to issues of multicollinearity.

We have adopted a model which includes the proportion of load treated at works at band 6, following feedback from our consultation. Companies have argued that using only the proportion of load treated at small works will understate the effect of economies of scale in sewage treatment, particularly at the largest size treatment plants.

Our models show a statistically significant economies of scale effect on sewage treatment costs.

Topography

In hillier terrains, lifting sewage in order to transport it to treatment works requires more energy, hence more pumping stations or capacity. In flatter regions, fewer pumping stations or capacity is needed.

To capture the effect of topography on the cost of running the sewage network, we use pumping capacity per sewer length. This variable was generally favoured by companies in response to our consultation and provides the best statistical results with the correct sign across all specifications. Variables tested, but rejected, include pumping station density (ie the number of pumping stations per unit sewer length) and pumping capacity (without being normalised by the length of sewers).

Complexity

Complexity is a key cost driver of sewage treatment. More onerous discharge consent limits tend to require more, or larger, treatment process units and are therefore more costly to comply with.

In our consultation, we proposed using the proportion of load with treatment work consents with ammonia <=1mg/l to account for treatment complexity. Consistent with responses to our consultation we replaced the 1mg/l threshold with a 3mg/l threshold. There are very few companies with treatment works of <=1mg/l ammonia consent. The 3 mg/l threshold provides more variability across companies. The new variable also produces more statistically robust results than other potential measures tested.

The coefficient on our complexity variable is positive, indicating that a tighter ammonia consent increases costs. This is to be expected as the wastewater needs to have a longer residence time in the treatment process units, which therefore need to be larger and use more energy to operate. This variable performs more strongly in bioresources + sewage treatment models than in sewage treatment-only models. This may also be expected, given that sludge rich in ammonia may also need separate treatment before being returned to the sewage treatment stream.

Density

The population density of company service areas could affect costs in different ways. Higher density may allow for the use of larger, more efficient, treatment works. However, for sewage collection mainly, higher density may be associated with a more complicated operating environment and higher access costs. We find that such intuition, particularly for collection activities, is supported by the results from our sewage collection and bioresources models.

For sewage collection, we use two measures of density: the number of connected properties per sewer length and ‘weighted average density’ (see chapter 3 for description of the weighted average density). Both measures perform well in the models and are statistically significant. The estimated coefficient is consistently positive, indicating that for networks of similar sewer length, denser networks are more expensive to operate and maintain, eg due to higher access costs in urban areas, a greater likelihood of need for traffic management, service diversions etc. This variable may also capture effects from higher wages in more urban and therefore denser areas. We triangulate two models using both measures to utilise the subtly different insights we can gain from both. Network density, ie the number of connected properties per sewer length, is a more direct measure of the cost driver and reflects that companies with a larger number of properties per km of sewer are likely to incur higher costs. The weighted average density has the advantage that it is fully exogenous (ie beyond management control).

For bioresources models, we have selected the weighted average density and the number of sewage treatment works per properties. Our models show that bioresources costs decrease with density. A bioresources provider can use larger sewage treatment works for larger population centres with lower associated unit costs, due to economies of scale.

We also explored the specification of non-linear relationships between density measures and costs across wastewater models, as in wholesale water. However, we do not include quadratic density terms, as these were not found to be statistically significant. Such a finding is unsurprising given wastewater companies in our sample are relatively similar, whereas water companies are more heterogeneous.

Other cost drivers

In addition to scale, economies of scale at the treatment works level, topography, complexity and density, we also extensively tested other cost drivers through our own analysis, with our consultants Vivid Economics and through consulting with companies.

For sewage collection we tested variables relating to drainage costs. This variable was suggested in our consultation by some companies, such as United Utilities. United Utilities constructed an urban runoff variable using data on urbanisation rates, rainfall and soil permeability, as developed by ARUP. Data on soil permeability is not sufficiently transparent. We developed a slightly different urban runoff variable to capture differences between wastewater companies in urbanisation rates and rainfall. Including this variable in a model aims to control for the effect of surface runoff on combined sewage collection system costs.

