July 2024

PR24 draft determinations

Expenditure allowances – Base cost modelling decision appendix

Ofwat

Summary

This document sets out the econometric cost models we have used to help set efficient base expenditure allowances for our PR24 draft determinations. It follows our April 2023 'Econometric base cost models for PR24' consultation, and sets out how we considered stakeholder responses to decide on our model suite for draft determinations.

Base costs are routine, year-on-year costs, which companies incur in the normal running of the business to provide a base level of service to customers and maintain the long-term capability of assets. This covers both wholesale and retail activities.

There are three key elements to setting efficient base expenditure allowances:

- Base cost econometric benchmarking models
- Cost adjustment claims
- Unmodelled base cost assessment

This document focuses on our base cost econometric benchmarking models, which are the starting point of our base cost assessment.

Our econometric benchmarking models allow us to compare base costs between companies on a like-for-like basis by taking into account multiple factors that drive differences in efficient base costs between companies and over time. For example, company size, population density, treatment complexity, etc. They help to overcome information asymmetry between Ofwat and water companies, and challenge companies to be efficient. We triangulate across a set of models with different cost drivers and levels of cost aggregation to mitigate the risk of error and bias in any one model.

Overall, we have made a limited number of changes to our proposed set of models we consulted on. These were mainly to reduce the number of wastewater network plus and bioresources base cost models. Our selected models perform well against our model selection criteria and are sufficiently robust to set efficient base expenditure allowances at PR24.

Wholesale water base cost models

We use **6 water resources plus (WRP) models**; **6 treated water distribution (TWD) models**; and **12 wholesale water (WW) models** to help set efficient wholesale water base expenditure allowances at PR24 draft determinations.

The key drivers of wholesale water activities are **scale**; **treatment complexity**; **network topography** and **population density**.

We have made the following improvements to our PR19 wholesale water cost models:

- We include **average pumping head** in a subset of our proposed treated water distribution and wholesale water models to capture network topography.
- We include **three alternative population density measures** in our proposed models. Two of the measures are based on granular population density data from the Office for National Statistics.

We have made no changes to our wholesale water base cost models following our April 2023 base cost modelling consultation.

Wastewater network plus base cost models

We use **3 sewage collection (SWC) models, 2 sewage treatment (SWT) models, and 2 wastewater network plus (WWNP) models** to help set efficient wastewater network plus base expenditure allowances at PR24.[1]

The key drivers of wastewater network plus activities are **scale; economies of scale at sewage treatment works (STWs); treatment complexity; network topography; population density; and urban rainfall**.

We have made the following improvements to our PR19 wastewater network plus models:

- **Include an alternative economies of scale at STWs variable** to better capture economies of scale at large STWs. Our weighted average sewage treatment works size (WATS) variable is used alongside the PR19 economies of scale at STWs variable – percentage of load treated in STWs bands 1 to 3.
- **Include alternative weighted average population density drivers** in SWC models based on Middle Super Output Area (MSOA) population density data from the ONS.
- **Include urban rainfall in our SWC and WWNP models**. This variable aims to reflect the volume of inflows into drainage and sewerage networks.
- **Add top-down WWNP models** to the modelling suite, which allows us to triangulate between models of different levels of cost aggregation.

Since our April 2023 base cost modelling consultation we have:

- **Removed one alternative economies of scale at STWs variable**. We dropped the percentage of load treated in STWs serving more than 100,000 people variable due to low company support and superiority of the WATS measure.
- **Developed a more granular urban rainfall variable (urban MSOA rainfall).** This variable captures rainfall within urban MSOAs. We developed this variable in response to company feedback that urban rainfall should reflect actual rainfall within urban areas.
- **Dropped SWC and WWNP models** that do not include urban rainfall.
- **Estimated a post-modelling adjustment** that funds efficient ongoing opex associated with PR19 WINEP / NEP phosphorus removal schemes.

[1] Wastewater network plus = sewage collection + sewage treatment.

Bioresources base cost models

We use **4 bioresources unit cost models** to help set efficient bioresources expenditure allowances at PR24 draft determinations.

We consider the key exogenous drivers of bioresources unit costs are **economies of scale in sludge treatment;** and the **location of sewage treatment works relative to sludge treatment centres**, which causes differences in efficient sludge transport costs**.**

We use the same explanatory variables to proxy the key cost drivers as we did in PR19:

- **Weighted average population density, sewage treatment works (STWs) per property, and percentage of load treated at band sizes 1 to 3** to control for economies of scale in sludge treatment and the location of sewage treatment works relative to sludge treatment centres.

Since our April 2023 base cost modelling consultation, we have decided **not to use bioresources total cost models**. Bioresources unit cost models performed better after we included the additional 2022-23 year of data and are more consistent with the average revenue bioresources control.

Residential retail cost models

We use **2 bad debt cost models**, **2 other retail cost models**, and **4 total retail cost models** to help set efficient residential retail expenditure allowances at PR24. In each model, the dependent variable is specified as cost per household.

We consider the key residential retail base cost drivers are: the **amount of revenue at risk** if a customer does not pay their water bill; a customer's **propensity to default**; **type of customer**; and **economies of scale**.

Covid-19 led to an increase in companies' bad debt provisions, which was not explained by the key residential retail base cost drivers. This weakened the performance of PR19 residential retail models. We have addressed these issues through the following changes to our PR19 residential retail cost models:

- **Inclusion of two Covid-19 dummy variables for 2019-20 and 2020-21.**
- **Removal of transience variable.**
- **Removal of proportion of metered households variable.**

Following our April 2023 base cost modelling consultation, **we decided to exclude the average number of county court judgements/partial insight accounts per household**, which we consulted on as a potential alternative explanatory variable to proxy a customer's propensity to default. The variable received mixed support from companies, with some expressing concerns around it being somewhat endogenous, and its performance in the retail models worsened with the addition of 2022-23 outturn data.

Contents

1. Introduction

1.1 Aims of document

This document sets out the econometric cost models we have used to help set efficient base expenditure allowances for our PR24 draft determinations. It follows our April 2023 'Econometric base cost models for PR24' consultation, and sets out how we considered stakeholder responses to decide on our model suite for draft determinations.

The scope of the document includes wholesale water, wastewater network plus, bioresources and residential retail base cost models. We also describe our approach to triangulating between models (ie the weight we apply to each model to set efficient base expenditure allowances).

The document accompanies, and should be read alongside, our 'PR24 draft determinations: Expenditure allowances' document.

1.2 Background

Base costs are routine, year-on-year costs, which companies incur in the normal running of the business to provide a base level of service to customers and maintain the long-term capability of assets. This covers both wholesale and retail activities.

There are three key elements to setting efficient base expenditure allowances:

- Base cost econometric benchmarking models
- Cost adjustment claims
- Unmodelled base cost assessment

This document focuses on our base cost econometric benchmarking models, which are the starting point of our base cost assessment. Cost adjustment claims and unmodelled base cost assessment are discussed in our 'PR24 draft determinations: Expenditure allowances' document.

Our econometric benchmarking models allow us to compare base costs between companies on a like-for-like basis by taking into account multiple factors that drive differences in efficient base costs between companies and over time. For example, company size, population density, treatment complexity, etc. They help to overcome information asymmetry between Ofwat and water companies, and challenge companies to be efficient. We triangulate across a set of models with different cost drivers and levels of cost aggregation to mitigate the risk of error and bias in any one model.

We consulted on our proposed set of base cost models in April 2023.[2] We received responses from all incumbent water and wastewater companies. We have since carefully considered consultation responses to arrive at the set of base cost models we have used to help set efficient base expenditure allowances for PR24 draft determinations.

Overall, we have made a limited number of changes to our proposed set of models we consulted on. These were mainly to reduce the number of wastewater network plus and bioresources base cost models. Our selected models perform well against our model selection criteria and are sufficiently robust to set efficient base expenditure allowances at PR24.

1.3 Structure of the document

The remainder of this document is structured as follows:

- Chapter 2 outlines our approach to model development and selection.
- Chapter 3 presents our selected wholesale water base cost models.
- Chapter 4 presented our selected wastewater network plus base cost models.
- Chapter 5 presents our selected bioresources base cost models.
- Chapter 6 presents our residential retail base cost models.

All the accompanying data sets and Stata do files that we used to produce the econometric models which have been used to set efficient base expenditure allowances at PR24 draft determinations are available on our website.

[2] Ofwat, 'Econometric base cost models for PR24', April 2023.

2. Approach to model development and selection

This chapter outlines our approach to developing and selecting the econometric cost models we have used to help set efficient base expenditure allowances at PR24 draft determinations.

2.1 Scope of modelled base costs

The scope of modelled base costs for draft determinations includes operating expenditure (opex), capital maintenance expenditure, and some enhancement as set out in the table below.

The main differences from PR19 are the exclusion of the following growth related costs from the base cost models at PR24:

- **Site-specific developer services costs** – site-specific developer services are removed from the price control at PR24 for English water companies, so it does not make sense to continue to include in the base cost models.[3]
- **Growth at sewage treatment works** – following Arup's recommendation, we have assessed growth at sewage treatment works enhancement separately from base costs at PR24.

[3] Wastewater site-specific developer services are removed from the price control at PR24 for companies operating in Wales. But water site-specific developer services remains in the price control for companies operating in Wales, and has been assessed as part of unmodelled base costs.

Table 1: scope of modelled base costs for draft determinations

Cost area	Modelled base cost definition
Wholesale water	• Opex • Capital maintenance expenditure • Network reinforcement expenditure • Addressing low pressure enhancement expenditure
Wastewater network plus	• Opex • Capital maintenance expenditure • Network reinforcement expenditure • Reducing risk of sewer flooding enhancement expenditure • Transferred private sewers and pumping stations enhancement expenditure • Enhancement opex for a subset of enhancement lines where we have reasonable certainty the costs are ongoing (nitrogen removal, phosphorus removal; reduction of sanitary parameters; ultraviolet (UV) disinfection; chemical removal schemes)
Bioresources	• Opex • Capital maintenance expenditure • Sludge growth enhancement expenditure • Sludge quality enhancement opex
Residential retail	• Doubtful debt • Debt management costs • Other retail costs (including customer services, meter reading, depreciation)

In response to our base cost modelling consultation, we only received a small number of comments on the scope of modelled base costs.

Wessex Water recognised we included enhancement opex for a subset of enhancement lines into the scope of modelled base costs. However, it suggested we also request further data from companies to identify all elements of enhancement opex where expenditure is ongoing and include that in our base cost models. We consider we have added the large majority of enhancement opex that is ongoing. Wessex Water did not identify material expenditure areas that we had not included in the scope of modelled base costs. No other company suggested doing any further work in this area, and we consider it would be disproportionate to request further data from companies for PR24.

Portsmouth Water argued for assessing network reinforcement separately as it will depend on network capacity which it considers is not captured well in our models. We continue to consider that network reinforcement expenditure should be included in the scope of modelled base costs due to substantial interactions with capital maintenance expenditure and a close relationship with base cost drivers (eg scale and density). Portsmouth Water could have submitted a cost adjustment claim if it expected to deliver a higher amount of network reinforcement work than is funded through the base cost models. For example, if it expects to experience higher population growth than most companies in the sector, and the network reinforcement costs associated with that high growth are material.

United Utilities argued that including historical bioresources growth enhancement expenditure in the scope of bioresources base costs may not provide a sufficient bioresources growth allowance due to phosphorus removal increasing sludge production. Our base cost models provide a long-term bioresources growth allowance for the sector, and many companies have funded upgrades of sludge treatment centres to advanced anaerobic digestion (AAD) through base expenditure allowances in the past. We therefore consider our efficient bioresources base expenditure allowances allow companies to invest in additional capacity to respond to future sludge growth. United Utilities did not submit a cost adjustment claim relating to this issue.

Dŵr Cymru recognised that we included historical quality enhancement operating expenditure in the scope of bioresources modelled base costs. However, it stated we should consider if the allowances for PR24 are sufficient to fund future changes in enhancement opex due to new legislation. We include historical enhancement opex in our models so that ongoing opex resulting from historical enhancement upgrades are reflected in efficient base expenditure allowances. This aligns with our approach to assessing wastewater network plus base costs. A step-change in enhancement opex resulting from new legislation arriving in the 2025-26 to 2029-30 period would be assessed as enhancement.

2.2 Level of cost aggregation

We triangulate across a range of models with different cost drivers and levels of cost aggregation. This reduces the risk of error and bias in any one model.

The levels of cost aggregation we have used to help set efficient base expenditure allowances at PR24 draft determinations is summarised below. Disaggregated cost models can enable a wider range of cost drivers to be captured in our cost assessment approach. But more aggregated models capture interactions between different services and mitigate potential cost allocation issues.

Compared to PR19, we have added wastewater network plus (sewage collection + sewage treatment) models to, and removed bioresources plus (sewage treatment + bioresources) models from, the base cost modelling suite. We set separate efficiency challenges for wastewater network plus and bioresources at PR24, which has been facilitated by work to improve cost allocation between sewage treatment and bioresources since PR19.

Table 2: level of cost aggregation for PR24 base cost models

	High level of cost aggregation	Medium level of cost aggregation	Disaggregated cost models
Wholesale water	**Wholesale water**: water resources + raw water distribution + water treatment + treated water distribution	**Water resources plus**: water resources + raw water distribution + water treatment	**Treated water distribution**
Wastewater network plus	N/A	**Wastewater network plus**: sewage collection + sewage treatment	• **Sewage collection** • **Sewage treatment**
Bioresources	N/A	N/A	**Bioresources**
Residential retail	**Residential retail**: bad debt + other retail costs	N/A	• **Bad debt** • **Other retail costs**

We have made no changes to the levels of cost aggregation following our base cost modelling consultation. Companies generally supported the level of cost aggregation with only a couple of potential issues raised.

Firstly, Dŵr Cymru, United Utilities and Yorkshire Water disagreed with the absence of bioresources plus models because of perceived cost allocation issues and trade-offs between sewage treatment and bioresources. Since PR19, we have improved cost allocation between sewage treatment and bioresources. We consider this allows us to assess wastewater network plus and bioresources costs separately and set separate efficiency challenges at PR24.

Secondly, SES Water suggested we remove the bottom-up residential retail models from the modelling suite due to concerns over the predictive power of the 'other retail costs' models in particular. We do not consider these concerns have any merit as 'other retail costs' are primarily driven by the total households served, which is not reflected in the reported R-squared due to the unit cost model specification. Once included, the R-squared increases to around 0.97. On this basis, we see the low R-squared in our other retail cost models as a cosmetic issue. We consider our bottom-up residential retail models are sufficiently robust to set efficient residential retail expenditure allowances, and allow us to triangulate across models with different cost drivers and levels of cost aggregation. We therefore retain the bottom-up residential retail models in our modelling suite.

2.3 Panel data structure and sample period

We use a long time series of historical data from water companies, going back to 2011-12 for wholesale water and wastewater, and 2013-14 for residential retail, to estimate our base cost econometric models. This allows us to use panel data analytical techniques. We use the full historical data series to develop the base cost models to maximise model precision and accuracy. This also helps to capture the cyclical nature of capital maintenance expenditure. We have extended the dataset to include 2022-23 outturn data since the April 2023 base cost modelling consultation.

The panel data structure used for model development is summarised below.

Table 3: panel data structure and sample period

	Number of companies	Number of years	Number of observations	Treatment of company mergers
Wholesale water	17	2011-12 to 2022-23 (12 years)	204	• South West Bournemouth (SWB) is used instead of South West Water (SWT) and Bournemouth Water (BWH) separately for the entire sample period. • Severn Trent Water (SVT) and Dee Valley (DVW) are used up to 2017-18. Severn Trent Water England (SVE) and Hafren Dyfrdwy (HDD) are used from 2018-19 onwards.
Wastewater network plus	10	2011-12 to 2022-23 (12 years)	120	• The combined entity of Severn Trent Water England (SVE) plus Hafren Dyfrdwy (HDD) is used for the entire sample period.
Bioresources	10	2011-12 to 2022-23 (12 years)	120	• As above for wholesale wastewater network plus.
Residential retail	17	2013-14 to 2022-23(10 years)	170	• As above for wholesale water.

We did not receive any specific comments relating to the historical time series used to estimate the econometric base cost models.

Several companies emphasised the importance of ensuring efficient base expenditure allowances reflect forward looking cost pressures. We considered including business plan forecasts in the dataset used to estimate the base cost models. But several companies raised concerns that this would introduce endogeneity into the base cost assessment in response to our PR24 draft determination. We tested the inclusion of forecast costs into base cost models. However this benefited those companies with high forecasts, rather than better reflecting forward looking trends. Instead, we focused on sector wide cost adjustments where we identified clear cost drivers that suggest the future is likely to be different to the past: energy prices; ongoing opex related to enhanced phosphorus removal; meter replacement; mains replacement; and net zero. Further details are provided in our 'PR24 draft determinations: Expenditure allowances' document. We also cross-checked our efficient base expenditure allowances against business plan forecast expenditure and historical expenditure to provide further reassurance.

2.4 Model estimation method

We use random effects to estimate the base cost econometric models. We also used random effects at PR19, and so did the CMA in the PR19 redeterminations. Random effects estimation explicitly takes into account the panel data structure, which is why it is preferred over standard ordinary least squares (OLS) estimation. The Breusch-Pagan test results consistently support use of the random effects method over OLS.

In response to our April 2023 base cost modelling consultation, Yorkshire Water and South East Water said that Ofwat should consider the validity of alternative estimation methods such as OLS and stochastic frontier analysis either to directly inform allowances or as a robustness test. We do not consider this is necessary. We did not consider using OLS to estimate our base cost models as the Breusch Pagan test results always supported random effects instead of OLS estimation. We set out reasons for not adopting alternative estimation methods such as fixed effects and stochastic frontier analysis in our assessing base costs at PR24 consultation.[4]

Severn Trent Water suggested we should use the Swamy-Arora estimator rather than the Random Effects estimator when using an unbalanced panel. As stated by Severn Trent Water, this affects the standard errors rather than the estimated coefficients. We do not consider it is proportionate or necessary to change our estimation method as the company did not identify any cases where using the Swamy-Arora estimator would lead to a different model selection or improve the accuracy of our models.