We consider that the measure does not perform well in the model. While it is statistically significant and positive in sewage collection models, it attenuates the main scale variable to insignificance.

For sewage treatment we considered the proportion of load from trade effluent. We found that the estimated coefficient of this variable fluctuates materially across specifications and does not plausibly explain costs.

For bioresources, we considered disposal factors such as intersiting (ie the degree that sludge has to be transported to a central treatment centre), the percent of intersiting work done by trucks and tankers and the percent of sludge disposed via farmland. We found these factors not consistently important in determining costs. We also tested the inclusion of sludge treated using anaerobic digestion. We did not include this in our models, as there was no clear narrative for the expected sign of the coefficient.

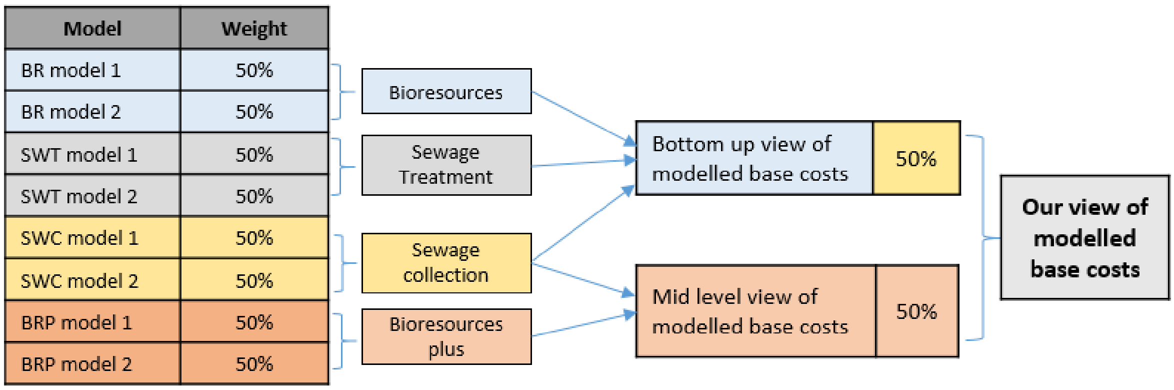
As in wholesale water, we considered regional wages as a cost driver but such variable did not perform well in models.

4.5 Triangulation and setting allowances

In the initial assessment of business plans we used our set of models to assess efficiency at the wholesale wastewater level.

Figure 3 sets out our triangulation approach for the eight models in wholesale wastewater to achieve a view of average wholesale modelled base costs. At each level of aggregation we have two models. We average their results in the first step. In the second step we add the results of the sewage collection, sewage treatment and bioresources model to form our ‘bottom up’ view. We add the results of the sewage collection and bioresources plus to form our ‘mid-level’ view. We do not use wholesale wastewater models. In the third step we average our bottom up and mid-level views to arrive at our view of modelled base costs in wholesale wastewater. At the IAP we focus on efficiency at the wholesale level. At draft determinations we will set cost allowances for sub-services within wholesale wastewater.

Figure 3: Triangulation of wholesale wastewater econometric models



In draft determinations we will set an allowance for the bioresources and the network plus controls. Our models can be readily used to set allowances for these controls – by using the bioresources models for the bioresources controls, and the treatment and collection models for the network plus control.

The bioresources plus models cut across two controls. We will apportion the results of these models between bioresources and treatment, so that these components can also be used for determining the allowance for the PR19 controls.

5. Cost models for residential retail controls

In this chapter we present the econometric models we have used to assess residential retail costs in the IAP. The chapter is structured as follows:

- Our econometric models for residential retail activities;
- Data;
- Our choice of dependent variables;
- Our choice of cost drivers;
- Triangulation of our residential retail models.

5.1 Our econometric models for residential retail activities

Table 5 presents the nine econometric models we use to benchmark costs of residential retail activities.

Table 5: Econometric models for residential retail

Model name	RDC1	RDC2	RDC3	ROC1	ROC2	RTC1	RTC2	RTC3	RTC4
Dependent variable (log)	Bad debt and bad debt management costs per household			Other retail costs per household		Total retail costs per household			
Average bill size (log)	1.138***	1.070***	1.079***			0.458***	0.518***	0.488***	0.378***
Households with default (%)	0.060**					0.021 (0.146)	0.030**		
Council tax collection rate		-0.324***							-0.263***
Income deprivation (%)			0.057**					0.042**	
Net migration (%)			-0.015 (0.511)						
Dual customers (%)				0.002**	0.003**				
Metered customers (%)				0.006***	0.006***	0.003 (0.392)	0.004 (0.218)	0.002 (0.559)	0.003 (0.250)
Number of connected households (log)					-0.054 (0.234)		-0.065 (0.121)	-0.058 (0.176)	
Constant term	-5.63***	28.08***	-4.33***	2.47***	3.18***	0.08	0.34	0.78*	26.89***
Overall R-Squared	0.78	0.78	0.76	0.16	0.19	0.65	0.69	0.65	0.72
Number of observations	88	88	88	88	88	88	88	88	88

Notes: Dependent variable is modelled total costs in 2017/18 prices, using the CPIH adjustment for each level of aggregation. P values expressed in parentheses are based on clustered standard errors at the company level. *, ** and *** denote significance level at 10, 5 and 1 per cent respectively.

5.2 Data

To estimate the models' parameters, we use panel data of 88 observations. The panel data has five years of data. The first three years, from 2013-14 to 2015-16, include data on 18 water companies. The last two years, from 2016-17 to 2017-18, include data on 17 water companies due to the merger between South West Water and Bournemouth Water.

Our main source of data is the Annual Performance Reports, which the water companies report yearly to Ofwat. We also use data from other reports to Ofwat (eg accounting separation and blind year tables). Some of our cost driver data is sourced externally. We discuss cost driver data as part of our discussion of cost drivers below.

5.3 Our choice of dependent variables

The dependent variable includes all residential retail costs, including depreciation and recharges, but excluding third party costs and pension deficit repair costs. We make an allowance for these costs separately.

Levels of aggregation

Table 6 presents the levels of cost aggregation that we tested for econometric modelling, and whether a model at that level was adopted.

These levels of aggregation are those we proposed in our PR19 methodology and in our March consultation on econometric modelling. Companies generally agreed or did not raise an issue with this proposal.

We model bad debt and debt management costs together as they are closely interlinked. For example, an increase in bad debt may trigger an increase in debt management costs. An increase in debt management costs, particularly if related to preventing bad debt, may lead to lower levels of bad debts. Due to annual reporting, it is impossible to disentangle causality between bad debt costs and debt management costs, hence we model them jointly. Modelling bad debt and debt management costs together also allows us to better capture the specific relationship between debt-related costs and their unique drivers, such as bill size and deprivation.

Table 6: Levels of aggregation of the dependent variable in residential retail

Dependent variable	Adopted?
Bad debt and debt management	✓
Other retail costs Other retail costs is total retail costs less bad debt and debt management costs: customer services + other operating expenditure + meter reading + local authority rates plus exceptional items + depreciation + net recharges	✓
Total retail costs	✓

Specification of the dependent variable as cost per household

We specify the dependent variables in all our retail models as retail costs per connected household (that is, as a unit cost) rather than as total costs. We consider that comparing cost per connected household is more intuitive given that retail costs are driven primarily by the number of customers. Our conclusion is supported by academics, as well as several companies, who felt it was a more precise predictor of retail costs.

A few companies raised concern that a unit cost model imposes restrictions on the model. Specifically, a restriction that costs vary in the same proportion to the number of households (this is known as “constant returns to scale”). However, as we said in our consultation, specifying the dependent variable as cost per household does not, by itself, impose restrictions on our models. Constant returns to scale are assumed only if we do not include the number of households as an explanatory factor.

Indeed in most of our models we adopted the constant returns to scale assumption in relation to the number of households and did not include it as an additional explanatory factor in the model. That was a choice informed by analysis, not an assumption inherent to the specification of the dependent variable. For those models, an additional advantage of the unit cost specification is that it frees up one degree of freedom for the estimation of the model’s parameters. In three of our models we included the number of households as a cost driver, relaxing the constant returns to scale assumption.