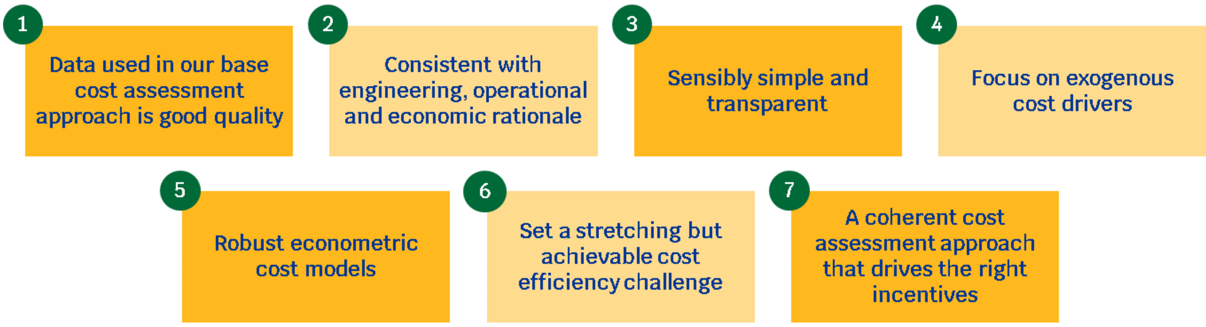
2.5 Model selection process, including the process we followed to review stakeholder responses

In our PR24 final methodology, we set out our intention to build on our PR19 base cost models, making improvements where appropriate.[5] Our model selection process reflects this, and we set a high bar for making changes to our PR19 base cost models.

Our principles of PR24 base cost assessment are summarised below.

[4] Ofwat, 'Assessing base costs at PR24', December 2021, pp. 35-36.
[5] Ofwat, 'Creating tomorrow, together: Our final methodology for PR24. Appendix 9 Setting expenditure allowances', December 2022, pp.8-9.

Figure 1: Principles of PR24 base cost assessment



Source: Ofwat, 'Creating tomorrow, together: Our final methodology for PR24. Appendix 9 Setting expenditure allowances', December 2022, p.8.

We took steps to help ensure that the data used to estimate the base cost models is of good quality. We went through a comprehensive data review process in summer/autumn 2022, and water companies reviewed their own data as part of this process. Since the April 2023 base cost modelling consultation, we have added 2022-23 outturn data to the historical data set following a thorough review of the data we received in July 2023.

Our emphasis has been to develop and select simple and transparent cost models that are consistent with engineering, operational and economic rationale. This allows the models to capture the key cost drivers, and that the resulting efficiency analysis reflects actual differences in relative efficiency instead of other factors.

We have focused on selecting exogenous cost drivers to support the independence of our efficient base expenditure allowance and avoid the risk of perverse incentives. For example, inflating cost driver forecasts to receive a higher allowance and/or causing suboptimal investment decisions (eg deciding to increase replacement of certain assets to receive a higher allowance even if it is not needed).

Our cost models should accurately and precisely predict and forecast efficient costs. To achieve this, we have assessed the models against a range of model robustness tests:

- Are the estimated coefficients of the **right sign and of plausible magnitude**?
- Assess the **ability of the models to explain variations in efficient base historical expenditure** between companies and over time (eg adjusted R-squared and efficiency score ranges).
- How do the models perform across a range of **statistical diagnostic tests** (eg statistical significance of individual parameters, RESET test for omitted non-linearities, multicollinearity test, etc.)?
- Are the estimated model results **stable / robust to changes in the underlying assumptions and data** (eg different sample period; alternative model specification)?

- Cross-check efficient base allowances against business plan forecast costs, PR19 base allowances, and outturn spend over the past 5-years.

We recognise that any one econometric model may not pass all model robustness tests. Setting such a high standard would not be a desirable outcome given the importance of econometric cost models in reducing information asymmetry between Ofwat and water companies.

Annex A1 includes the model robustness tests that we used to assess the performance of each model, with its relative degree of importance. We considered the relevant importance of each test result when selecting the base cost models used to help set efficient base expenditure allowances at PR24 draft determinations. We show how our selected base cost models perform against the model robustness tests below.

We have also re-assessed the performance of our proposed set of base cost econometric models with the addition of 2022-23 data. We explain any changes to our base cost models since our April 2023 consultation in the sections below.

3. Wholesale water base cost models

Summary

We use **6 water resources plus (WRP) models**; **6 treated water distribution (TWD) models**; and **12 wholesale water (WW) models** to help set efficient wholesale water base expenditure allowances at PR24 draft determinations.

The key drivers of wholesale water activities are **scale**; **treatment complexity**; **network topography** and **population density**.

We have made the following improvements to our PR19 wholesale water cost models:

- Including **average pumping head** in a subset of TWD and WW models to capture network topography. We also include models that include booster pumping stations per length of mains, which was the topography variable used at PR19.
- Including models that include three different population density measures:
    i. **weighted average density – local authority districts (LAD) from Middle Super Output Area (MSOA)**;
    ii. **weighted average density – MSOA**; and
    iii. **properties per length of mains**.

We have made no changes to our wholesale water base cost models following our April 2023 base cost modelling consultation.

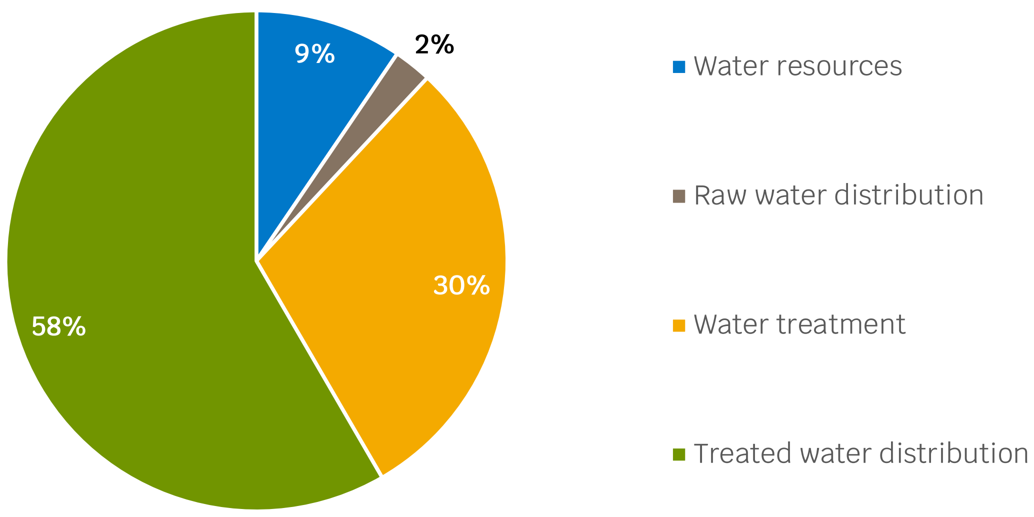
This section presents our econometric benchmarking models used to help set efficient wholesale water base expenditure allowances at PR24 draft determinations. It is structured as follows:

- defining the dependent variable;
- selected cost drivers;
- cost drivers not included in our proposed models; and
- wholesale water base cost econometric models.

3.1 Defining the dependent variable

Wholesale water base costs included in our models were £4.6 billion across the sector in 2022-23. Treated water distribution expenditure made up over half of wholesale water modelled base expenditure in 2022-23.

Figure 2: make-up of wholesale water base expenditure in 2022-23



Our dependent variable for wholesale water modelled base costs includes:

- Operating expenditure (opex)
- Capital maintenance expenditure (capex)
- Network reinforcement expenditure
- Addressing low pressure enhancement expenditure

In April 2023,[6] we consulted on the proposed econometric models that we intend to use to help set efficient base expenditure allowances at PR24, as per the following levels of aggregation:

- **High level of aggregation:** Wholesale water: water resources + raw water distribution + water treatment + treated water distribution
- **Medium level of aggregation**: Water resources plus (WRP): water resources + raw water distribution + water treatment
- **Disaggregated cost models:** Treated water distribution

3.2 Selected cost drivers

We consider the key wholesale water base cost drivers are:

- Scale
- Treatment complexity

[6] Ofwat, 'Appendix 9 -Setting expenditure allowances', April 2023.

- Network topography
- Population density

The remainder of this section discusses these cost drivers and the corresponding explanatory variables that are included in our wholesale water base cost models.

3.2.1 Scale

Scale is a key cost driver. All things equal, a company serving a larger customer base would be expected to incur higher costs.

We use the same explanatory variables we used at PR19 to capture scale. We expect the estimated coefficients on the scale variables to be close to one, indicating that doubling the scale variable results in a doubling of costs (ie constant returns to scale).

Water resources plus (WRP) models

In the WRP models, we use **number of properties** (household plus non-household) as the measure of company scale. This is an intuitive scale variable because WRP costs include expenditure for sourcing and treating water, and we expect the amount of water to be related to the number of properties served. Stakeholders supported this in response to our April 2023 base cost modelling consultation.

Treated water distribution (TWD) models

In the TWD models, we use **length of potable water mains** as the measure of company scale. This is the most intuitive scale variable because TWD costs are associated with running a distribution network consisting mainly of water mains. Companies have a degree of control over length of mains, but it remains substantially determined by exogenous factors.

Stakeholders generally supported this decision in response to our April 2023 base cost modelling consultation. But South East Water and Yorkshire Water asked us to revisit the use of total connected properties as a scale variable in the TWD models because in their view it captures certain aspects of TWD modelled base expenditure better, including network reinforcement.

After consideration, we have decided not to include connected properties in the TWD models. Connected properties is the most intuitive scale drive of TWD base costs from an engineering perspective, and connected properties is highly correlated with length of mains. So, we do not consider doubling the number of TWD models is proportionate or needed given the impact on the outcome would be very small.

Wholesale water (WW) models

In the WW models, we use **number of properties** as the measure of company scale.

South West Water recommended that both number of properties and length of potable water mains are used as the scale variable in the WW models. It argued that TWD costs represent a large proportion of WW costs, and the number of properties and length of potable water mains are used as scale variables in the WRP and TWD models.

After consideration, we have decided not to include length of potable water mains as a scale variable in the WW models. It is not an intuitive driver of water resources and water treatment costs, which are largely driven by quantity and quality of water sourced and treated, rather than network length.

In addition, because number of properties and length of mains are highly correlated, using both variables as scale drivers in separate wholesale water models would lead to similar results, not justifying doubling the number of wholesale water models. And models using properties per length of main as the density variable produce the same outcome irrespective of whether properties or length of mains are used as the scale variable due to the laws of logarithms.

3.2.2 Treatment complexity

Water treatment works can reflect both the quality of the raw water sources supplying the works and any requirements for the quality of the treated output. Where the treatment complexity is higher, costs are expected to increase due to the challenge of maintaining and operating multiple stages of treatment that use more power and chemicals.

Companies report the volume of water treated at treatment works of different complexity levels, ranging from zero to six.[7]

The explanatory variables we use to capture complexity of treatment are **the proportion of water treated at complexity levels from 3 to 6**, and **the weighted average treatment complexity**. The same variables were used at PR19.

The first variable **is the proportion of water treated at complexity levels 3 to 6**. As set out in PR19,[8] statistical analysis and engineering rationale show 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

[7] Ofwat, 'RAG 4.11 – Guideline for the table definitions in the annual performance report', April 2023, p.109
[8] Ofwat, 'Supplementary technical appendix: Econometric approach', January 2019, p.13

those treating good quality groundwater sources, while level 3 will introduce works with multiple treatment stages treating lower quality raw water sources.

The second measure is a **weighted average treatment complexity measure (WAC).** Each level of complexity, as defined in our annual reporting tables (ie levels 0 to 6), is weighted by the proportion of water treated at that level.

Table 4: weighted average treatment complexity (WAC) measure calculation

	Complexity level 0	Complexity level 1	Complexity level 2	Complexity level 3	Complexity level 4	Complexity level 5	Complexity level 6
Weight	1	2	3	4	5	6	7
% water treated	1%	1%	17%	17%	14%	50%	0%
(C) = (A) x (B)	0.0	0.0	0.5	0.7	0.7	3.0	0.0
WAC = sum of row C	4.9						

The estimated coefficient on weighted average treatment complexity is not statistically significant at the 10 percent level in the WRP models. We do not consider this requires us to disregard this variable. The underlying engineering rationale is sound, and the magnitude of the estimated coefficient is in line with expectations.

In response to our April 2023 base cost modelling consultation, Severn Trent Water argued there are material cost differences between the treatment processes within bands. For example, it considers that ultraviolet (UV) treatment is cheaper than other processes listed as a band 4/5 treatment process, and that there are different levels of interstage pumping within a given band. To account for these factors, it suggests either adding average pumping head (APH) water treatment in the WRP models and/or using alternative weights to calculate the weighted average treatment complexity variable. We disagree. APH water treatment reduces the statistical significance of our water treatment complexity variables, which are the closest approximation of water treatment complexity available, and are well established and understood in the sector. We remain with the simple treatment complexity weights to calculate the weighted average treatment complexity variable as they are simple, intuitive and generally supported by companies.

Yorkshire Water suggested taking the logarithm of the weights used to calculate the weighted average treatment complexity variable. This implies the cost impact of moving from complexity band 1 to 2 is greater than the cost impact of moving from complexity band 2 to 3. We do not adopt Yorkshire Water's suggestion as we do not consider the alternative weights align with engineering rationale or are an improvement on the weights we used at PR19, which are simple and intuitive.

3.2.3 Network topography

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

We use two measures to capture network topography:

- **Booster pumping stations per length of mains.**
- **Treated water distribution (TWD) average pumping head (APH)**, which is a more direct measure of pumping requirements as it captures the volume of water pumped and the pressure at which it is pumped.

We used booster pumping stations per length of mains to proxy differences in network topography at PR19, and the CMA supported its use in its PR19 redeterminations.[9]

We considered APH at PR19, but did not include it in the models due to concerns over data quality and because it was not statistically significant. The CMA agreed with this assessment and did not use it in its PR19 redeterminations.[10]

Since PR19, we have worked with the industry to review APH reporting practices and improve consistency of reporting across companies,[11] and sent a letter to regulatory directors setting out our expectations on how companies should take on board the report recommendations when reporting APH in annual performance reports (APRs).[12]

Companies have taken steps to improve APH data quality since we published the APH data quality improvement report and accompanying letter. Companies revisited historical APH data through the 2022-23 annual performance review process and made comments in their APR submission about methodology improvements, for example:

- Anglian Water refers to an extensive overhaul of the APH reporting process, with daily data from the telemetry points used to produce APH figures. 85% of treated water distribution APH data is now measured.[13]

[9] Competition and Markets Authority, 'Anglian Water Services Limited, Bristol Water plc, Northumbrian Water Limited and Yorkshire Water Services Limited price determinations: final report', March 2021, pp. 139-142.
[10] Competition and Markets Authority, 'Anglian Water Services Limited, Bristol Water plc, Northumbrian Water Limited and Yorkshire Water Services Limited price determinations: final report', March 2021, pp. 139-142.
[11] Turner and Townsend, 'Average Pumping Head: data quality improvement Ofwat. Final report', March 2022.
[12] Ofwat, 'Average Pumping Head data quality improvement report is published', May 2022.
[13] Anglian Water, 'Annual Performance Report 2023', January 2024, pp. 248.

- Thames Water points to 69% of its treated water distribution APH data being measured data, 29% being partially measured, and only 2% being estimated in its 2023 APR submission.[14]

We conclude that APH data quality is better than at PR19, therefore we propose to include it in a subset of our models given it is supported by strong engineering rationale and performs well statistically.

For PR24, we triangulate across a range of treated water distribution and wholesale water models. 50 percent include treated water distribution APH to proxy network topography, and 50 percent include booster pumping stations per length to proxy network topography.

We consider this balances the pros and cons of each measure, and reflects the mixed feedback received in consultation responses.[15]

Booster pumping stations has better data quality than APH as it is uses 100 percent measured data, and consistently performs well in the econometric models. But it has weaker engineering rationale than APH as it only counts the number of boosters.

APH has a better engineering rationale as it is a more direct measure of pumping requirements as it captures the volume of water pumped and the pressure at which it is pumped. APH TWD also performs well in the TWD and WW models. It is statistically significant, increases the overall predictive power of the models, and is not sensitive to changes in the underlying sample. But APH data quality remains lower than booster pumping stations despite improvements made since PR19, and further improvements are needed to reach the target of 80% measured inputs. A collaborative forum led by water companies to share ideas and best practice should help improve APH data quality further. There is also some risk that including APH in the base cost models reduces the incentive on companies to reduce pumping head through pump optimisation.

We do not consider it is appropriate to include booster pumping stations per length of main and TWD APH in the same model.

Severn Trent Water, Wessex Water, Yorkshire Water and South East Water argue that booster pumping stations per length of mains and TWD APH should be included in the same model as it would help to fully account for topography as both measures capture different things. They consider TWD APH is a direct measure of pumping requirements and energy usage, whereas booster pumping stations per length of mains is a measure

[14] Thames Water, 'Annual Performance Report 2023', June 2023, p.224
[15] Northumbrian Water, Southern Water, United Utilities, Dŵr Cymru, Affinity Water and Portsmouth Water support booster pumping stations but not APH. Anglian Water, South West Water, Thames Water, SES Water and South Staffs Water support APH and not booster pumping stations. Severn Trent Water, Wessex Water, Yorkshire Water and South East Water support both APH and booster pumping stations.

of asset intensity. Severn Trent Water argue that many small boosters are needed to move water through hilly terrain to serve customers that live in rural areas.

TWD APH and booster pumping stations per length of main are both statistically significant when included in the same model. But we do not consider it is appropriate to include TWD APH and boosters in the same model.

Firstly, from an engineering perspective, booster pumping stations per length of mains is used as an imperfect proxy for pumping requirements, and not a measure of asset intensity or capital maintenance requirements. Network configuration is complex, and focusing on the number of boosters ignores other aspects of network complexity such as service reservoirs, water towers, and the degree of interconnectivity within a network. It is also not clear that operating many small boosters leads to higher maintenance costs than operating a large booster. Large boosters can have complex controls and high maintenance costs, and small boosters can have simple control arrangements and low maintenance costs.

Secondly, triangulating across models that include TWD APH and booster pumping stations per length of main separately also leads to a more intuitive outcome. For example, Severn Trent Water would receive a considerably higher allowance when TWD APH and booster pumping stations per length of main are included in the same model, but are around the sector average on both measures. Severn Trent Water did not argue that TWD APH and booster pumping stations per length of main should be included in the same model at PR19.

Thirdly, triangulating across models helps to mitigate omitted variable bias, and is consistent with our modelling principle of 'sensibly simple' models that include one variable for each key cost driver.

We do not include APH in water resources plus models

Severn Trent Water and SES Water argued for the inclusion of APH in WRP models. Severn Trent Water also argued for the inclusion of WRP APH alongside TWD APH in the wholesale water models. Both companies argued that excluding WRP APH from the base cost models means pumping before the network is being treated as an inefficiency.