Depreciation

In our ‘other retail costs’ and total retail cost models we include depreciation. Depreciation accounts for the reduction in the value of a company’s fixed retail assets over time. The depreciation data in our sample is quite lumpy (being impacted by the lumpy nature of investment). We decided to smooth depreciation costs over the five-year period, to help reflect a more appropriate relationship of the cost with the explanatory factors in the model.

Recharges

We include net recharges as these represent a cost for the retail business. Net recharges are the differences between recharge costs and income. Retail incurs recharge costs when it uses assets principally attributed to another price control (eg wholesale) and earns recharges income when other price controls use its assets.

5.4 Our choice of cost drivers

We use the following cost drivers in our residential retail models:

- The average **bill size** per retailer;
- The **propensity to default** in a company service area (three measures);
- **Net migration**, a measure of population transience**;**
- The proportion of **dual service customers**;
- The proportion of **metered customers**; and
- The **number of households** served to capture economies of scale.

We derive our measures for propensity to default and our transience measure by aggregating local authority (LAD) data to company service areas using information submitted by the water companies.

We discuss each driver below.

Average bill size

Customer bill size represents the amount of revenue at risk if a customer defaults. Over time we expect a one to one relationship between bill size and the level of bad debt.

Average bill size is a key driver of bad debt and debt management costs. We include this variable in all our **bad debt models**, where it is statistically significant with a coefficient slightly above 1. The value of the coefficient is within a reasonable range. It suggests that an increase of one percent in average bill increases bad debt and debt management costs by slightly more than 1 percent. The fact that it is higher than 1 may suggest that as bills increase there are two factors that affect costs. First, the revenue at risk increases. Second, the likelihood of default increases.

We include average bill size also in our **total retail cost models**. The size of the coefficient more than halves as compared to its size in our debt models, reflecting that bad debt is a smaller proportion of total costs in these models.

There was wide agreement in response to our consultation that average bill size is a key driver of debt costs. A few companies were concerned that this driver might unfairly penalise water only companies, which often have lower bills. When collecting debt, a water-only company may face the same costs, but collect less bad debt due to the smaller bill size. Larger bills also come with more debt recovery tools and court enforcement options. We tested an interaction term to measure the difference in the impact of bill size on bad debt between water-only companies and water and sewerage companies. We concluded that the difference was not significant.

Propensity to default

A company that operates in an area with a higher propensity to default on payments, is expected to incur higher debt and debt management costs, all else equal.

We use three variables to proxy for a company's customers' propensity to default.

- The level of income deprivation in the company's area, sourced from ONS;
- The percentage of households with default in the company's area; and
- Council tax collection rate in the company's area, sourced from ONS.

We use these variables in our **bad debt models** and in our **total retail cost models**. All three variables perform well in our models.

All companies agreed that propensity to default is an important driver of bad debt. Some companies used different proxies in their models, such as unemployment rate, mortgage repossession or proportion of customer on prepayment meters. Amongst the proposed proxies, the ones we use had the widest support.

Some companies argued that deprivation may be associated with more frequent contact and therefore relevant to other retail services. We did not find statistical evidence that deprivation measures were relevant in our other retail costs models.

The percentage of households with default at company level is sourced from United Utilities. United Utilities originally procured the data from Equifax at postcode level, which it then aggregated up to LAD and then company level. In response to our March consultation, several companies were in favour of using this variable as this is a direct measure of propensity to default in an area. A fewer number of companies had concerns that this variable was partly under management control and was, thereby, endogenous, or that its construction lacked transparency. We have considered these arguments, but do not consider them to be persuasive, so we use this variable in some of our bad debt and total retail cost models. The variable is a direct measure of propensity to default and has the longest time series out of the three measures of deprivation we use. The variable performs well in our models. We do not think endogeneity is a significant issue as many sectors contribute to the construction of this variable. We consider that there is sufficient visibility on how this variable is constructed in Reckon's working paper for United Utilities[4].

Respondents to our consultation were strongly in favour of the income deprivation domain as a proxy for propensity to default. They consider this variable to be intuitively correct and exogenous.

Transience

High transience rates can result in reduced ability for companies to recover unpaid bills and consequently higher bad debt and debt management costs.

To capture the impact of transience, we use total inflows and outflows of internal and international migration rates. Internal migration captures migration between local authorities within the UK, and international migration captures migration to and from the UK.

We considered this variable in our models following feedback to our consultation.

[4] Source: Reckons, *Capturing deprivation and arrears risk in household retail cost assessment*. Working paper for United Utilities, 10 May 2017, page 32. For IAP, we source the Equifax data through United Utilities who confirmed to us that the company level data can be shared with others. For draft determinations, we may procure the data directly from Equifax.

We include the variable in one of our **bad debt models**, despite its weak statistical significance, as the estimated coefficient is consistent with the narrative above, and stable.

The variable does not perform well in two of our bad debt models – the ones including ‘customer with default’ and ‘council tax collection rate’ – perhaps because these proxies for propensity to default capture the effect of transience.

Proportion of dual service customers

Dual service customers receive both water and wastewater services from the same company. Dual customers may generate more contact and enquiries relative to single service customers, which in turn drives customer service costs. We expect such incremental costs associated with dual customers to be small.

We include the proportion of dual customers in our **other retail costs** models. The variable is statistically significant, positive, and small in magnitude as expected.

Dual customers also drive higher bad debt relative to single service customers given their larger average bill. We do not include the proportion of dual customers as a driver in total retail cost models because it is highly correlated with the average bill size.

Proportion of metered customers

We expect retailers to incur additional costs with metered customers, due to meter reading and additional enquiries relative to unmetered customers.

In responses to our consultation there was wide support for this driver. We include the proportion of metered customers in our **other retail costs models**. The variable is significant and positive as expected. We also use the variable in our **total retail cost models** where it is positive with a stable and plausible value, although statistically insignificant.

Number of connected households

The number of connected households is the main driver of retail costs. Based on our analysis, retail costs increase at the same rate as the increase in the number of households served. For this reason, as discussed above, we specify our dependent variable as costs per households rather than total costs. This specification is intuitively appealing for benchmarking analysis of retail costs, and it allows us to use one less explanatory variable in the model, which has statistical benefits.

With a dependent variable specified as cost per household, the purpose of the driver ‘number of connected households’ is to capture economies of scale. That is, if average costs (ie cost per household) decreases with scale (ie with number of households) the variable would have a negative coefficient.

A number of companies commented on the need to allow for economies of scale in retail models. Some companies said that our assumption (in those models where we did not include households as an explanatory variable) that costs grow at the rate as the rate of household growth is too restrictive. There were also supporting view for such assumption. United Utilities commented that “we have seen evidence of companies taking action to benefit from economies of scale through joint ventures and joint billing for example. Including economies of scale could therefore disincentivise efficient company activity.”

We tested the number of connected households in our other retail costs models and total retail costs models. While the estimated coefficients are not statistically significant under the common thresholds of statistical significance, we consider that they are relatively robust. The estimated coefficients are of the expected sign (negative), are relatively stable and their p-values are not too high. In some models, including the number of households as an explanatory factor improves the statistical significance of other cost drivers (eg of the percentage of dual customers) and the R squared. We said in our consultation: “With a relatively small sample we are careful not to dismiss mechanistically variables that are not strictly statistically significant, so long as the significance is still reasonable and the estimation seems robust.”

In light of these results, we include this variable in one of our two **other retail costs models** and two of our four **total retail costs models**.

We do not include this variable in our debt models. Economies of scale do not seem to be an important factor for bad debt costs. While economies of scale could be relevant for bad debt management costs, we do not consider that the scale of the retailer is relevant given availability of third party providers for this service. Controlling for economies of scale could disincentivise efficiency procurement of third party services.