We disagree with the inclusion of APH in our water resources plus models, and with the inclusion of WRP APH in the wholesale water models, for three reasons:

- APH water resources is not statistically significant in our WRP base cost models, which suggests it is not a material driver of water resources base costs when considered in-the-round against capital maintenance cost savings a company with a relatively high number of boreholes achieves versus a company with a relatively high number of raw water reservoirs.

- APH water resources plus is statistically significant in our WRP base cost models. But this is driven by APH water treatment, which is very weakly correlated with power costs, suggesting a spurious relationship.
- APH water resources plus reduces the statistical significance of the water treatment complexity variables, which suggests it is capturing differences in water treatment complexity rather than differences in pumping requirements. We consider our water treatment complexity variables are superior as they directly use water treatment works complexity data. No other company suggested using APH water resources plus as a proxy for water treatment complexity.

3.2.4 Population density

Population density can have two opposing effects on wholesale water base costs.

On one hand, companies operating in densely populated areas may have the opportunity to source and treat water using larger and fewer sources / treatment works, leading to lower unit costs. They may also be able to make more efficient use of resources, such as reduced travelling distances for maintenance and duplication of depots and spare parts to deliver good service.

On the other hand, companies operating in densely populated areas may bear higher property, rental, labour, and access costs. They also face a more complex operating environment, which may lead to higher costs:

- congestion of underground assets complicates access;
- higher electricity requirement to pump water to taller buildings;
- traffic which affects ground movement, increasing the frequency of repairs; and
- longer travel times due to congestion.

As a result, our wholesale water base cost models include a density variable and a quadratic density variable to allow for the opposing effects of population density on costs described above (ie parabolic relationship between costs and density).

Severn Trent Water has indicated that including the squared density in water resources plus models does not have a clear engineering rationale. But we disagree for the reasons set out above. Severn Trent Water also points to the Cook's Distance for Thames Water increasing when a quadratic term is included. But this is not surprising given Thames Water operates in the most densely populated area of England and Wales. And our analysis suggests the water base cost models remain robust to the exclusion of

Thames Water. We therefore continue to include a squared density term in the water base cost models, which is supported by most companies.

We include three measures of population density in our wholesale water models:

- **Weighted average density – Middle Super Output Area (MSOA).** This measure uses granular MSOA level data, mapped directly to company boundaries. Population density data is weighted by the population of the MSOA.
- **Weighted average density – Local Authority Districts (LADs).** This measure uses MSOA level data, mapped first to Local Authority Districts (LADs), and then from LADs to company boundaries. Population density data is weighted by the population of the LAD.
- **Properties per length of mains**.

Weighted average density – MSOA is the most granular measure of population density. There are more than 7,000 MSOA areas in England and Wales. But only around 350 LADs. So this measure may best reflect differences in population density within a company's operating region. It also has the advantage of being less sensitive to changes in geographical boundaries over time given MSOAs are less likely to change over time than LADs. But the MSOA weighted average density measure does lead to relatively large changes in efficiency scores.

Weighted average density – LADs is closest to the weighted average population density measure used at PR19. Compared to the PR19 LAD measure, it applies a more consistent and accurate approach to the mapping of LADs to company boundaries based on shape file published under the Open Government Licence,[16] instead of each company individually identifying the percentage allocation of LADs to their boundaries. This measure also provides a more accurate representation of density in shared LADs compared to the PR19 measure as it uses the information on the company's population density within the share of the shared LAD. Whereas the PR19 measure apportioned the average density per LAD to each company that operates in the shared LAD.

Properties per length of mains does not rely on external ONS data and is an intuitive measure of population density. But it is less exogenous than the weighted average population density measures and may not capture the differences in population density within a company's operating region as well.

Consultation responses were mixed, with each population density measure receiving similarly equal support. **We therefore include all three measures of population density in our wholesale water modelling suite**. We follow the suggestion to triangulate equally between the two weighted average density measures within each set of models (WRP,

[16] House of Commons Library, 'Constituency information: Water companies', October 2022.

TWD and WW) and the properties per length measure by Dŵr Cymru, Yorkshire Water and South East Water so that weighted average density measures have the same weight as properties per length of mains.

3.3 Other cost drivers proposed by companies

Responses to our April 2023 base cost modelling consultation included other cost driver suggestions. We set out why we have not included these in our wholesale water base cost models below.

3.3.1 Reservoir maintenance requirements

In our April 2023 base cost modelling consultation, we sought views on the need to collect additional data on the number of high-risk reservoirs subject to the inspection and maintenance requirements under the Reservoirs Act 1975.[17]

Nine companies[18] supported the collection of additional data on the number of reservoirs as they consider reservoir maintenance costs may be material. But six companies[19] disagreed with the proposal because they consider: the costs are likely to be immaterial; there is insufficient time to produce a high-quality dataset; or there are interactions with treatment complexity variables.

In the round, we proceeded with the information request to collect data on **large raised reservoirs that fall under the Reservoirs Act, 1975** as we understood it was easy for companies to provide. We constructed two variables with the data collected, that we tested in the water resources plus models:

- Reservoirs in category A normalised by the number of properties.
- Reservoirs in categories A and B normalised by the number of properties.

Categories were defined as follows:

- Category A: a breach could endanger lives in a community (where a community is considered to be not less than 10 people).

[17] A raised reservoir is "large" if it is capable of holding 25Ml (in England) or 10Ml (in Wales) of water above the natural level of any part of the surrounding land. See the definition in section A1 of the Reservoirs Act 1975.
[18] Severn Trent, Hafren Dyfrdwy, Thames Water, United Utilities, Dŵr Cymru, Wessex Water, Yorkshire Water, South East Water and South Staffs Water
[19] Affinity Water, Anglian Water, Northumbrian Water, Southern Water, South West Water and Bristol Water.

- Category B: a breach could endanger lives not in a community (inhabitants of isolated houses and operatives in treatment works immediately below the dam and in other places of work in the flood path and/ or could result in extensive damage).

Following careful consideration, we decided not to include either of the reservoir explanatory variables in the water resources plus models. The estimated coefficients on the reservoir variables were positive and small in magnitude, but were not statistically different from zero. This is likely to be because the additional costs of maintaining a relatively large number of reservoirs is offset by power cost savings achieved relative to a company that abstracts a relatively large proportion of distribution input from boreholes. The inclusion of the reservoir variables in the water resources plus models also reduced the statistical significance of the population density drivers.

3.3.2 Economies of scale at water treatment works

In response to our April 2023 base cost modelling consultation, South East Water and Southern Water disagreed with our decision not to include an explanatory variable in the water resources plus (WRP) models that directly captures economies of scale in water treatment works (WTWs). Both companies consider economies of scale at the water treatment works is a material cost driver.

We maintain our decision not to include a variable in the WRP models that directly captures economies of scale at water treatment works. CEPA tested different explanatory variables in the WRP models to capture economies of scale at WTWs[20]. For example, the proportion of distribution input treated in size bands 1 (small), 1-2, 1-3, 8 (large), 7-8, and 6-8. But the estimated coefficients had a counterintuitive sign and were statistically insignificant.

This suggests the inclusion of population density and water treatment complexity variables in the WRP models already capture the impacts of economies of scale at WTWs. Or that economies of scale in water treatment is not a material cause of cost differences between companies. The latter may be because inefficient small WTWs have been decommissioned over time, meaning the remaining small WTWs are not very expensive to operate and maintain.

[20] CEPA, ' PR24 Wholesale Base Cost Modelling'https://commonslibrary.parliament.uk/constituency-information-water-companies/', April 2023

3.3.3 Time trend, year dummies and other dynamic factors

In our April 2023 base cost modelling consultation, we decided not to include a time trend in the wholesale water base cost models for several reasons. We did not see clear evidence to explain the increase in water base costs in recent years, meaning there is a risk that the time trend would capture factors that are inside company control. We were also concerned that the increase in wholesale water base costs in recent years is not permanent and/or will not continue at the same rate. We prefer to focus on cost drivers that are exogenous and have a clear engineering, operational and economic rationale, as set out in our principles of PR24 base cost assessment. For similar reasons, we rejected the inclusion of year dummies and spatial lag dummies proposed by Wessex Water and Severn Trent Water. It is also not obvious how a time trend or year dummies should be used to forecast efficient allowances if included in the models.

In response to our consultation, South West Water and Wessex Water disagreed with our decision not to include a time trend or year dummies to capture wider cost pressures that the industry faces. South West Water claims the data indicates a structural break in 2016/17 with costs increasing by 12% across the industry. And Wessex Water consider our decision not to include a time trend conflicts with standard econometric practice.

South West Water and Wessex Water have not presented any new evidence that is sufficiently compelling to justify a change in approach. The arguments for not including a time trend set out above remain. We have also introduced sector wide cost adjustments for energy costs, mains and meter replacement, and net zero where the past may not be a good reflection of the future. And there is a risk that a time trend would double count the impact of these sector wide cost adjustments. Particularly the energy cost adjustment. We have also funded leakage reductions over the 2025-30 period through enhancement expenditure allowances instead of through base expenditure allowances.

And we set the catch-up efficiency benchmark on the last 5-years of outturn information, which also helps to capture other cost pressures not explained by the explanatory variables.

3.4 Selected wholesale water base cost models

Our wholesale water base cost model suite includes:

- 6 water resources plus (WRP) models
- 6 treated water distribution (TWD) models
- 12 wholesale water (WW) models

Table 5: Summary of wholesale water base cost models

Level of cost aggregation	Cost drivers	Explanatory variables
Water resources plus (6 models)	Scale	• Number of properties - included in 6 models.
	Treatment complexity	• Proportion of water treated at complexity levels from 3 to 6 – included in 3 models. • Weighted average treatment complexity – included in 3 models.
	Population density	• Weighted average density – LAD from MSOA (+ quadratic term) – included in 2 models. • Weighted average density – MSOA (+ quadratic term) – included in 2 models. • Properties per length of mains (+ quadratic term) – included in 2 models.
Treated water distribution (6 models)	Scale	• Length of the potable water mains – included in 6 models.
	Network topography	• Booster pumping stations per length of mains – included in 3 models. • Treated water distribution – Average pumping head – included in 3 models.
	Population density	• Weighted average density – LAD from MSOA (+ quadratic term) – included in 2 models. • Weighted average density – MSOA (+ quadratic term) – included in 2 models. • Properties per length of mains (+ quadratic term) – included in 2 models.
Wholesale water (12 models)	Scale	• Number of properties – included in 12 models.
	Treatment complexity	• Proportion of water treated at complexity levels from 3 to 6 – included in 6 models. • Weighted average treatment complexity – included in 6 models.
	Network topography	• Booster pumping stations per length of mains – included in 6 models. • Treated water distribution – Average pumping head – included in 6 models.
	Population density	• Weighted average density – LAD from MSOA (+ quadratic term) – included in 4 models. • Weighted average density – MSOA (+ quadratic term) – included in 4 models. • Properties per length of mains (+ quadratic term) – included in 4 models.

All models are consistent with engineering, operational and economic rationale, and all estimated coefficients on the explanatory variables are of the expected sign and plausible magnitude.

All estimated coefficients are statistically significant at the 10 percent level apart from weighted average treatment complexity and water treated at complexity levels 3 to 6 in some water resources plus and wholesale water models.

We do not consider the marginal statistical insignificance of the water treatment complexity variables is a reason to exclude them from the water base cost models given they are supported by strong engineering and operational rationale and produce sensible results that are consistent across model specifications. CEPA included both water treatment complexity variables in its recommended models, and the variables are generally supported by water companies.[21]

The models perform well against all other model robustness tests of medium and high importance. The statistical significance of some variables decrease when removing the most and/or least efficient company or the first/or last year of the sample, leading to an amber rating. But the sign and magnitude of the estimated coefficients remain in line with a priori expectations.

3.4.1 Triangulation approach

We combine the results of each model to arrive at an initial view of efficient wholesale water expenditure allowances before consideration of cost adjustment claims and our assessment of unmodelled base costs. We apply a 50 percent weight to the outcome of our medium level of cost aggregation and disaggregated models (water resources plus and treated water distribution) and 50 percent weight to the outcome of our high-level of cost aggregation models (wholesale water).

The weights applied to individual models allows models that include weighted average density as the population density variable to have the same weight as models that include properties per length as the population density variable. Please see water base cost feeder model 3 for more details on our triangulation approach.

[21] CEPA, 'PR24 Wholesale Base Cost Modelling'https://commonslibrary.parliament.uk/constituency-information-water-companies/, April 2023.

4. Wastewater network plus base cost models

Summary

We use **3 sewage collection (SWC) models, 2 sewage treatment (SWT) models, and 2 wastewater network plus (WWNP) models** to help set efficient wastewater network plus base expenditure allowances at PR24.[22]

The key drivers of wastewater network plus activities are **scale; economies of scale at sewage treatment works (STWs); treatment complexity; network topography; population density; and urban rainfall**.

We have made the following improvements to our PR19 wastewater network plus models:

- **Include an alternative economies of scale at STWs variable** to better capture economies of scale at large STWs. Our weighted average sewage treatment works size (WATS) variable is used alongside the PR19 economies of scale at STWs variable – percentage of load treated in STWs bands 1 to 3.
- **Include alternative weighted average population density drivers** in SWC models based on Middle Super Output Area (MSOA) population density data from the ONS.
- **Include urban rainfall in our SWC and WWNP models**. This variable aims to reflect the volume of inflows into drainage and sewerage networks.
- **Add top-down WWNP models** to the modelling suite, which allows us to triangulate between models of different levels of cost aggregation.

Since our April 2023 base cost modelling consultation we have:

- **Removed one alternative economies of scale at STWs variable**. We dropped the percentage of load treated in STWs serving more than 100,000 people variable due to low company support and superiority of the WATS measure.
- **Developed a more granular urban rainfall variable (urban MSOA rainfall).** This variable captures rainfall within urban MSOAs. We developed this variable in response to company feedback that urban rainfall should reflect actual rainfall within urban areas.
- **Dropped SWC and WWNP models** that do not include urban rainfall.
- **Estimated a post-modelling adjustment** that funds efficient ongoing opex associated with PR19 WINEP / NEP phosphorus removal schemes.

[22] Wastewater network plus = sewage collection + sewage treatment.

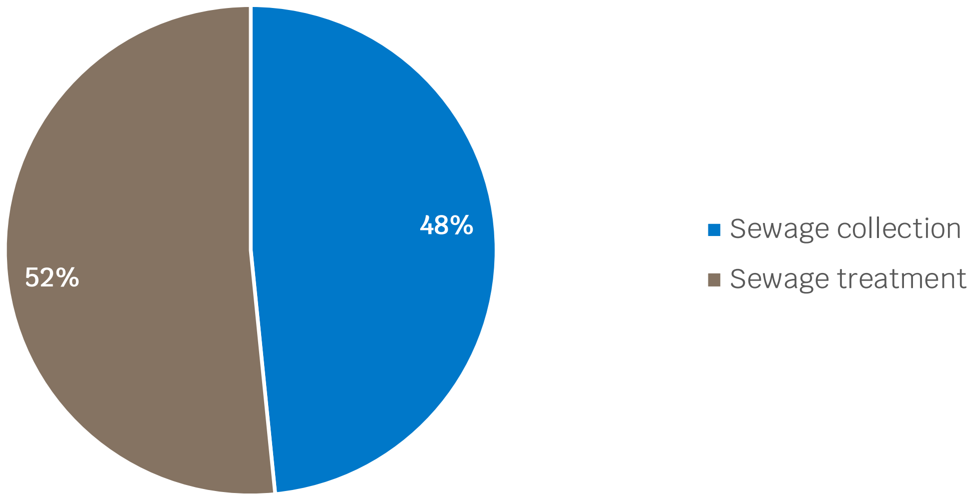
This section presents our econometric benchmarking models used to help set efficient wastewater network plus base expenditure allowances at PR24 draft determinations. It is structured as follows:

- defining the dependent variable;
- selected cost drivers;
- cost drivers not included in our proposed models; and
- wastewater network plus base cost econometric models.

4.1 Defining the dependent variable

Wastewater network plus modelled base costs across the sector equalled £3.7 billion in 2022-23. Figure 3 below shows the share of expenditure of each activity. Sewage collection (SWC) and sewage treatment (SWT) expenditure both account for around half of wastewater network plus (WWNP) modelled base expenditure.

Figure 3: makeup of wastewater network plus base expenditure in 2022-23



Our dependent variable for wastewater network plus modelled base costs includes:

- Operating expenditure (opex)
- Capital maintenance expenditure (capex)
- Network reinforcement expenditure
- Transferred private sewers and pumping stations enhancement
- Reduce flooding risk for properties enhancement expenditure

- Enhancement opex for a subset of enhancement lines where we have reasonable certainty the costs are ongoing – nitrogen removal; phosphorus removal; reduction of sanitary parameters; ultraviolet disinfection; chemical removal schemes.

We use models at different levels of cost aggregation:

- **high level of aggregation:** aggregate "top down" models assess SWC and SWT expenditure together in WWNP models;
- **disaggregated cost models:** granular "bottom up" models are based on modelling the two business units of wastewater network plus separately – SWC and SWT.

4.2 Selected cost drivers

We consider the key wastewater network plus base cost drivers are:

- Scale
- Economies of scale in sewage treatment works
- Treatment complexity
- Network topography
- Population density
- Urban rainfall

The remainder of this section discusses these cost drivers, the corresponding explanatory variables that are included in our models in addition to exploring relevant stakeholder responses to our April 2023 base cost modelling consultation.

4.2.1 Scale

Scale is a key driver of wastewater network plus costs. Other things being equal, a company serving a larger customer base would be expected to incur higher costs.

We use the same explanatory variables to capture the company's scale of operations as we did in PR19. We expect the estimated coefficients of the scale variables to be close to one, indicating that doubling the scale variable results in a doubling of costs (ie constant returns to scale).

Sewage collection (SWC) models

In SWC models, we use **sewer length** as the measure of company scale as it is the most direct measure of sewerage network size. We recognise that companies have some control over sewer length. But we consider it remains substantially determined by exogenous factors (eg location of properties in the company's region).

Severn Trent Water suggested using the number of properties instead of sewer length in sewage collection models. We consider that sewer length continues to be the most appropriate sewage collection scale driver from an engineering perspective as it is the most direct measure of sewerage network size. In addition, the proposed sewage collection models using properties per sewer length as the density variable lead to the same outcome irrespective of whether we use properties or sewer length as the scale driver due to properties of logarithmic functions.