A low R squared in our 'other retail costs' econometric models

Our 'other retail costs' models have a low R squared, at 0.16 and 0.19. The low R squared means that the explanatory variables explain only a small proportion of the variation in the dependent variable, other retail costs per household. This is to some extent a cosmetic point which results from our specification of the dependent variable as cost per household. With this specification, we neutralise the main driver of costs – the number of households served. The remaining variation is relatively small – significantly smaller from the variability of bad debt costs per household and total retail costs per household.

To some extent, our modelling suggests that using an average cost to serve approach for other retail costs is a sensible approach – any variation not explained by the number of households served may be regarded as noise. However, we consider that our models provide a small advantage over an average cost approach, with two variables that are intuitive, statistically significant, and explain some of the variation in unit costs across companies.

Other cost drivers not included in our models

In our consultation we presented models that included **dummy variables**. The year dummies capture changes in costs that are common to all companies in a given year. The year dummies suggested a drop in costs from 2015-16 onwards, namely from the first year that we introduced a separate retail control.

We have excluded the year dummies from our models. This is because their statistical significance has reduced with the addition of 2017-18 data and with the move from the OLS method that we used in our consultation to the random effects method that we use in the IAP.

Companies suggested a range of other potential cost drivers, for example **regional wage, density, sparsity** and **service quality** and **peak traffic speed**.

As outlined in our PR19 methodology, we consider that an efficient company can substantially mitigate or remove the impact of high regional labour costs on their total retail costs, possibly with the exception of metering, which is around 5% of total retail costs. We do not consider variation in regional wages to be an important factor in explaining variation in retail costs across companies. We found no statistical evidence that it is. Most respondents to our consultation agreed with this reasoning.

As for density and sparsity, there is little reason to assume that these variables should affect other retail costs. Whilst some companies argued that sparsity and density may be associated with metering costs, our tests show contradicting coefficient signs for these variables. Therefore, we do not consider there to be a strong enough theoretical or econometric justification for their inclusion.

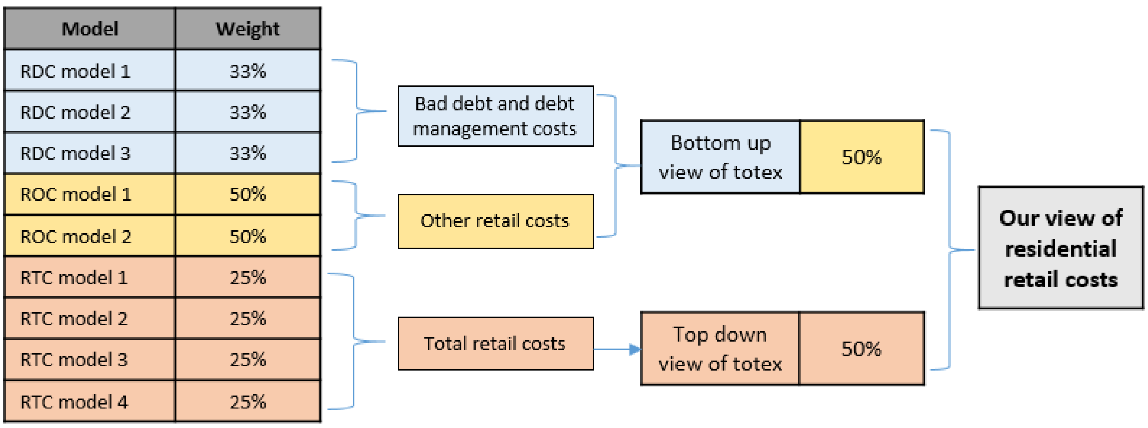
One company proposed retail service quality as a cost driver in its models. We are concerned that such drivers are strongly endogenous and it is therefore not appropriate to include them in an econometric model. We consider that our wider framework rewards a high service level via the C-mex mechanism.

One company proposed peak traffic speed as a cost driver of the meter reading activity. In response to our consultation a few companies argued against this variable, as articulated by South Staffs Water: "The meter reading costs may be affected by traffic however this is only one small element of the retail cost and we would expect this to be a marginal cost impact given that optimisation of metering routes could significantly negate the issue."