Sewage treatment (SWT) models

In SWT models, we use **load** as the measure of company scale as it is the most direct measure of wastewater that is subject to treatment at sewage treatment works (STWs).

There was almost universal support for retaining load as the sewage treatment scale variable. Only Wessex Water suggested using population equivalent. But we see no benefit in also using population equivalent as a scale driver as load and population equivalent are very closely related. For example, our regulatory accounting guidelines state that load received by sewage treatment works must be calculated on the bases of a contribution of 60g BOD_5 per head of equivalent population per day.[23]

Wastewater network plus (WWNP) models

In WWNP models, we use **load** as the measure of company scale. Our statistical testing suggests that load performs better in explaining WWNP costs compared to sewer length. That is consistent with engineering insight as sewer length is not expected to be a good predictor of sewage treatment costs. We did not receive any specific comments on this issue in response to our base cost modelling consultation.

4.2.2 Economies of scale in sewage treatment works

We expect large treatment works to have a lower unit cost of treatment than small treatment works due to economies of scale. The size of sewage treatment works is mostly outside of company control as it depends on where company customers are located. Companies serving sparsely populated areas tend to have smaller sewage treatment works (STWs).

[23] Ofwat, 'RAG 4.12 – Guideline for the table definitions in the annual performance report', April 2024.

At PR19, we used the percentage of load treated in small works (bands 1 to 3 ie serving up to 2000 resident population equivalent) and the percentage of load treated in large works (band 6 ie serving more than 25,000 resident population equivalent) to capture economies of scale in sewage treatment works.

In our April 2023 base cost modelling consultation, we consulted on three economies of scale at sewage treatment works explanatory variables:

- retain the percentage of load treated in STWs serving less than 2,000 people (bands 1 to 3) used in PR19;
- add **the percentage of load in STWs serving more than 100,000 people** – this variable replaces the PR19 band 6 variable, which was the percentage of load treated in STWs serving more than 25,000 people; and
- add a **weighted average sewage treatment works size (WATS) variable**. This variable captures the weighted average sewage treatment works size for each company in kg of BOD5/day.

We use bands 1-3 to capture economies of scale in sewage treatment when setting efficient base expenditure allowances at PR24 draft determinations

We recognise the bands 1-3 variable is not as statistically significant as in PR19. But it still has a strong engineering and economic rationale and produces an estimated coefficient that has the right sign and is of a sensible magnitude. The variable also remains statistically significant in WWNP models and bioresources models (see section 5). The variable is also supported by some companies and helps us to maintain a triangulated approach where we use more than one model at each level of cost aggregation to determine efficient base costs.

There was a mixed company response to this variable. Anglian Water, Southern Water, United Utilities and Yorkshire Water disagreed with the use of the PR19 variable since it does not robustly capture higher unit costs in smaller bands. They were concerned with the weak statistical significance of the variable. However, Dŵr Cymru, Northumbrian Water, South West Water and Thames Water agreed with the continued use of the variable. Thames Water said that while the variable is statistically insignificant in the STW model, it is statistically significant in the WWNP model and should be retained.

Anglian Water and Wessex Water proposed to capture higher unit costs driven by population sparsity by replacing bands 1-3 in SWT models with a weighted average density variable.[24] Anglian Water argued density can help address the relatively poorer performance of bands 1-3. Wessex Water supported the use of density as it argued it is more exogenous than variables that capture the actual size of company assets. It

[24] Local authority district (LAD) from Middle Super Output Area (MSOA) weighted average density.

highlighted the importance of the opportunities for economies of scale rather than actual economies of scale achieved at sewage treatment works. We disagree. Our economies of scale explanatory variables directly account for economies of scale at STWs. The size of STWs is mostly exogenous as it is driven by the location of population served given the localised nature of sewage treatment and wide use of gravity sewers. Companies can sometimes close STWs and transfer the effluent a larger nearby STWs. However, this tends to be limited and depends on specific local circumstances.

We do not use the percentage of load in STWs serving more than 100,000 people to capture economies of scale in sewage treatment when setting efficient base expenditure allowances at PR24 draft determinations

This decision recognises the low company support for this variable and the inferior properties and performance when compared to the WATS variable.

Dŵr Cymru and Severn Trent Water agreed with the use of the percentage of load in STWs serving more than 100,000 people on the basis of clear engineering rationale. Dŵr Cymru said it considers the variable may allow for an easier interpretation of the estimated coefficient compared to WATS. Thames Water was the only company that expressed a clear preference for this variable over the WATS variable.

But Anglian Water, Northumbrian Water, Southern Water, South West Water, United Utilities and Yorkshire Water do not support the use of the percentage of load in STWs serving more than 100,000 people. They said that the variable does not capture a continuous unit cost decrease relationship which may be prevalent even beyond the 100,000 threshold. In addition, they argued that choosing any particular threshold is arbitrary and inferior to WATS and was mainly driven by the more limited dataset available in the PR19 price review.

We use WATS to capture economies of scale in sewage treatment when setting efficient base expenditure allowances at PR24 draft determinations

This decision recognises its methodological advantages, strong statistical performance and wide company support.

The WATS variable uses information on the distribution of all STWs sizes rather than focusing on the largest or smallest STWs. This can help explain the overall economies of scale at sewage treatment the company faces more accurately. WATS allows for a more continuous relationship with sewage treatment costs. This is different from the size threshold variables (discussed above) which model step-like changes in sewage treatment costs beyond a certain threshold.

The WATS variable was supported by most companies as the variable helps capture the continuous unit cost decrease as the size of STWs increases. Most companies considered this is more aligned with economic intuition and engineering insight. The only company that raised concerns with the WATS variable was Thames Water. The company recognised some of the benefits of the WATS metric. However, it expressed concern about the inconsistency of measuring the variable for bands 1-5 (using a simple average per band) and band 6 (weighting each large works separately). It argued that this could lead to measurement error and inconsistent estimates. It also suggested that WATS assumes a linear relationship, but economies of scale opportunities diminish as STWs size increases. It proposed to address this by using a logarithm of capacity within the summation formula.

We consider that the arguments raised by Thames Water against WATS do not warrant removing this variable from our modelling suite. We recognise the measure uses data at a different level of granularity for large (>25,000 population equivalent) STWs and small works driven by data availability. However, the degree of measurement error is likely to be limited as the vast majority of load is treated in large STWs. The constructed WATS measure is also intuitive in that it measures the representative size of STWs for each water company in kg BOD5/day. Thames Water's proposal to the take logs of capacity within the formula would make interpretation of the estimated coefficient more complex and it is not clear that it is supported by engineering rationale.

4.2.3 Treatment complexity

Treatment complexity is a key driver of sewage treatment costs. Tighter discharge permit limits tend to require more, or larger, treatment process units and are therefore more costly to comply with. In addition, tighter permits are associated with additional raw material costs, mainly driven by energy and chemical requirements.

Our sewage treatment (SWT) and wastewater network plus (WWNP) base cost models include **percentage of load with ammonia permit <= 3mg/l** to explain differences in treatment complexity between companies. We used the same variable at PR19.

Anglian Water, Dŵr Cymru, Northumbrian Water, Thames Water, United Utilities, and Wessex Water agree with this approach. Thames Water stated that tight ammonia permits are known to be a material driver of sewage treatment costs, is robust to sensitivity tests and is highly significant across all model specifications. Anglian Water and Northumbrian Water agree with the rationale behind the retained driver and do not see a better alternative to capture sewage treatment complexity.

Southern Water, South West Water and Severn Trent Water did not agree with this approach. These companies reiterated their view that composite treatment complexity measures that combine different treatment permits together need to be considered.

Severn Trent Water said that a composite variable with tight phosphorus permits and ammonia permit <= 3mg/l, fixed at 2024-25 levels is its preferred option. It also said that in absence of detailed evidence, it is most appropriate to use equal weights on phosphorus and ammonia within the composite variable.

- Southern Water stated that not considering different permits including phosphorus and BOD effectively means we set the weight of these to zero in a composite permit variable. It argued we should consider percentage of load with BOD permit <=7mg/l and P permit <=0.5mg/l. It also argued that exclusion due to non-sensical impact on allowances of BOD carries a higher risk than inclusion.

South West Water said that our argument on the difficultly of interpreting composite measures is weak as we use a composite variable for water treatment complexity and Ofgem also uses them. It also argued that composite treatment complexity variables more closely resemble company processes where costs are a function of a combination of different treatment complexity requirements rather than being incremental to each requirement. It said there was little evidence why composite variables proposed by different companies have been dismissed and asked that load with an ultra-violet (UV) treatment permit is reconsidered.

As stated in our April 2023 base cost modelling consultation, we tested alternative sewage treatment complexity variables using data on phosphorus (P) permits, biochemical oxygen demand (BOD) permits, and ultra-violet (UV) permits. But none of the alternative treatment complexity variables improved on our PR19 sewage treatment complexity variable.

We also considered all different combinations of composite treatment complexity variables, and found strong evidence that composite variables tend to mask the insignificant individual impact of different treatment complexity variables such as P, BOD and UV, and lead to non-sensical allowances when extrapolated into the future. We also maintain the view that composite treatment complexity variables are more challenging to interpret than the ammonia treatment variable. We therefore do not include composite sewage treatment complexity variables in our sewage treatment and wastewater network plus base cost models.

We received several cost adjustment claims for the ongoing costs related to PR19 phosphorus removal enhancement schemes, which companies argue are not captured in the base cost models. We have subsequently developed a sector wide cost adjustment to address this issue, which we discuss below. No other cost adjustment claims were submitted related to sewage treatment complexity.

Accounting for the additional ongoing cost associated with PR19 phosphorus removal schemes

We recognise that the additional ongoing cost associated with more stringent phosphorus removal programmes across the sector may not be fully captured in our base cost models. We considered several options to address this issue:

- sewage treatment and wastewater network plus models with a phosphorus removal explanatory variable (eg percentage of load with P permit <= 0.5mg/l). We would fix the permit levels at 2024-25 values to fund additional base expenditure associated with phosphorus removal enhancement schemes funded at PR19 and completed by the end of AMP7;
- post-modelling sector wide cost adjustment that funds efficient ongoing opex associated with phosphorus removal using data provided by companies in annual performance reports (APRs); and
- the cost adjustment claim process.

In response to our consultation, companies had different views on how to account for the additional ongoing costs associated with the PR19 phosphorus removal schemes.

Southern Water said that the ongoing opex associated with phosphorus removal should be accounted for through our wastewater network plus models. It said this is preferable compared to a post-modelling adjustment or a cost adjustment claim.

Dŵr Cymru, Northumbrian Water and Wessex Water acknowledge that a phosphorus removal driver does not currently work well within our wastewater network plus models. Therefore, their preferred approach was to account for ongoing phosphorus removal costs through a post-modelling adjustment using industry wide data.

Anglian Water, Severn Trent Water, United Utilities and Yorkshire Water have submitted cost adjustment claims for ongoing costs associated with PR19 phosphorus removal schemes. These are the companies with the largest PR19 phosphorus removal enhancement programmes.

Including a phosphorus treatment complexity variable in the base cost models continues to not produce sensible results due to the relatively small number of sewage treatment works currently operating at tight permit levels. So we consider a sector wide phosphorus cost adjustment is the best option that funds ongoing costs associated with PR19 phosphorus removal enhancement schemes. This was supported by several companies and helps to achieve consistency of treatment of different companies, which would have been difficult to achieve if we assessed the four cost adjustment claims. Further details of our approach are included in 'PR24 draft determinations: Expenditure allowances'.

4.2.4 Network topography

We use **pumping capacity per sewer length** to capture network topography in our sewage collection (SWC) and wastewater network plus (WWNP) models. In hillier terrains, lifting sewage to transport it to treatment works requires more energy, hence more pumping capacity compared to flatter regions. In addition, higher pumping capacity may be needed in flatter areas due to inability to use gravity sewers where sewage needs to travel over longer distances. Therefore, pumping capacity is a driver that captures the complexity of the sewage collection unit. We did not receive any views on the use of pumping capacity per sewer length.

4.2.5 Population density

The population density of company service areas could affect costs in different ways. Higher density may allow for the use of larger and more efficient treatment works which reduces sewage treatment unit costs. However, higher density may also be associated with a more complicated operating environment and higher property, rental, labour and access costs, which increase sewage collection costs.

Population density was a key cost driver in our PR19 sewage collection models. At PR19, we developed a weighted average density variable, based on population density data at Local Authority District (LAD) level from the Office for National Statistics (ONS). This measure was more exogenous than the alternative density measure of properties per sewer length, and better reflected density within company regions.

As discussed in section 3.2.4, we found the PR19 weighted average density measure to be sensitive to changes in LAD boundaries (some LADs have merged in the ONS dataset). We also found that the mapping of LADs to company boundaries used at PR19 had some errors. These two issues could affect the overall density of a company.

For PR24, we developed alternative weighted average density measures using more granular Middle Super Output Area (MSOA) population density data from the ONS:

- **Weighted average density – LAD from MSOA**
- **Weighted average density – MSOA**
- **Properties per sewer length**

The consultation responses were mixed, with each population density measure receiving similarly equal support. We therefore include all three measures of population density in our wastewater network plus modelling suite.

Like in water, we have implemented the suggestion of Dŵr Cymru and Yorkshire Water to triangulate equally between the two weighted average density measures and the properties per sewer length measure within sewage collections models. This allows density measures based on ONS data to have the same triangulation weight as properties per sewer length like in the PR19 sewage collection models.

We assume a log-linear relationship between population density and sewage collection base costs

We received mixed responses to whether we should assume a log-linear relationship between population density and sewage collection (SWC) base costs. Companies at the extreme ends of the density distribution, including the relatively sparse Anglian Water, Dŵr Cymru, South West Water and the relatively dense Thames Water supported the use of a squared density relationship. But all other companies supported a log-linear relationship, apart from Yorkshire Water who did not express a strong view.

Companies that support the inclusion of a quadratic density term in the SWC models

Anglian Water and South West Water said both ends of extremes (ie highly sparse and highly dense) lead to higher sewage collection costs and may lead to omitted variable bias if they are not captured. But provided limited evidence of why there are higher costs in sparse areas, besides noting higher transport and intervention costs.

- Thames Water argues that dense areas might be put under more pressure on the wastewater sewage network. It showed that squared densities are statistically significant in the sewage collection models. It also showed there is a "U-shape" relationship between density and residuals in the linear model but no systematic relationship in the squared density model. It argued this provides evidence that the linear model is not well specified and the squared density model performs better.
-
- Dŵr Cymru argued that wastewater assets are more localised but this does not influence costs. It said that in sparse areas there is additional travel time, sewer diameters are smaller and there are land drainage issues. These drive the cost of interventions such as blockages, collapses and flooding incidents.

Companies in support of a log-linear relationship between density and SWC base costs

Northumbrian Water said the squared term of properties per sewer length is statistically insignificant, which suggests a less robust model. It agreed the wastewater network is different to the water network, making the squared density term less relevant. Southern Water expressed similar views.

Severn Trent Water and United Utilities strongly agreed with the use of a linear term. They said rural sewage networks can be very localised and gravity dominated and in rural areas companies often do not collect sewage since they are privately drained with waste services typically connected to septic tanks. This differs from water networks that are more universal and require pumping water to rural areas.

Our decision for PR24 draft determinations

We do not include a quadratic population density term in our SWC base cost models.

We only include explanatory variables in our base cost models that are underpinned by strong engineering and economic rationale. And there is not a strong engineering rationale for including a quadratic population density term in our SWC base cost models. This was reflected in our PR19 sewage collection models, which assumed a linear relationship between density and SWC base costs.

As we said in our April 2023 base cost modelling consultation, sewerage networks tend to be more localised than water networks and are more of a passive asset. More than 90% of legacy sewers of the water sector are gravity sewers. This reduces travel and intervention costs compared to water networks.

In addition, some of the factors causing companies operating in densely populated areas to have relatively high treated water distribution base costs do not apply to sewage collection. For example, pumping of water to tall buildings. Other arguments do not apply to sewage collection to the same degree, and mean that sewers in densely populated areas tend to require less maintenance than water mains:

- gravity sewers tend to be deeper than water mains. So, heavy traffic loading in urban areas, which may result in greater ground movement and stresses on the pipework, likely affect water mains to a greater degree; and
- gravity sewers which account for more than 90% of legacy sewers are unpressurised and are therefore not subject to the same internal stresses as water mains. In addition, they are predominantly made of vitrified clay, an inert material not subject to corrosion like some water mains.

We recognise the quadratic population density term is statistically significant in the sewage collection models. But including a quadratic population density in the SWC models based on statistical performance alone would be inconsistent with our base cost assessment principle of requiring strong engineering insight to underpin our model specifications and functional form.

Thames Water's analysis shows a relatively weak "U-shaped" relationship between SWC model residuals and population density compared to the treated water distribution models. This shows that the economic and engineering case for a quadratic density relationship is much weaker in the sewage collection models. There is also the risk that Thames Water's findings are driven by very dense and sparse companies being relatively inefficient, rather than because of an omitted cost driver.

4.2.6 Urban rainfall

In our April 2023 base cost modelling consultation, we consulted on the use of an urban rainfall variable, defined as the **average rainfall falling in a company area multiplied by the urban company area**. The measure accounts for the overall amount of rain in a company area and how likely it is for rain to fall in an urban area with impermeable surfaces thereby ending up draining into the sewerage network.

The greater the volume of inflows into drainage and sewerage networks, the larger network and storage assets need to be, and the greater amount of pumping and capital maintenance costs are needed to:

- avoid sewer flooding incidents;
- avoid discharges of wastewater from storm overflows; and
- maintain good asset health.

Urban rainfall can also help account for climate change impacts where periods of extreme rainfall could become more prevalent over time. We also recognised that forecasting urban rainfall would be challenging, and the variable we consulted on does not consider that the volume of rainfall may differ within a company's operating area.

Consultation responses on the inclusion of urban rainfall in our sewage collection and wastewater network plus models were mixed. Dŵr Cymru, Severn Trent Water, Thames Water, United Utilities, Wessex Water and Yorkshire Water all agreed with the inclusion of urban rainfall in the sewage collection and wastewater network plus models. But Anglian Water, Northumbrian Water, Southern Water and South West Water disagreed with the use of the variable.

Companies that disagreed with the urban rainfall variable made the following points:

- Anglian Water stated that more precise geographic data should be used to account for the specific amount of rain in urban areas.
- Anglian Water suggested that companies with higher rainfall do not appear to incur higher sewage collection costs or a higher number of blockages.
- Anglian Water, South West Water and Southern Water raised concerns about the correlation between the urbanisation element of urban rainfall and density. They argued that using total rainfall is more appropriate as density is already captured in sewage collection models.
- South West Water argued that the measure fails to capture potential impacts of rainfall in rural areas. It said that while sewers could be less extensive in rural areas, they are also smaller in diameter so could still have a higher propensity to have blockages.
- Southern Water agreed that forecasting rainfall could be difficult. It said that future weather patterns could lead to arbitrary winners and losers.
- Anglian Water and Northumbrian Water argued that network capacity and the associated costs of pumping and maintaining assets are dependent on the peakiness of flows, which is not captured by the annualised measure of urban rainfall. Anglian Water suggested an alternative measure based on storms with a rainfall intensity of >25mm/hr.
- Northumbrian Water consider pumping capacity is sufficient to explain variations in pumping and capital maintenance costs between companies resulting from rainfall.

Overall, we continue to consider urban rainfall has a strong engineering rationale. But recognise the drawbacks with the proposed urban rainfall measure highlighted by companies in response to our consultation. Most notably:

- the metric does not directly capture rainfall in urban areas but rather captures rainfall and urban areas; and
- concerns about correlation between the urbanisation element of urban rainfall and density in sewage collection models.

We have aimed to addressed these concerns. We engaged with the Environment Agency (EA) and obtained rainfall data for middle super output areas (MSOAs). There are over 7000 MSOAs in England and Wales, which allows us to capture rainfall at a high level of granularity. We have a mapping of MSOAs to company sewerage boundaries used in deriving the weighted average density variables. We used this additional data to derive an improved **urban MSOA rainfall** that truly measures how much rainfall falls in urban areas across England and Wales.

We went through the following steps to derive the urban MSOA rainfall variable:

- use data from the EA on rainfall (in mm) for each MSOA;
- check whether the MSOA is urban which is based on the ONS classification;

- apportion the rainfall falling in each urban MSOA to relevant companies;
- aggregate total urban rainfall falling across each company's MSOAs; and
- normalise by sewer length.

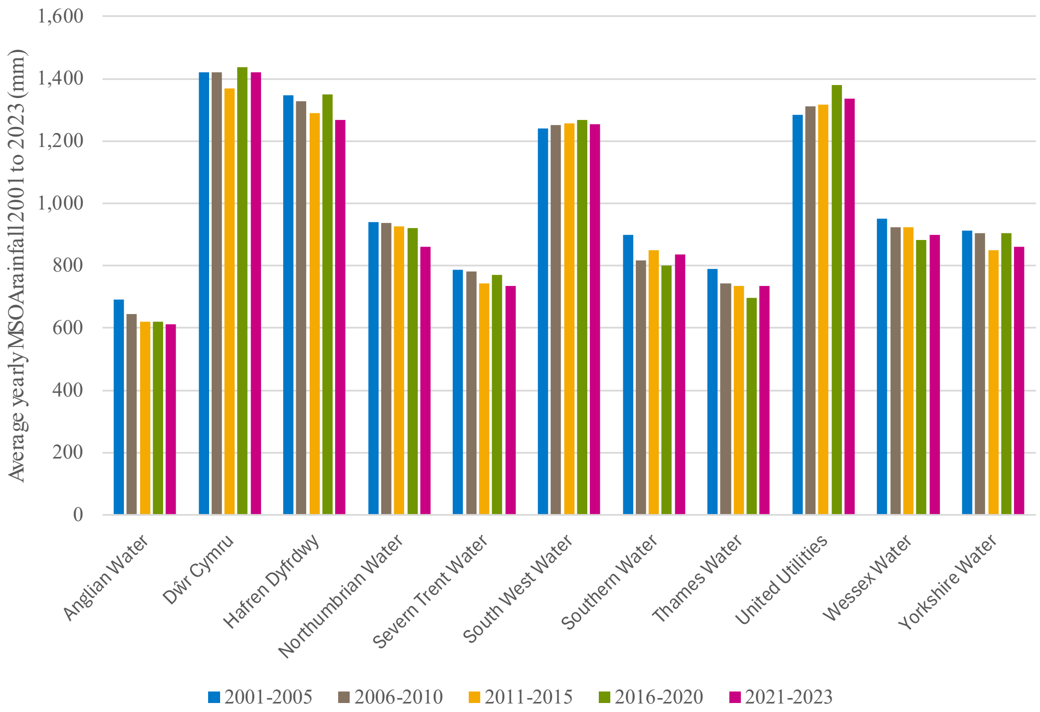
The improved urban MSOA rainfall variable has a stronger engineering rationale and performs well in our sewage collection and wastewater network plus models. We therefore included it in our sewage collection and wastewater network plus models when assessing base cost allowances at PR24 draft determinations.[25]

We have dropped the sewage collection and wastewater network plus models which did not include urban rainfall as an explanatory variable from the modelling suite. As explained above, we consider there is strong engineering rationale for using urban MSOA rainfall. So it is appropriate to use it to set efficient wastewater network plus base expenditure allowances.

We agree with the concerns Southern Water raised about the difficulty in forecasting rainfall. We are unlikely to be able to accurately forecast year-on-year regional rainfall patterns over a five-year period. But we have a long time series of historical rainfall back to April 2000, which we have used to forecast urban MSOA rainfall. Figure 4 shows that average rainfall over five-year price control periods tends to be relatively stable for companies in each of the last five AMPs (AMP7 up to 2023). While there is year-on-year variation in rainfall, that variation is around a relatively constant average value. So we consider our forecast based on rainfall over 2001-2023 period should be reasonably accurate for each water company.

[25] We have published the derivation of the urban MSOA rainfall on our website. Our urban MSOA rainfall appears to use the same dataset proposed by Anglian Water in its consultation response.

Figure 4: Average yearly MSOA rainfall over time (mm) – 2001 to 2023



We consider the urban MSOA rainfall somewhat captures the variability caused by extreme rainfall events. If there are more extreme rainfall events in urban MSOAs on average in a given year, we would expect urban MSOA rainfall to be higher too. But we recognise that extreme rainfall in a short space of time may be offset by drier summers, which would not be captured by urban MSOA rainfall. Pumping capacity per length of sewer is also a good proxy for capital maintenance costs. So both variables help to capture the full impact of rainfall on sewage collection base costs.

We do not consider there is a strong engineering rationale for capturing rural rainfall in our sewage collection and wastewater network plus base cost models as rainfall in more rural areas is less likely to drain into the sewerage network as most rainfall falls on permeable land.

Northumbrian Water, United Utilities and Yorkshire Water said that the impact of urban rainfall must be considered alongside the effect of combined sewers. They argued that engineering rationale suggests that the two factors have a compounding relationship on performance and costs. Severn Trent Water supported the use of combined sewers in its PR24 business plan. We do not include percentage of combined sewers in our sewage collection and wastewater network plus base cost models for several reasons.

Percentage of combined sewers does not have a clear engineering rationale and could drive perverse incentives as it is endogenous.

It is not clear that having a high percentage combined sewers makes it more challenging to deliver good internal sewer flooding performance. For example, Dŵr Cymru has relatively high percentage of combined sewers and urban rainfall but performs well on internal sewer flooding. This may be because:

- Percentage of combined sewers is a blunt instrument and does not consider the complexity of network configuration. Arguably, the focus should be on combined sewers in urban areas. And even then, a company may have lots of separated sewers that fall into a combined sewer on its way to a wastewater treatment works.
- Sewer blockages explain a large proportion of internal sewer flooding incidents, as corroborated by United Utilities PR14 business plan submission that said only 13-15 percent of sewer flooding incidents are caused by hydraulic overload.[26] One could argue that combined sewers reduce rather than increase the risk of sewer blockages due to rainfall clearing any blockages.
- Combined sewers is endogenous and including it in the base cost models may reduce the incentive to separate sewers and / or influence network configuration.

Risk that percentage combined sewers captures other factors.

Yorkshire Water and United Utilities both suggested including percentage of combined sewers in the wastewater network plus base cost models, and both companies have relatively poor sewer asset health based on the percentage of legacy sewers classified as condition grade 4 (poor) or 5 (very poor). So there is a risk that this variable is acting as an asset health explanatory variable, which risks customers paying twice if the poor asset health reflects under-delivery of capital maintenance in previous regulatory periods. United Utilities has spent less than the industry average on sewage collection infrastructure capital maintenance in each of the last three regulatory periods.

Data limitations and quality concerns.

Due to data limitations, it is necessary to make an assumption on the percentage of transferred private sewers that are combined. The modelled outcome is somewhat sensitive to the assumption that is applied – all combined sewers; all separated sewers; or the same proportion of combined and separated sewers as legacy sewers. We are also concerned around the quality of company data on the length of combined and separated legacy sewers, which could skew the modelled outcome.

[26] Source: https://webarchive.nationalarchives.gov.uk/ukgwa/20150624091829/http:/ofwat.gov.uk/pricereview/pr14/pap_tec201412uqintsewerfloodfd.xlsx

4.3 Other cost drivers proposed by companies

Responses to our April 2023 base cost modelling consultation included other cost driver suggestions. We set out why we have not included these in our wastewater network plus base cost models below.

4.3.1 Population living in coastal areas

Southern Water argued that having a higher percentage of population living in coastal areas can lead to higher sewage treatment costs for the following reasons:

- companies in coastal areas face different treatment complexity due to discharging to bathing or shellfish waters – tighter ultra-violet and nitrogen treatment permits may apply;
- operating in a saline environment increases corrosion with higher repair costs;
- double pumping costs due to coastal space constraints requiring placing sewage treatment works inland;
- coastal works might need to be oversized to address peak of tourist demand;
- additional pumping costs for long sea outfalls – higher costs compared to gravity discharges inland; and
- tighter spill frequency permits to sea waters compared to fresh waters inland.

Southern Water developed a coastal variable defined as population living in coastal towns and cities as a share of total population.

This variable is exogenous as management cannot influence the population located in coastal areas within their operating areas. We also recognise that there could be higher costs related to wastewater companies operating near the coast. These costs might not be evenly distributed as some companies like Severn Trent Water and Thames Water have no or little coastal areas. While not having coastal areas creates additional cost due to more discharges to sensitive water bodies inland with tighter than average phosphorus and/or ammonia permits, these impacts are partly controlled for via the ammonia variable.

In our April 2023 base cost modelling consultation, we expressed some concerns with Southern Water's suggested coastal variable. Our analysis suggests the estimated coefficient on the coastal variable is sensitive to dropping Southern Water from the dataset. The estimated coefficient turns negative and/or is not statistically significant when included in our proposed sewage treatment models. This suggests that the variable may be capturing a Southern Water specific impact, rather than an overall industry-wide impact of operating in coastal areas. On this basis, we decided not to include the coastal variable in our sewage treatment models but we asked for company views before making a final decision.

Southern Water said the use of a coastal variable in sewage treatment models improves the efficiency assessment of treatment costs. It stated that the coastal variable fulfils all requirements to introduce a new explanatory variable in base cost models. It also allows models not to be biased towards inland companies by capturing additional costs incurred by coastal companies. South West Water also supported the inclusion of the coastal variable for similar reasons.

Anglian Water, Northumbrian Water, Severn Trent Water, Thames Water, United Utilities and Yorkshire Water stated that they do not agree with Southern Water's proposal to include the coastal variable in the sewage treatment models. Dŵr Cymru and Wessex Water did not object to or support the metric. Companies questioned the reliability of the metric due to the instability of the model. They stated that this is inappropriate and may lead to data mining from companies in future consultations on base cost models. They said the coastal driver may be capturing a Southern Water specific impact, rather than an industry-wide impact of operating in coastal areas.

United Utilities also added that the correlation with the scale driver (load) could be driving a spurious relationship between coastal population and overall cost. It showed the coefficient is 20-30% higher in models that included coastal population. That is why Thames Water benefits from adding coastal population despite having no coastal population. The company changed position in PR24 business plans stating that there is a downward bias on the scale coefficient when coastal is excluded from the models because of omitted variable bias.

Following careful consideration, we do not use Southern Water's coastal population explanatory variable to set efficient wastewater network plus expenditure allowances for the following reasons:

Percentage of the population served that live in coastal areas does not have a clear engineering rationale.

The coastal variable proposed by Southern Water aims to proxy for various different potential cost drivers (eg stricter ultraviolet and nitrogen consents; space constraints and planning restrictions; stricter spill frequency constraints on coastal discharge). We consider it is more appropriate to include explanatory variables that have a direct link to a specific cost driver.

The estimated relationship between Southern Water's coastal variable and sewage treatment base costs is sensitive to the inclusion of Southern Water in the dataset.

This suggests the variable could be picking up other factors driving differences in base costs that are inside of company control (eg inefficiency). This reiterates the importance of identifying explanatory variables that have a clear engineering and/or economic rationale.

The inclusion of Southern Water's coastal variable in the sewage treatment base cost models leads to counterintuitive outcomes.

For example, Southern Water would receive a large upwards cost adjustment, but South West Water with the second highest percentage of coastal population receives no upwards cost adjustment. And Thames Water has no coastal population but would receive a higher sewage treatment base expenditure allowance. This reiterates the importance of identifying explanatory variables with a clear engineering and economic rationale that produce sensible outcomes.

4.3.2 Time trend, year dummies and other dynamic factors

Wessex Water consider there is evidence of sector wide cost changes, relative to CPIH, beyond what is explained by the cost drivers captured in our wastewater network plus base cost models. It states that corresponding sewage treatment models that include a time trend perform better against our model selection criteria.

For the reasons set out in section 3.3.3, we do not include a time trend, year dummies of other dynamic factors in our wastewater network plus models.

4.4 Selected wastewater network plus base cost models

Our wastewater network plus base cost model suite includes:

- 3 sewage collection (SWC) models
- 2 sewage treatment (SWT) models
- 2 wastewater network plus (WWNP) models

Table 6: Summary of wastewater network plus base cost models

Level of cost aggregation	Cost drivers	Explanatory variables
Sewage collection (3 models)	Scale	• Sewer length – included in 3 models.
	Network topography	• Pumping capacity per sewer length – included in 3 models.
	Population density	• Properties per sewer length – included in 1 model. • Weighted average density – LAD from MSOA – included in 1 model. • Weighted average density – MSOA – included in 1 model.
	Urban rainfall	• Urban MSOA rainfall per sewer length – included in 3 models.
Sewage treatment (2 models)	Scale	• Load – included in 2 models.
	Treatment complexity	• Load treated with ammonia permit ≤ 3mg/l – included in 2 models.
	Economies of scale in sewage treatment	• Load treated in size bands 1 to 3 (%) – included in 1 model. • Weighted average treatment size – included in 1 model.
Wastewater network plus (2 models)	Scale	• Load – included in 2 models.
	Treatment complexity	• Pumping capacity per sewer length - included in 2 models.
	Network topography	• Load treated with ammonia permit ≤ 3mg/l – included in 2 models.
	Economies of scale in sewage treatment	• Load treated in size bands 1 to 3 (%) – included in 1 model. • Weighted average treatment size – included in 1 model.
	Urban rainfall	• Urban MSOA rainfall per sewer length – included in 2 models.

All models are consistent with engineering, operational and economic rationale, and all estimated model coefficients are of the expected sign and plausible magnitude.[27]

Almost all estimated coefficients are statistically significant at the 10 percent significance level. The exceptions are load treated in bands 1 to 3 in SWT1. We do not consider the marginal insignificance of these variable is a reason to exclude it given it is supported by strong engineering and operational rationale; produces sensible results in terms of sign and magnitude of the estimated coefficient; and is statistically significant in other wastewater network plus model specifications.

The models perform well against all other model robustness tests of medium and high importance. Please see Annex A2 for further details on how the models perform against model robustness tests.

[27] We have maintained the April base cost consultation model numbers for ease of reference.

4.4.1 Triangulation approach

We combine the results of each model to arrive at our view of efficient wastewater network plus base cost allowances.

We apply 50 percent weight to the outcome of our disaggregated models (ie sewage collection; sewage treatment) and 50 percent weight to the outcome of our middle level of cost aggregation models (ie wastewater network plus).

We apply equal weight to each model within each level of cost aggregation. The exception being in sewage collection where the weights applied allows models that include weighted average density as the density variable to have the same weight as models that include properties per sewer length as the density variable.

Please see wastewater network base cost feeder model 3 for more details on our triangulation approach.

5. Bioresources base cost models

Summary

We use **4 bioresources unit cost models** to help set efficient bioresources expenditure allowances at PR24 draft determinations.

We consider the key exogenous drivers of bioresources unit costs are **economies of scale in sludge treatment;** and the **location of sewage treatment works relative to sludge treatment centres**, which causes differences in efficient sludge transport costs.

We use the same explanatory variables to proxy the key cost drivers as we did in PR19:

- **Weighted average population density, sewage treatment works (STWs) per property, and percentage of load treated at band sizes 1 to 3** to control for economies of scale in sludge treatment and the location of sewage treatment works relative to sludge treatment centres.

Since our April 2023 base cost modelling consultation, we have decided **not to use bioresources total cost models**. Bioresources unit cost models performed better after we included the additional 2022-23 year of data and are more consistent with the average revenue bioresources control.

This section presents our econometric benchmarking models used to help set efficient bioresources plus base expenditure allowances at PR24 draft determinations. It is structured as follows:

- defining the dependent variable;
- selected cost drivers;
- cost drivers not included in our proposed models; and
- bioresources base cost econometric models.

5.1 Defining the dependent variable

Bioresources modelled costs across the sector equalled around £0.7 billion in 2022-23.[28] The main activities in the bioresources value chain are:

[28] In 2022-23 prices.

- **Sludge transport** – relates to transporting untreated sludge from sewage treatment works to sludge treatment centres.
- **Sludge treatment** – all sludge treatment activities before treated sludge is disposed.
- **Sludge disposal** – the collection of treated sludge, onward transport and disposal to landfill, agricultural land, land reclamation sites and to other end users.

Our dependent variable for bioresources modelled base costs includes:

- operating expenditure;
- capital maintenance;
- bioresources growth enhancement; and
- quality enhancement operating expenditure.

The addition of bioresources growth enhancement is new for PR24. Bringing more costs into our econometric models reduces potential distortions created by taking different approaches for different categories of cost and come closer to a market process where costs are reflected in the service's price.[29] The models will also produce an allowance for future growth enhancement costs.

We also made several pre-modelling cost adjustments to facilitate accurate cost comparisons between companies and over time. In particular, the backcasting adjustment accounts for our updated guidance on how to allocate the costs of sludge liquor treatment[30], energy generation[31] and overheads[32] between bioresources and sewage treatment. That improves comparability of bioresources costs across the industry, which helps to promote a market-based approach.