5.5 Triangulation and setting allowances

Figure 4 sets out our triangulation approach of the nine models to achieve a final view of residential retail costs. In the first step we average the set of models at each level of aggregation. In the second step we add the results of the debt and other retail costs models to form our 'bottom up' view. Our 'top down' view is simply the result of averaging the four total retail cost models in the first step. In the third step we average our bottom up and top down views to arrive at our view of modelled residential retail costs.

Figure 4: Triangulation of wholesale wastewater econometric models



Appendix 1: Approach to company mergers and business reconfiguration

In AMP6 there were two changes to company structure in the water sector: The incorporation of Bournemouth Water by South West Water, and the reconfiguration of Severn Trent Water and Dee Valley Water. Below we discuss how we treated these structural changes in our modelling.

South West Water and Bournemouth Water Merger

From 2016-17 onwards, South West Water incorporates Bournemouth Water.

This merger happened during our modelling sample period. Our approach is to use the actual structure of the companies in each year of our modelling sample.

In wholesale water and residential retail we keep South West Water and Bournemouth Water as separate entities for the years up to the merger (ie up to 2015-16). During these years we have observations on 18 companies. For the remaining years, namely for 2016-17 and 2017-18, we use the merged company with aggregated data. We therefore have observations on 17 companies. In econometrics this is called an unbalanced panel.

There is no impact on wholesale wastewater modelling as Bournemouth Water did not provide wastewater services.

Severn Trent Water and Dee Valley Water business reconfiguration

In July 2018 the respective businesses of Severn Trent Water (SVT) and Dee Valley Water (DVW) were reconfigured into an English water company, Severn Trent Water (SVE) and a Welsh water company, Hafren Dyfrdwy (HDD). SVE and HDD do not serve the same customers and areas to those previously served by SVT and DVW and HDD (unlike DVW) now provides wastewater services as well as supplying water.

As the reconfiguration did not occur in our modelling sample period, our models are based on data for SVT and DVW. Below we clarify our approach to setting cost allowances for the reconfigured companies, SVE and HDD.

To set allowances for SVE and HDD in wholesale water activities we follow the steps below:

1. We estimate efficient costs for SVT and DVW using model coefficients and our independent forecast of their cost drivers.
2. We sum these costs to derive a total allowance for the combined business.
3. We estimate efficient costs for SVE and HDD using model coefficients and forecasts of cost drivers as provided by SVE and HDD.[5]
4. We apportion the costs estimated in step 2 to SVE and HDD based on their respective estimate of efficient costs calculated in step 3.

This approach ensures that our cost allowance for the combined company remains independent to its reconfiguration. We rely on company forecasts of cost drivers only for the purpose of apportioning the total cost of the combined company between the SVE and HDD. This approach ensures that our cost allowance for the combined company remains independent. We rely on company forecast of cost drivers only for the purpose of apportioning the total cost of the combined company between the SVE and HDD.

This approach also appropriately takes into consideration differences in cost drivers between SVE and HDD (for example, relative to the simpler approach we use in wastewater as described below).

To set cost allowances for SVE and HDD in wholesale wastewater activities we use a simpler approach:

1. We estimate an allowance for the combined entity of SVE and HDD for the AMP7 period based on models' coefficients and our independent forecast of the cost drivers for SVT (as historical SVT provided wastewater services for the combined supply area).
2. We apportioned the allowance to SVE and HDD based on their respective business plan forecasts for total wholesale wastewater costs.

This approach is appropriate for wastewater as all the companies in our sample are substantially larger than HDD (DVW has not historically provided wastewater services). We consider that under these circumstances using model coefficients to estimate an allowance for HDD would be inappropriate. Such an estimate would be unreliable as the level of HDD's cost drivers are far outside the bounds of the sample used to estimate coefficients for wastewater models.

[5] An exception is the weighted average density. As this was not available for the new company boundaries, the level of weighted average density for SVT was used for SVE and the level for DVW was used for HDD.

We chose to take the same approach in residential retail. We think it is reasonable to apportion costs to SVE and HDD on the basis of their business plan forecasts as the retail function of both companies, and their cost drivers, has not changed significantly since the reconfiguration of companies.