Total vs unit cost models

In our April 2023 base cost modelling consultation, we sought views on whether to use **'total cost'** or **'unit cost'** models to assess the relative efficiency of each company's bioresources base expenditure. Unit cost models divide the dependent variable defined above by sludge produced. This is like the approach taken to benchmark residential retail costs. A unit cost modelling approach aims to explain variations in companies' bioresources costs above and beyond the amount of sludge produced, which subsequently leads to a lower adjusted R-squared.

Modelling on a 'total cost' basis is broadly consistent with our PR19 approach.

[29] Ofwat, 'Our final methodology for PR24. Appendix 4: Bioresources control', December 2022, page 25.
[30] Reporting-of-sludge-liquor-treatment-costs-final-decisions.pdf (ofwat.gov.uk)
[31] Bioresources_Cost_Allocation_Energy_Generation_Odour_Control_Final_Decision.pdf (ofwat.gov.uk)
[32] RAG-2.09---Guideline-for-classification-of-costs-across-the-price-controls.pdf (ofwat.gov.uk)

The unit cost bioresources models we consulted on omitted the sludge produced scale variable from the explanatory variables, which imposed a constant returns to scale assumption. This was supported by the econometric model results.[33] The bioresources average revenue control also aligns better with the use of unit cost models.. Unit cost models also perform well against our model robustness tests.

In response to our April 2023 base cost modelling consultation, Northumbrian Water, Wessex Water, Yorkshire Water, Southern Water, South West Water and United Utilities supported unit cost benchmarking. But Dŵr Cymru, Anglian Water, Severn Trent Water and Thames Water supported total cost benchmarking.

Companies that support unit cost benchmarking made the following arguments:

- Total cost models produce diseconomies of scale, which is counterintuitive.
- Population density variables in total cost models are statistically insignificant.
- Unit cost models are consistent with an average revenue control and will support the bioresources market.
- Total volume of sludge produced is not statistically significant in the unit cost bioresources models.

Companies that support total cost benchmarking made the following arguments:

- Total cost bioresources models show diseconomies of scale, which they argue suggests a constant returns to scale assumption is not valid.
- Unit cost models are too simple and have a low R-squared. The companies argue this suggests the unit cost models do not explain the costs companies face when delivering bioresources services. Thames Water showed the inclusion of transport explanatory variables and a quadratic density term in the unit cost models make the estimated coefficient of sludge produced negative and statistically significant, which it considers is evidence of omitted variable bias.

Following careful consideration, we have decided to solely use unit cost benchmarking models to help set efficient bioresources base expenditure allowances at PR24 draft determinations.

Unit cost models were supported by the majority of wastewater companies, they are more consistent with an average revenue control and will help to support the bioresources market. We are not concerned about the lower adjusted R-squared compared to the total cost models because unit cost models aim to explain variations in

[33] The estimated coefficient on sludge produced in the unit cost models was not statistically significant.

companies' bioresources costs above and beyond what is explained by differences in the volume of sludge produced.

In addition, after adding 2022-23 outturn data into the historical dataset used to estimated our bioresources base cost models, the bioresources unit cost models clearly perform better than the total cost models against out model selection criteria. The population density and the number of sewerage treatment works per property variables are statistically insignificant in the total cost models. And our analysis indicates that the estimated coefficient on sludge produced in the bioresources total cost models is not significantly different from one, which supports the use of unit of cost models from a statistical perspective.

We consider Thames Water's proposal to include additional sludge transport variables and a quadratic density term are inconsistent with our base cost assessment principles, which we discuss further below.

5.2 Selected cost drivers

The key exogenous drivers of bioresources unit costs are **economies of scale in sludge treatment;** and the **location of sewage treatment works relative to sludge treatment centres**, which causes differences in efficient sludge transport costs**.**

The remainder of this section discusses these cost drivers and the corresponding explanatory variables that are included in our proposed models, which align with PR19.

5.2.1 Economies of scale in sludge treatment, and location of sewage treatment works relative to sludge treatment centres

Large sludge treatment centres should have a lower unit cost of sludge treatment than small treatment centres because of economies of scale. In addition, the location of sewage treatment works (STWs) relative to sludge treatment centres (STCs) impacts sludge transport costs.

Both cost drivers are somewhat under company control. Companies have more say over the size and location of sludge treatment centres than STWs. STWs were historically located consistently with sewer network configuration to avoid the transportation of raw sewage and to comply with effluent discharge requirements. In contrast, there is more flexibility in locating sludge treatment centres as sludge can be transported more cost effectively and there are no discharges to water bodies. We focus on explanatory variables that capture external factors that increase / decrease opportunities to achieve economies of scale at sludge treatment centres, or increase / decrease sludge transportation costs.

Population density and the **size of STWs** are largely exogenous factors that can be used to proxy these cost drivers.

Companies operating in densely populated areas tend to have larger STWs, with sludge treatment centres on the same site (ie co-location). This allows them to achieve economies of scale in sludge treatment and at the same time minimise sludge transportation costs.

In contrast, companies operating in sparsely populated areas are more likely to operate and maintain a relatively high number of small sewage treatment works. This means sludge cannot be treated cost-effectively on site and needs to be transported to a larger sludge treatment centre in order to achieve economies of scale. This leads to higher sludge transport costs.

Our bioresources cost models include the following population density and size of sewage treatment works explanatory variables:

- **Weighted average density – LAD from MSOA**
- **Weighted average density – MSOA**
- **Proportion of load treated in bands 1 to 3 (ie small STWs)**
- **Number of STWs per property**

These are largely the same explanatory variables used to capture differences in population density and the size of STWs at PR19. The only difference being the weighted average density variables, which we have developed using more granular MSOA population density data from the ONS for PR24 (discussed above).

Our analysis shows that all four explanatory variables are highly correlated (a correlation coefficient of 0.7 or higher), and therefore capture similar information. This is reflected in our bioresources unit cost models, which only include one of the explanatory variables listed above in any one model.

In response to our April 2023 base cost modelling consultation, Severn Trent Water and Thames Water argued that companies do not have control over location of STCs, transport and disposal routes. Suggesting that companies operating in densely populated areas are likely to have STCs co-located with STWs, benefitting from economies of scale in sludge treatment and reduce sludge transportation costs. But on the other hand, more densely populated areas may not be able to dispose treated sludge easily because of higher distances to landbank.

Severn Trent Water argued that the exogeneity assumption should be relaxed to be able to more effectively benchmark bioresources costs. United Utilities stated that our bioresources cost models do not include a cost driver for asset configuration. Thames Water included the "Total measure of 'work' done in sludge disposal operations by truck" and added a squared density term to the models.

We agree with Severn Trent Water and Thames Water that there are factors that affect the appropriate location of STCs including economies of scale of sludge treatment and sludge transport / disposal costs. However, companies still have significant discretion to manage how to balance competing priorities to achieve the most efficient operation of the bioresources unit. For example, trading off distances to STWs and distances to disposal locations. Indeed, this has resulted in some consolidation of STCs during the current price control period which will continue into the next price control period based on PR24 business plans. Company responses to our Industrial Emissions Directive (IED) data request suggest that the number of STCs is expected to fall from 117 to 99 during the 2025-30 period. This is a clear indication that companies have more control over the location of their STCs compared to STWs.

In response to our April 2023 base cost consultation, Thames Water suggested including the squared density term in the bioresources models. It stated that density has a positive impact on sludge disposal costs as companies with more urban areas face longer travel distances due to lower landbank availability. Thames Water also included the squared density term in its PR24 business plan bioresources cost models. As we said in the April 2023 base cost modelling consultation, we do not consider the inclusion of a squared density term in the bioresources unit cost models is appropriate. Sludge disposal accounts for less than 20% of bioresources expenditure, and there is no noticeable correlation between sludge disposal costs and weighted average density. So, we consider this factor has an immaterial impact on costs. Particularly when considered alongside the fact that companies operating in dense areas are likely to benefit from relatively lower sludge transport and treatment costs. Severn Trent Water agreed that the significance of the squared density term is likely to be spurious.

Our PR24 bioresources unit cost models used to help set efficient bioresources base expenditure allowances focus on explanatory variables that capture exogenous factors that increase / decrease opportunities to achieve economies of scale at sludge treatment centres, or increase / decrease sludge transportation costs. We consider it is inappropriate to include explanatory variables that are inside company control or do not have a clear engineering and/or economic rationale as this would go against our base cost assessment principles, and would not support the bioresources market.

5.3 Other cost drivers proposed by companies

Responses to our April 2023 base cost modelling consultation included other cost driver suggestions. We set out why we have not included these in our bioresources base cost models below.

5.3.1 Sludge treatment technologies

South West Water said that companies do not have control over their treatment options as these are affected by exogenous factors such as environmental legislation. South West Water stated that liming is an exogenous technology choice because to get the sludge to land requires the alkalinity that liming adds. The company stated that this provides strong evidence that the technology choice is exogenous and should be included in models.

The company submitted a cost adjustment claim relating to sludge treatment liming technology which used similar arguments, which we have rejected as we consider South West Water's decision to use liming to treat sludge was inside its control.[34] For example, in its PR19 business plan, South West Water stated that during 2014-2016 it evaluated the business case to shift sludge treatment to advanced anaerobic digestion (AAD) technology. But South West Water decided it was not beneficial due to tight economies of scale and the emerging new bioresources market.

We retain the view that companies have discretion to make efficient bioresources investment decisions. Including variables directly related to bioresources activity like sludge treatment technology may remove the incentive to make efficient decisions and is not aligned with our base cost assessment principles to use exogenous cost drivers. Therefore, we do not include sludge treatment options as cost drivers in our models.

5.3.2 Sludge disposal route

In response to our April 2023 base cost modelling consultation Thames Water suggested including total work done in sludge disposal operations by truck (ie the sum of sludge mass multiplied by distance travelled for all sludge disposal journeys by truck). Thames Water also included this cost driver in its PR24 business plan bioresources cost models.

We consider that companies have control over the sludge disposal route and the distance travelled to disposal sites (through the location of their sludge treatment

[34] See South West Water's cost adjustment claim excel file for more details.

centres). Therefore, we do not include sludge disposal route cost drivers in our models as they are inconsistent with our cost assessment principles.

5.3.3 Impact of sewage treatment complexity on bioresources costs

United Utilities and Severn Trent Water said that our models lack important cost drivers such as phosphorus permits that reflect additional bioresources costs associated with phosphorus removal in wastewater network plus.

In our April 2023 base cost modelling consultation we considered controlling for the impact of sewage treatment complexity on bioresources costs through explanatory variables which control for tight phosphorus or ammonia permits. Iron salts used for phosphorus removal can impact sludge treatment and biogas yields. A low ammonia content requirement for final effluent can increase bioresources costs due to the need for more costly sludge liquor treatment. Yorkshire Water in its PR24 business plan developed cost models including the percentage of load with ammonia permit <= 3mg/l as an explanatory variable. However, the company stated that it has not identified models that perform better than the ones in the consultation.

We recognise sewage treatment explanatory variables are exogenous and there is a clear engineering rationale. But after careful consideration, we do not include these in our bioresources unit cost models as they do not perform well against our model assessment criteria. Most notably, differences in sewage treatment complexity between companies do not appear to be a significant driver of bioresources costs.

5.4 Selected bioresources base cost models

Our bioresources base cost model suite includes **4 bioresources unit cost models**.

Table 7: Summary of proposed bioresources cost models

Level of cost aggregation	Cost drivers	Explanatory variables
Bioresources unit cost (4 models)	Economies of scale in sludge treatment, and location of sewage treatment works relative to sludge treatment centres	• Percentage of load treated at band sizes 1 to 3 – included in 1 model. • Weighted average density – LAD from MSOA - included in 1 model. • Weighted average density – MSOA – included in 1 model. • Sewage treatment works (STWs) per property – included in 1 model.

All models are consistent with engineering, operational and economic rationale, and all estimated coefficients on the explanatory variables are of the expected sign and plausible magnitude.

The unit cost models perform well against all other model robustness tests of medium and high importance. They appear less sensitive to changes in the underlying data than the bioresources total cost models, and the variables that proxy economies of scale in sludge treatment and the location of STWs relative to sludge treatment centres are all statistically significant at the 10 percent significance level.

5.4.1 Triangulation approach

We combine the results of each model to arrive at our view of efficient bioresources base cost allowances. We weight the 4 bioresources unit cost models equally.

6. Residential retail cost models

Summary

We use **2 bad debt cost models**, **2 other cost models**, and **4 total retail cost models** to help set efficient residential retail base expenditure allowances at PR24. In each model, the dependent variable is specified as cost per household.

We consider the key residential retail base cost drivers are: the **amount of revenue at risk** if a customer does not pay their water bill; a customer's **propensity to default**; **type of customer**; and **economies of scale**.

Covid-19 led to an increase in companies' bad debt provisions, which was not explained by the key residential retail base cost drivers. This weakened the performance of PR19 residential retail models. We have addressed these issues through the following changes to our PR19 residential retail cost models:

- **Inclusion of two Covid-19 dummy variables for 2019-20 and 2020-21.**
- **Removal of transience variable.**
- **Removal of proportion of metered households variable.**

Following our April 2023 base cost modelling consultation, **we decided to exclude the average number of county court judgements/partial insight accounts per household**, which we consulted on as a potential alternative explanatory variable to proxy a customer's propensity to default. The variable received mixed support from companies, with some expressing concerns around it being somewhat endogenous, and its performance in the retail models worsened with the addition of 2022-23 outturn data.

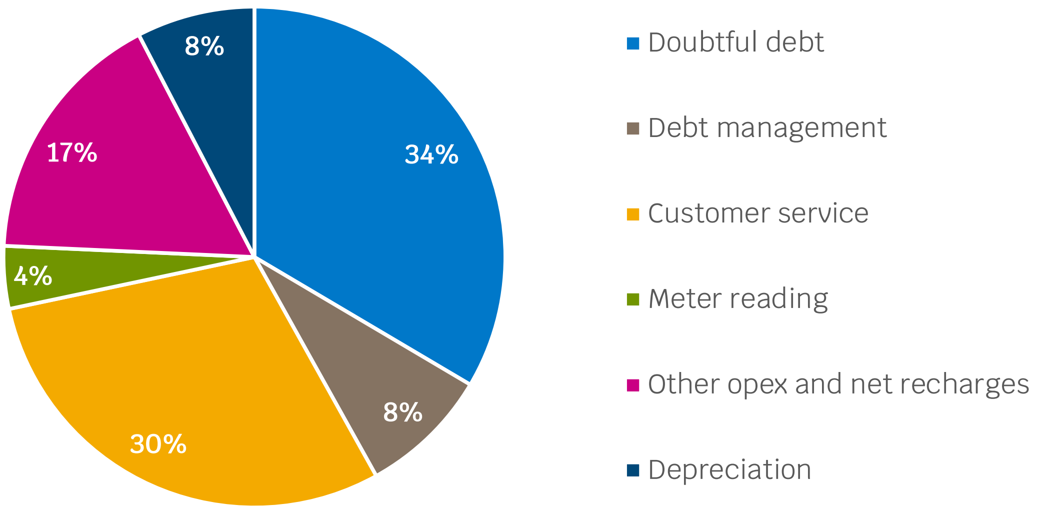
This section presents our econometric benchmarking models used to help set efficient residential retail expenditure allowances at PR24. It is structured as follows:

- defining the dependent variable;
- selected cost drivers;
- cost drivers not included in our proposed models; and
- residential retail econometric cost models.

6.1 Defining the dependent variable

Residential retail modelled base costs across the sector equalled £0.9 billion in 2022–23.[35] Figure 5 below shows the share of expenditure of each activity in 2022-23.

Figure 5: make up of residential retail expenditure in 2022-23



We use three dependent variables in our residential retail cost models:

1. **Bad debt related costs per household,** defined as the sum of doubtful debt and debt management costs divided by the total number of households served. We used the unsmoothed data provided in companies APRs to construct this variable.
2. **Other retail costs per household,** defined as the sum of costs associated with other retailer functions including customer services, meter reading, and depreciation. We calculate other costs by subtracting bad debt costs from total retail costs.
3. **Total retail costs per household,** defined as the sum of bad debt related costs and other retail costs..

We also use models at different levels of cost aggregation:

- **Aggregated 'top down' cost models:** Total retail costs: bad debt + other retail costs
- **Disaggregated 'bottom up' cost models:** Bad debt costs, other retail costs

[35] In 2022-23 prices.

The dependent variable is specified as retail cost per connected household in each model. We chose to maintain a unit cost approach at PR24 as the total number of customers is the main driver of retail costs.

The unit cost models present a lower adjusted R-squared than if the dependent variable was defined as total costs. But this is purely cosmetic. The number of households is the main driver of residential retail costs, with it explaining more than 90 percent of the variation in residential retail costs between companies alone. A unit cost modelling approach aims to explain variations in companies' residential retail costs above and beyond the number of households. In doing so, we change the variation of the dependent variable, leading to a lower adjusted R-squared.

Depreciation

At draft determinations, we have specified the dependent variable using smoothed depreciation.[36] This is consistent with our approach at PR19 where we smoothed depreciation costs due to their lumpy nature and our small data sample size. At the time, it was our view that specifying the dependent variable in this way reflected a more appropriate relationship of the costs with the explanatory factors in the model.

At PR24, we now have more years in our data sample and expect the models to be less impacted by lumpy costs in the early years of the sample. We are therefore considering whether to change our approach at final determinations, to specify the dependent variable using unsmoothed depreciation. This point was also recommended by Wessex Water in response to our April 2023 base cost modelling consultation. We welcome views from the wider sector on this proposal in response to our draft determinations.

6.2 Selected cost drivers

We consider the key residential retail base cost drivers are:

- Amount of revenue at risk if a customer defaults on their water bill
- Propensity to default on water bill payments
- Type of customer
- Economies of scale

[36] We have noticed an error in our retail do file which means that our calculation of smoothed depreciation includes forecast retail depreciation costs for years 2024-30. This is therefore reflected in our model coefficients. We will correct for this error at final determinations.

In addition, we include two Covid-19 dummy variables (2019-20 and 2020-21) in our bad debt costs and total retail costs models to isolate the additional impact of Covid-19 on bad debt costs.

This section discusses the cost drivers and corresponding explanatory variables included in our set of residential retail cost models that we used to help set efficient residential retail expenditure allowances at PR24 draft determinations. We also set out how we considered responses to our April 2023 base cost modelling consultation.

6.2.1 Amount of revenue at risk

We include average bill size in bad debt and total retail cost models to capture the amount of revenue at risk if a customer defaults on its water bill. Average bill size has a clear rationale, whereby as bill size increases, the amount of revenue that the company is at risk of not collecting if a customer is unable to pay their bill increases. The coefficient is positive and is statistically significant.

The estimated coefficient on average bill size is slightly above one in our bad debt models. This suggests that an increase of one percent in average bill size results in an increase in bad debt costs that is slightly above one percent. An estimated coefficient above one may suggest that as bills increase, the likelihood of default increases.

We received comments from three companies in relation to average bill size. Southern Water and SES Water asked us to consider improving our forecasting method for average bill size at PR24 given inflation and the larger enhancement programmes relative to PR19. We have retained the way which we calculate average bill size, which divides total wholesale and residential retail revenue (in 2022-23 prices) by total households served. This is based on companies' business plan forecasts and reflects the larger enhancement programme in PR24. We also reflect forecast input price pressures faced by retail companies in the nominal residential retail cost to serve.[37]

South Staffs Water reiterated comments made in its January model submission. These relate to a perceived structural difference between water only companies (WOCs) and water and wastewater companies (WaSCs) that average bill size does not adequately capture. South Staffs Water relate this to instances where companies bill on behalf of other companies. The proposed solution is to include a WOC dummy variable in our models. We found the arguments made by the company to be convoluted, and difficult to follow. We also consider that the decision of a WOC to bill customers on behalf of a WaSC is inside its control, and so would be inconsistent with our PR24 base cost assessment principle to focus on exogenous cost drivers. On this basis, we do not

[37] More details provided in 'PR24 draft determinations: Expenditure allowances'.

consider there to be clear rationale for the inclusion of a WOC dummy in our retail models. South Staffs Water is the only company to propose this.

6.2.2 Propensity to default on water bill payments

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 being equal.

We include two variables in our residential retail base cost models to proxy for customers' propensity to default.

- **The percentage of households with payment default in a company's operating area**, sourced from Equifax.
- **The level of income deprivation in the company's area**, sourced from ONS.

For the ONS variable, we use linear interpolation to create additional data points for the years between the last two ONS data releases instead of holding the variable constant between 2016 and 2019. No companies disagreed with this approach.

In response to our consultation, no company disagreed with including variables in our model suite that proxy for the propensity to default, and most companies expressed support for the selected variables. A summary of the key feedback points raised by companies is below.

Equifax data

Severn Trent Water expressed concern that the customers of Hafren Dyfrdwy appear as relatively "too affluent" under the Equifax data when compared to ONS income score data. We have reviewed the data and found that Hafren Dyfrdwy is not the only company to rank differently under the different datasets. We are not concerned by this given that the two metrics are capturing different aspects of deprivation, and we triangulate between models.

ONS income score

SES Water expressed concern that the calculation of our ONS income score variable risks not capturing pockets of higher deprivation in an otherwise affluent area. It is reasonable to assume that all companies operate across areas where there is a range of deprivation levels. However, this is challenging to mitigate when calculating a single metric for a widespread area. We use the average as it is reflective of all available data points. We also triangulate across a range of models to avoid placing too much weight on any single propensity to default variable.

Dŵr Cymru comment on the differences in how the English and Welsh income score data is calculated and recommend that we use the combined dataset published by the ONS. [38] We reviewed this argument and the associated dataset, but decided to proceed with our original income score variable for draft determinations. We did not consider this a proportionate change on the basis that the dataset produces only two data points, and the ONS states that the overall impact on the relative position of small areas in Wales is small across the combined ONS dataset and Welsh indices.[39] Hafren Dyfrdwy did not propose this variable. We will continue to monitor future data releases and, consider changes to our approach where appropriate.

Number of county court judgements/partial insights accounts per household

In our April 2023 base cost modelling consultation, we sought views on the inclusion of a third deprivation variable in our retail cost models– the average number of county court judgements/partial insights accounts per household. Based on company feedback and statistical performance, we have not included this variable in our final retail model suite. In particular, Northumbrian Water challenged the inclusion of this variable based on proportionality and statistical performance, and Dŵr Cymru and Yorkshire Water expressed concern that it could be influenced by companies or by local government initiatives, which is not consistent with our PR24 principles of base cost assessment. In terms of statistical performance, we found that this variable was less statistically significant than the other deprivation variables, with a slight deterioration in model performance with the inclusion of 2022-23 data.

Credit risk score

Thames Water, United Utilities, South West Water and Anglian Water all supported our proposed approach to modelling deprivation. But also encouraged us to reconsider including credit risk score as an alternative propensity to default variable in our retail cost models once tested with an additional year of data.

We did not find a significant improvement in the statistical performance of credit risk score in our models with the inclusion of 2022-23 data. So we decided not to include credit risk score in our retail cost models.

Composite deprivation metric

Yorkshire Water challenged our decision not to include a composite deprivation metric in our April 2023 base costs consultation model suite. As stated in our consultation,

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[38] The English data is sourced from the Office of National Statistics (ONS), where as the Welsh data is sourced from StatsWales.

[39] Indices of Deprivation 2019: income and employment domains combined for England and Wales - guidance note - GOV.UK (www.gov.uk)

triangulating across models that include different deprivation metrics leads to a similar outcome. On that basis, we prefer not to include a composite deprivation metric as it would introduce unnecessary complexity without any benefit.

6.2.3 Type of customer

Customer characteristics may influence the cost of serving customers or the propensity of customers to make contact with companies.

We include **the proportion of dual customers** in our other retail cost models to capture this cost driver, which is supported by companies. Dual customers are those that 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. Proportion of dual customers is statistically significant, with a small, positive estimated coefficient.

We do not include the proportion of dual customers in our bad debt cost models or total retail costs models. This is due to the high correlation with average bill size.

We do not include the proportion of metered households in our retail models. At PR19 we included metering penetration in a subset of our retail models under the assumption that a greater number of metered customers results in additional costs associated with meter reading and additional meter enquiries. In our April 2023 consultation, we proposed to exclude this variable from our PR24 retail cost models because its statistical performance deteriorated and the share of total retail costs attributable to meter reading has decreased.

We received a mixed response to our proposal. Most companies responded that they still agreed with the operational rationale for including the proportion of metered households in our models. However, six companies agreed with our decision to remove the variable.[40] These companies recognised that the driver has a very small impact on companies' costs, and that its inclusion does not significantly improve model performance. United Utilities also argued that, given the shift towards increased smart metering, we should expect associated costs to decrease. So, including this variable is no longer reflective of future circumstances.

For the remaining companies that disagreed with removing the variable, they expressed concern that the rollout of smart meters could lead to an increase in the

[40] Northumbrian Water, Portsmouth Water, United Utilities, Severn Trent and Yorkshire. Dŵr Cymru also shared similar views, but commented that our decision on inclusion should be based on statistical performance.

number of customer queries coming from customers. But we do not consider there is sufficient evidence to show this will lead to a material increase in retail costs over the long term given we expect the smart metering programme to deliver cost efficiencies.

6.2.4 Economies of scale

We include **the number of connected households** in our other retail costs and a subset of total retail costs models to capture economies of scale. This allows us to relax the constant returns to scale assumption, allowing for increasing or decreasing returns to scale. In the context of retail costs, this means that, if average costs (ie cost per household) decreases with scale (ie the number of households served) the variable would have a negative coefficient.

We retain our PR19 position that economies of scale is not a relevant bad debt cost driver due to the availability of third party providers which means all retail companies can benefit from the same economies of scale. So, we do not include the number of connected households in our bad debt models, and only include it in a subset of our total retail cost models.

In response to our April 2023 base cost consultation, Dŵr Cymru, SES Water, South West Water and Bristol Water expressed a preference for determining allowances based on top down models including economies of scale. SES Water also submitted a cost adjustment claim relating to economies of scale in retail which argues the same point.

As discussed above, we assume constant returns to scale in our bad debt models, and bad debt costs make up just under half of total retail costs. So we do not consider it appropriate to include an economies of scale driver in all total retail cost models. We include the number of connected households in two out of four total retail cost models, which we consider strikes a fair balance between bad debt and other retail costs.

6.2.5 Covid-19 dummy variables

We include two Covid-19 dummy variables in our retail cost models to help mitigate the short term impact of Covid-19 on retail costs. This allows us to isolate the atypically high costs in 2019-20 and 2020-21 associated with bad debt provisions during the pandemic.

Most companies supported our proposal to include dummy variables in response to consultation. However, the sector did not support this as a long-term solution and welcomed our proposal to reconsider the inclusion of the Covid-19 dummy variables once we were able to test the models with an additional year of 2022-23 outturn data.

Some companies also suggested that we explore alternative solutions, summarised below.

South East Water was the only company that disagreed with our proposal. The company advised that we explore more equitable and specific ways of isolating the cost impact of COVID-19, for example through smoothing bad debt costs or considering a sequence of dummies that account for both high and low cost periods.

Dŵr Cymru and Yorkshire Water also suggested defining our dependent variable using smoothed bad debt costs to mitigate the impact of Covid-19 instead of using the Covid-19 dummy variables. As stated in our consultation, we tested this approach but found that it did not significantly improve the statistical performance of the models. We still consider that, given that the dummy variables are able to isolate the additional Covid-19 impact, this is the best option at this time. We will consider our approach again with the inclusion of 2023-24 data.

Yorkshire Water proposed the idea of multiple time dummies, and Wessex Water asked us to consider whether a third Covid-19 dummy was required for 2021-22. Based on the outturn cost data, we do not believe there is a clear case for introducing additional dummies at this time. We consider the 2019-20 and 2020-21 dummy variables are sufficient to isolate the impact of Covid-19 on bad debt costs as our model estimation results are robust to changes in the underlying sample, and produce estimated coefficients that are in line with expectations.

The statistical performance of the models remains sensitive to the removal of the Covid-19 dummies, even with the inclusion of 2022-23 data. We have therefore included two dummies for years 2019-20 and 2020-21 in our final retail models for PR24 draft determinations. We will revisit our decision ahead of final determinations with the addition of 2023-24 outturn data.

6.3 Other cost drivers proposed by companies

Responses to our April 2023 base cost modelling consultation included other cost driver suggestions. We set out why we have not included these in our residential retail base cost models below.

6.3.1 Transience

At PR19, we included a cost driver to in our retail models to capture the impact of high transience rates on bad debt costs. We have removed this cost driver from our PR24 retail cost models.

During PR24 model development, we found the transience variable to be unstable, often presenting a negative, counterintuitive sign on the estimated coefficient sign and being highly statistically insignificant across most models. These conclusions suggested that transience does not have a material impact on bad debt costs. In addition, part of the ONS dataset used to construct this variable has since been discontinued. We have not been able to find any suitable alternative datasets, nor have companies suggested any.

As part of our April 2023 base cost consultation, we sought views from companies on our proposal to exclude this driver from our models at PR24. All companies, except for Thames Water, Affinity Water and South West Water agreed with our proposal. Several companies stated that they found similar outcomes as part of their own model testing.

The three companies that disagree proposed alternative solutions to modelling transience using the existing data. This included holding the variable constant and options for smoothing the variable over time. We do not support these approaches to modelling. Namely because we did not consider the assumptions made in these proposals to be underpinned by evidence, nor would we be able to verify any assumptions made with a future publication. We also reiterate that this does not resolve the conclusions we drew about the decrease in the size of the coefficient, indicating that it is not a material driver of retail costs.

6.3.2 Density

We do not consider density to be a relevant cost driver of retail costs. We retain our view at consultation that we do not consider there to be clear economic or operational rationale for its inclusion in our retail models. Severn Trent Water disagreed with our reasoning on the basis that we include density as a driver in our treated water distribution models to proxy for several factors. However, that is underpinned by clear economic and engineering rationale and is supported by the wider sector.

6.3.3 Time trend

We do not consider time trends to be a relevant cost driver in our retail cost models. In response to our consultation, Wessex Water reiterated its views that we should include a time trend in our other retail costs models to capture the underlying dynamics of industry-wide costs. The company also suggests that not including a time trend in our bad debt models has undermined our approach to modelling deprivation based on higher levels of statistical significance when a time trend variable is included in our bad debt models

We do not support the inclusion of a time trend in our retail cost models. A time trend lacks clear economic or operational rationale that links it to retail costs. Aside from the costs in years impacted by Covid-19, for which we include dummy variables, we do not observe significant, unexplained variation in sector wide costs between years in the sample period that may otherwise justify the inclusion of a time trend. Wessex Water do not present analysis to demonstrate this either. We also have concerns that if we were to include a time trend without clear rationale, there is a risk that the time trend may be capturing factors that are within company control or other factors that may not continue over time. This goes against our base cost assessment principles. On this basis, we disagree that not including a time trend undermines our approach to modelling deprivation.

6.4 Selected residential retail base cost models

Our residential retail base cost mode suite includes 8 models, made up of 2 bad debt costs models, 2 other retail cost models and 4 total cost models.

Table 8: Summary of residential retail cost models

Level of cost aggregation	Cost drivers	Explanatory variables
Bad debt models (2 models)	Amount of revenue at risk	• Average bill size – included in 2 models.
	Deprivation	• Proportion of households with default– included in 1 model. • Income deprivation score (interpolated) – included in 1 model.
	Covid-19 dummies	• 2019-20 dummy variable – included in 2 models. • 2020-21 dummy variable – included in 2 models.
Other retail costs (2 models)	Type of customer	• Proportion of dual customers – included in 2 models.
	Economies of scale	• Total number of households – included in 1 model.
Total retail costs (4 models)	Amount of revenue at risk	• Average bill size – included in 4 models.
	Deprivation	• Proportion of households with default– included in 2 model. • Income deprivation score (interpolated) – included in 2 model.
	Economies of scale	• Total number of households – included in 2 models.
	Covid-19 dummies	• 2019-20 dummy variable – included in 4 models. • 2020-21 dummy variable – included in 4 models.

All models are consistent with the economic rationale, and all estimated coefficients on the explanatory variables are of the expected sign and plausible magnitude. The models generally perform well against our sensitivity tests, with only a subset of models receiving an amber rating due to some of the explanatory variables becoming less statistically significant when the underlying sample is changed.

6.4.1 Triangulation approach

We combine the results of each model to arrive at our view of efficient residential retail base cost allowances. We apply 75 percent weight to our high-level of cost aggregation retail cost models (ie total residential retail costs), and 25 percent weight to our disaggregated retail cost models (ie bad debt; other retail costs). We applied the same approach at PR19, and this approach reflects feedback we received from some companies in response to our April 2023 base cost consultation that expressed a preference to place more weight on top down models.[41]

Please see residential retail feeder model 3 for more details on our triangulation approach.

[41] Severn Trent, Anglian Water, South West Water, South East Water and SES Water.

A1 Model robustness tests

Table 10 below includes the range of model robustness tests that we used to assess each econometric cost model, each with its relative degree of importance.

The key for the level of importance assigned to each test is as follows:

- high – failure of these tests and criteria would raise serious concerns about using the model;
- medium – failure of these tests and criteria would raise concerns about using the model, but the model could still be used with caution if it passes other tests; and
- low – failure of these tests and criteria would raise relatively limited concerns about using the model.

Table 9: Assessing model robustness

Test	Importance	Explanation and comments
Engineering, operational and economic rationale		
Consistency with prior expectations of sign and magnitude of estimated coefficients	High	The estimated model coefficients must be consistent with engineering, operational and economic logic. Assessing the estimated coefficients against a-priori expectations is an important check to ensure that we do not include variables that appear statistically related but where there is no clear rationale for their inclusion.
Predictive and forecasting power of models		
Goodness of fit (adjusted R^2)	High	The adjusted R-squared measures how closely the model fits the data. It measures the proportion of variation in the dependent variables (in our case, variation in costs) that is explained by the model. The statistic is within the range from 0 to 1. **The higher the value the closer the model fits the data.** Importantly, R-squared measures should only be used to compare models with the same dependent variable. If a model failed to explain a significant share of the costs of the industry, it would be inappropriate to use it for the estimation of costs. But equally, a strategy of searching for a model with a high R-squared has the risk of finding a model that fits the data well but is in fact incorrect. Because rather than reflecting the true underlying relationship, the model could be capturing accidental features of the data at hand. Like all the statistical diagnostics included in this table, the R-squared should not be used mechanistically.
Efficiency score distribution	Medium	Efficiency scores can be calculated for any given model as the ratio between a company's outturn costs and predicted modelled costs in the last 5 years of the sample. A large range of efficiency scores could indicate the presence of issues in the underlying model, such as the presence of omitted variables. The distribution of efficiency scores can help inform decisions on model selection across models at the same level of cost aggregation.
Statistical diagnostic tests		
Statistical significance of	High	The p-value of the t test gives the probability of observing the estimated coefficient (or one more extreme) if the true value was in fact zero. A lower value indicates a lower probability of observing the estimated

individual parameters (t-test)		coefficient if the true value was zero, and can thus be interpreted as giving a higher degree of confidence that the true value is not zero – ie that there is a relationship between the dependent and explanatory variables. Coefficients could fail this test due to absence of a relationship between the cost driver and the dependent variable, but also due to limitations in the data or multicollinearity. A higher p-value indicates a lower level of statistical significance (ie there is less confidence in the value of the estimated coefficient). However, there is a wide range of confidence levels in this category. Statistical significance of 80% and even 70% may be deemed valid in practical work.
RESET test	Medium	This is a test to detect if an alternative functional form may be superior, through missing non-linear terms (eg quadratic). However, failure of this test does not automatically mean that the linear relationship is wrong, but that other options should be explored. If alternative specifications using non-linear terms in the models do not lead to successful results, then failure of the RESET test on its own may not be a valid justification to dismiss a model. This is particularly the case if it is considered that the model offers useful information from an economic or engineering perspective. **The higher the p-value, the more confident we are that the functional form is adequate.**
Variance Inflation Factor (VIF)	Medium	This assessment is used to detect multicollinearity. High collinearity means that we cannot estimate the coefficients with confidence – their variance is high and statistical significance low. As a consequence, the individual coefficient estimates are not precise and unstable. **As a rule of thumb, a VIF >4 indicates medium risk and VIF >10 indicates harmful collinearity.** **An exception to this rule is when the model includes a variable and its quadratic term.** In such cases the VIF becomes high due to the correlation between these two related terms. But while the high collinearity may impair our ability to accurately estimate the impact of the individual terms on the dependent variable, it should not impair our ability to accurately estimate their collective impact. Since these two terms always move together, the collective impact is what is important.
Pooling/Chow test	Medium	This is a test to determine the appropriateness of using a panel dataset structure. When using a panel data estimation method, we assume that the estimated coefficients in the model are stable over time – ie the null hypothesis of this test is that the slope of the estimated relationship is stable over time. If the null hypothesis is rejected, it would imply that each individual cross-section has its own slope, and the panel data analysis may not be appropriate. **The higher the p-value, the more confident we are that panel data analysis is appropriate.**
Normality test	Low	Obtaining the best estimates using OLS requires the model residuals to be normally distributed with an average of zero and a constant variance. If this assumption is violated, the model estimation results are still unbiased and consistent. Hence, a low level of importance is attached to these test results. **Normality and heteroskedasticity tests are failed for lower p-values.** If the normality test fails, it would suggest that the model residuals are not normally distributed.
Heteroskedasticity test	Low	If the heteroskedasticity test fails, it means that the variance of the model residuals is not constant across observations. If the test fails, different measures could be introduced to address the issue (eg use cluster standard errors).