Appendix 2. Statement from our academic reviewers

Professor Andrew Smith

This review concerns Sections 1 to 4 of this report and covers the cost models for water and wastewater. I have acted as an independent academic advisor to OFWAT, challenging their approach to the water and wastewater cost modelling process at various stages of the modelling and consultation process. The presented document provides an accurate, summarised reflection of that process and its outcomes.

My role was to question and challenge Ofwat and its consultants on the approach taken, whilst not getting involved every detail of the model selection decisions. Overall I consider that Ofwat and its consultants have developed a pragmatic and robust set of econometric models that are suitable for use as part of PR19. As adviser to Ofwat during PR14 I have also seen how the modelling approach and process has developed between the two reviews.

Several points are worth noting:

1. Considerable effort has been put in to improving the engineering understanding and rationale for the variables included in the model.
2. Consultation has taken place with the companies, including through working groups.
3. Consideration has been given to academic and regulatory best practice and also to the points raised by the CMA during the challenge by Bristol Water at PR14. Ofwat has taken a balanced approach, taking on board the CMA’s comments, whilst also retaining its independence and leaving open decisions to be made based on appropriate engineering and statistical criteria. A sensible and pragmatic approach has been taken to the inclusion of squared terms in the modelling for example.
4. Model selection criteria were set out at the outset and Ofwat has in my view appropriately taken account of the different criteria to achieve a balanced and pragmatic set of models that also reflect the relatively small sample size available for analysis.

Possible areas for reflection going forward include: further consideration of how to model regional wage effects; and further development of the engineering understanding not only of the expected signs of the coefficients, but also of their magnitudes. Whilst the magnitudes of some of the core variables such as scale are discussed and compared against expectations (eg whether there are economies of scale or not), it has been harder to be precise about the expected size of some of the other coefficients from an engineering / business perspective. This is to some extent inevitable given that part of the aim of the econometric process is to yield new insights on the impact of variables on costs. However, consideration as to how to cross-validate against other evidence would be useful going forward.

Dr Thijs Dekker

This review concerns Sections 1, 2 and 5 of this report and covers the cost models for residential retail controls. I have acted as an independent academic advisor to Ofwat challenging their approach to retail cost modelling at various stages of the modelling and consultation process. The presented document provides an accurate reflection of that process and its outcomes.

Overall, I am of the opinion that the econometric models presented for residential retail costs in Section 5 are of the required standard for inclusion in PR19. It should be highlighted that retail cost models were not included in PR14 and were developed in a challenging context. As such, there are opportunities for further refinements in the future but the key cost drivers have been included.

Several reflections on the models are provided below.

1. First, the right decision has been made to develop the models at a unit cost rather than total cost level. Intermediate results had shown that models at the total cost level were dominated by the scale variable and thereby prevented identification of the effects of relevant cost drivers.
2. Second, the selection of the cost drivers proved to be challenging in particular in finding suitable measures of the propensity to default (ie deprivation). The adoption of the Equifax measures is therefore considered to be a reasonable second-best solution despite the small risk of endogeneity associated with these variables.
3. Third, the limited fit of the 'other retail' cost models is striking and this also has a direct impact on the total cost models. Indeed, the broad nature of this cost category makes it challenging to identify suitable cost drivers and it appears that the number of customers is the main cost driver.
4. Finally, the developed models have taken on board suggestions from the industry regarding the main drivers of these costs (eg the percentage of dual and metered customers). The estimated parameters for these drivers are of the right sign and show a plausible relationship.

Ofwat has been very transparent about the development of the retail cost models both to the industry and to the independent reviewers. I have appreciated the opportunity to challenge the models at various stages of the process.

Ofwat (The Water Services Regulation Authority) is a non-ministerial government department. We regulate the water sector in England and Wales. Our vision is to be a trusted and respected regulator, working at the leading edge, challenging ourselves and others to build trust and confidence in water.

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January 2019

This document is also available from our website at www.ofwat.gov.uk.

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