<table>
<tr><td>Breusch-Pagan LM test</td><td>Low</td><td>This is a test for pooled OLS versus random effects. This test is failed for lower p-values. Failure of this test would indicate that the random effects estimation method is preferred over the pooled OLS estimation.</td></tr>
<tr><td colspan="3">Sensitivity of model estimation results to changes in the underlying sample</td></tr>
<tr><td>Sensitivity of estimated coefficients to removal of most and least efficient company</td><td>Medium</td><td rowspan="2">This is a test to assess robustness of the model to changes in the underlying assumptions. Robustness under the first test should be assessed by removing the most efficient company, and separately the least efficiency company from the sample. Robustness under the second test should be assessed by removing the first year of the sample, and separately the last year of the sample.
Results of the test are reported using the following RAG rating (the lower the rating, the less confident we are in model stability):
• Red (R): the estimated coefficients present changes in sign, and the p-value changes by more than 0.1 for at least one explanatory variable;
• Amber (A): the estimated coefficients have the same sign for all explanatory variables, but the p-value changes by more than 0.1 for at least one explanatory variable; and
• Green (G): the estimated coefficients have the same sign for all explanatory variables, and the p-value does not change by more than 0.1 for any explanatory variable.</td></tr>
<tr><td>Sensitivity of estimated coefficients to removal of first and last year of the sample period</td><td>Medium</td></tr>
</table>

A2 Econometric base cost models for PR24 draft determinations

A2.1 Wholesale water

Table 10: Water resources plus models

Cost driver	Explanatory variable	WRP1	WRP2	WRP3	WRP4	WRP5	WRP6
Scale	Connected properties (log)	1.095*** {0.000}	1.092*** {0.000}	1.070*** {0.000}	1.070*** {0.000}	1.043*** {0.000}	1.041*** {0.000}
Complexity	Water treated at complexity levels 3 to 6 (%)	0.005*** {0.000}		0.004*** {0.002}		0.005*** {0.000}	
	Weighted average treatment complexity (log)		0.390 {0.148}		0.366 {0.178}		0.416 {0.108}
Density	LAD from MSOA – Weighted average density (log)	-1.741*** {0.001}	-1.661*** {0.006}				
	LAD from MSOA – weighted average density (log) – squared	0.111*** {0.001}	0.104*** {0.007}				
	MSOA – weighted average density (log)			-5.580*** {0.004}	-5.587** {0.011}		
	MSOA – weighted average density (log) – squared			0.341*** {0.005}	0.340** {0.011}		
	Properties per length (log)					-8.915*** {0.004}	-8.644*** {0.007}
	Properties per length (log) – squared					0.987*** {0.007}	0.951** {0.011}
Constant	Constant	-4.721*** {0.001}	-5.121*** {0.004}	11.679 {0.108}	11.585 {0.164}	9.282 {0.151}	8.595 {0.200}

Table 11: Water resources plus models – model robustness tests and additional information

Model robustness tests and additional information		WRP1	WRP2	WRP3	WRP4	WRP5	WRP6
Robustness tests	Adjusted R-squared	0.910	0.904	0.902	0.898	0.912	0.908
	RESET test	0.551	0.492	0.822	0.696	0.999	0.976
	VIF (max)	1.200	1.239	1.265	1.292	1.118	1.157
	Pooling / Chow Test	0.999	1.000	1.000	1.000	0.989	0.997
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.055	0.632	0.056	0.384	0.031	0.446
	Heteroskedasticity of model residuals	0.000	0.002	0.000	0.000	0.000	0.000
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	204	204	204	204	204	204
	Dependent variable	Water resources + Raw water distribution + Water treatment					
Efficiency score distribution	Minimum	0.58	0.55	0.54	0.52	0.55	0.53
	Maximum	2.22	2.17	2.19	2.15	2.16	2.12
	Range	1.64	1.62	1.64	1.63	1.61	1.59
Sensitivity checks	Removal most efficient company	G	A	G	G	G	G
	Removal least efficient company	G	A	G	G	A	A
	Removal first year	G	G	G	G	G	G
	Removal last year	G	A	A	G	A	A

Table 12: Treated water distribution models

Cost driver	Explanatory variable	TWD1	TWD2	TWD3	TWD4	TWD5	TWD6
Scale	Length of mains (log)	1.073*** {0.000}	1.026*** {0.000}	1.068*** {0.000}	1.069*** {0.000}	1.018*** {0.000}	1.048*** {0.000}
Topography	Booster pumping stations per length of mains (log)	0.308** {0.010}	0.312*** {0.004}	0.361*** {0.001}			
	Average pumping head TWD (log)				0.310*** {0.001}	0.374*** {0.000}	0.293*** {0.002}
Density	LAD from MSOA – Weighted average density (log)	-2.917*** {0.000}			-3.325*** {0.000}		
	LAD from MSOA – Squared weighted average density (log)	0.230*** {0.000}			0.255*** {0.000}		
	MSOA – Weighted average density (log)		-6.130*** {0.000}			-7.375*** {0.000}	
	MSOA – Squared weighted average density (log)		0.427*** {0.000}			0.500*** {0.000}	
	Properties per length – Weighted average density (log)			-16.187*** {0.000}			– 18.269*** {0.000}
	Properties per length – Squared weighted average density (log)			2.038*** {0.000}			2.254*** {0.000}
Constant	Constant	4.435*** {0.006}	17.668*** {0.000}	27.589*** {0.000}	3.468** {0.032}	20.060*** {0.000}	29.939*** {0.000}

Table 13: Treated water distribution models – model robustness tests and additional information

Model robustness tests and additional information		TWD1	TWD2	TWD3	TWD4	TWD5	TWD6
Robustness tests	Adjusted R-squared	0.955	0.955	0.961	0.957	0.962	0.962
	RESET test	0.077	0.131	0.496	0.286	0.774	0.895
	VIF (max)	1.836	1.611	1.886	1.045	1.110	1.060
	Pooling / Chow Test	0.702	0.768	0.810	0.852	0.860	0.908
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.104	0.033	0.226	0.384	0.950	0.562
	Heteroskedasticity of model residuals	0.114	0.033	0.000	0.770	0.807	0.226
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	204	204	204	204	204	204
	Dependent variable	Treated water distribution					
Efficiency score distribution	Minimum	0.83	0.77	0.75	0.77	0.75	0.80
	Maximum	1.31	1.33	1.33	1.37	1.30	1.28
	Range	0.48	0.56	0.58	0.60	0.54	0.48
Sensitivity checks	Removal most efficient company	G	G	G	G	G	G
	Removal least efficient company	G	G	G	G	G	G
	Removal first year	G	G	G	G	G	G
	Removal last year	G	G	G	G	G	G

Table 14: Wholesale water models (booster pumping stations)

Cost driver	Explanatory variable	WW1	WW2	WW3	WW4	WW5	WW6
Scale	Connected properties (log)	1.080*** {0.000}	1.070*** {0.000}	1.058*** {0.000}	1.053*** {0.000}	1.048*** {0.000}	1.043*** {0.000}
Complexity	Water treated at complexity levels 3 to 6 (%)	0.003*** {0.000}		0.003** {0.014}		0.003*** {0.001}	
	Weighted average treatment complexity (log)		0.350** {0.020}		0.320** {0.036}		0.360** {0.011}
Topography	Booster pumping stations per length of mains (log)	0.348*** {0.006}	0.366*** {0.003}	0.387*** {0.003}	0.399*** {0.002}	0.293** {0.011}	0.298** {0.011}
Density	LAD from MSOA – Weighted average density (log)	-2.018*** {0.000}	-1.820*** {0.000}				
	LAD from MSOA – Squared weighted average density (log)	0.142*** {0.000}	0.128*** {0.000}				
	MSOA – Weighted average density (log)			-5.346*** {0.000}	-4.930*** {0.000}		
	MSOA – Squared weighted average density (log)			0.341*** {0.000}	0.313*** {0.000}		
	Properties per length – Weighted average density (log)					-12.331*** {0.000}	-11.383*** {0.000}
	Properties per length – Squared weighted average density (log)					1.436*** {0.000}	1.320*** {0.000}
Constant	Constant	-1.649 {0.289}	-2.399 {0.112}	12.667** {0.014}	10.948** {0.035}	17.849*** {0.000}	15.731*** {0.000}

Table 15: Wholesale water models (booster pumping stations) – model robustness tests and additional information

Model robustness tests and additional information		WW1	WW2	WW3	WW4	WW5	WW6
Robustness tests	Adjusted R-squared	0.965	0.966	0.963	0.965	0.965	0.967
	RESET test	0.15	0.079	0.231	0.135	0.531	0.382
	VIF (max)	1.950	1.947	1.798	1.752	1.895	1.888
	Pooling / Chow Test	0.914	0.87	0.965	0.935	0.959	0.932
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.125	0.395	0.293	0.397	0.012	0.006
	Heteroskedasticity of model residuals	0.000	0.000	0.000	0.000	0.000	0.000
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	204	204	204	204	204	204
	Dependent variable	Wholesale water total					
Efficiency score distribution	Minimum	0.82	0.80	0.78	0.79	0.75	0.77
	Maximum	1.43	1.46	1.46	1.48	1.42	1.39
	Range	0.62	0.66	0.67	0.68	0.66	0.63
Sensitivity checks	Removal most efficient company	A	G	A	A	A	A
	Removal least efficient company	G	G	A	G	G	G
	Removal first year	G	G	G	A	G	G
	Removal last year	G	G	G	G	G	G

Table 16: Wholesale water models (average pumping head)

Cost driver	Explanatory variable	WW7	WW8	WW9	WW10	WW11	WW12
Scale	Connected properties (log)	1.083*** {0.000}	1.076*** {0.000}	1.052*** {0.000}	1.047*** {0.000}	1.035*** {0.000}	1.030*** {0.000}
Complexity	Water treated at complexity levels 3 to 6 (%)	0.002** {0.017}		0.001 {0.183}		0.002** {0.023}	
	Weighted average treatment complexity (log)		0.249 {0.130}		0.223 {0.174}		0.283* {0.067}
Topography	Average pumping head (log)	0.327*** {0.008}	0.324*** {0.009}	0.340*** {0.006}	0.336*** {0.007}	0.244* {0.078}	0.236* {0.091}
Density	LAD from MSOA – Weighted average density (log)	-2.612*** {0.000}	-2.487*** {0.000}				
	LAD from MSOA – Squared weighted average density (log)	0.179*** {0.000}	0.170*** {0.000}				
	MSOA – Weighted average density (log)			-7.318*** {0.000}	-7.036*** {0.000}		
	MSOA – Squared weighted average density (log)			0.460*** {0.000}	0.442*** {0.000}		
	Properties per length – Weighted average density (log)					-14.451*** {0.000}	-13.809*** {0.000}
	Properties per length – Squared weighted average density (log)					1.667*** {0.000}	1.588*** {0.000}
Constant	Constant	-2.181 {0.185}	-2.707 {0.111}	17.848*** {0.000}	16.647*** {0.001}	20.654*** {0.000}	19.222*** {0.000}

Table 17: Wholesale water models (average pumping head) – model robustness tests and additional information

Model robustness tests and additional information		WW7	WW8	WW9	WW10	WW11	WW12
Robustness tests	Adjusted R-squared	0.96	0.961	0.956	0.957	0.962	0.963
	RESET test	0.655	0.662	0.751	0.826	0.831	0.772
	VIF (max)	1.201	1.244	1.293	1.292	1.155	1.221
	Pooling / Chow Test	0.948	0.967	0.995	0.994	0.993	0.992
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.028	0.163	0.049	0.079	0.002	0.010
	Heteroskedasticity of model residuals	0.000	0.000	0.000	0.000	0.000	0.000
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	204	204	204	204	204	204
	Dependent variable	Wholesale water total					
Efficiency score distribution	Minimum	0.70	0.68	0.68	0.67	0.69	0.68
	Maximum	1.60	1.58	1.53	1.52	1.56	1.53
	Range	0.91	0.90	0.85	0.85	0.86	0.85
Sensitivity checks	Removal most efficient company	A	G	G	G	A	G
	Removal least efficient company	G	A	G	A	G	G
	Removal first year	A	A	A	A	A	A
	Removal last year	G	G	G	G	G	G

A2.2 Wastewater network plus

Table 18: Sewage collection models

Cost driver	Explanatory variable	SWC1	SWC2	SWC3
Scale	Sewer Length (log)	0.805*** {0.000}	0.867*** {0.000}	0.836*** {0.000}
Topography	Pumping capacity per sewer length (log)	0.328** {0.026}	0.550*** {0.001}	0.496*** {0.004}
Density	Properties per length (log)	1.128*** {0.000}		
	Weighted average density - LAD from MSOA (log)		0.267*** {0.000}	
	Weighted average density – MSOA (log)			0.441*** {0.000}
Urban rainfall	Urban rainfall per sewer length (log)	0.097*** {0.006}	0.140*** {0.007}	0.139*** {0.008}
Constant	Constant	-7.812*** {0.000}	-6.164*** {0.000}	-7.366*** {0.000}

Table 19: Sewage collection models – model robustness and additional information

Model robustness tests and additional information		SCW1	SCW2	SCW3
Robustness tests	Adjusted R-squared	0.917	0.906	0.903
	RESET test	0.093	0.074	0.085
	VIF (max)	2.388	1.912	1.995
	Pooling / Chow Test	0.879	0.977	0.987
	LM test (Pooled OLS vs RE)	0	0	0
	Normality of model residuals	0.327	0.084	0.184
	Heteroskedasticity of model residuals	0.217	0.014	0.004
Model information	Estimation method	RE	RE	RE
	Observations	120	120	120
	Dependent variable	Sewage collection		
Efficiency score distribution	Minimum	0.93	0.87	0.84
	Maximum	1.18	1.17	1.11
	Range	0.25	0.30	0.27
Sensitivity checks	Removal most efficient company	A	G	G
	Removal least efficient company	A	A	A
	Removal first year	A	A	A
	Removal last year	G	G	G

Table 20: Sewage treatment models

Cost driver	Explanatory variable	SWT1	SWT2
Scale	Load (log)	0.709*** {0.000}	0.818*** {0.000}
Treatment complexity	Load treated with ammonia consent ≤ 3mg/l	0.005*** {0.000}	0.005*** {0.000}
Economies of scale in sewage treatment	Load treated in size bands 1 to 3 (%)	0.029 {0.206}	
	Weighted average treatment size (log)		-0.228*** {0.000}
Constant	Constant	-4.244*** {0.000}	-3.317*** {0.000}
Model robustness tests and additional information			
Robustness tests	Adjusted R-squared	0.86	0.907
	RESET test	0.187	0.845
	VIF (max)	5.409	4.416
	Pooling / Chow Test	0.999	0.985
	LM test (Pooled OLS vs RE)	0	0
	Normality of model residuals	0.009	0.002
	Heteroskedasticity of model residuals	0.611	0.303
Model information	Estimation method	RE	RE
	Observations	120	120
	Dependent variable	Sewage treatment	
Efficiency score distribution	Minimum	0.84	0.93
	Maximum	1.62	1.36
	Range	0.78	0.43
Sensitivity checks	Removal most efficient company	G	G
	Removal least efficient company	G	G
	Removal first year	G	G
	Removal last year	G	G

Table 21: Wastewater network plus models

Cost driver	Explanatory variable	WWNP1	WWNP2
Scale	Load (log)	0.751*** {0.000}	0.730*** {0.000}
Topography	Pumping capacity per sewer length (log)	0.375*** {0.001}	0.293*** {0.006}
Treatment complexity	Load treated with ammonia consent ≤ 3mg/l	0.005*** {0.000}	0.005*** {0.000}
Economies of scale in sewage treatment	Load treated in size bands 1 to 3 (%)	0.023** {0.027}	
	Weighted average treatment size (log)		-0.087** {0.021}
Urban rainfall	Urban rainfall per sewer length (log)	0.071** {0.018}	0.076** {0.037}
Constant	Constant	-4.000*** {0.000}	-2.772*** {0.000}

Table 22: Wastewater network plus models – model robustness and additional information

Model robustness tests and additional information		WWNP1	WWNP2
Robustness tests	Adjusted R-squared	0.953	0.956
	RESET test	0.36	0.024
	VIF (max)	5.569	4.619
	Pooling / Chow Test	0.981	0.949
	LM test (Pooled OLS vs RE)	0	0
	Normality of model residuals	0.007	0.028
	Heteroskedasticity of model residuals	0.340	0.040
Model information	Estimation method	RE	RE
	Observations	120	120
	Dependent variable	Wastewater network plus botex plus	
Efficiency score distribution	Minimum	0.96	0.95
	Maximum	1.14	1.11
	Range	0.18	0.16
Sensitivity checks	Removal most efficient company	G	G
	Removal least efficient company	A	A
	Removal first year	A	A
	Removal last year	G	G

A2.3 Bioresources

Table 23: Bioresources unit cost models

Cost driver	Explanatory variable	BR1	BR2	BR3	BR4
Economies of scale in sludge treatment, and location of STWs relative to sludge treatment centres	Load treated in bands 1-3 (%)	0.053*** {0.000}			
	Weighted average density – LAD from MSOA (log)		-0.246** {0.026}		
	Weighted average density – MSOA (log)			-0.342** {0.031}	
	Number of sewage treatment works per property (log)				0.204** {0.012}
Constant	Constant	-0.861*** {0.000}	1.114 {0.152}	2.039* {0.098}	1.016 {0.117}

Table 24: Bioresources unit cost models – model robustness and additional information

Model robustness tests and additional information		BR1	BR2	BR3	BR4
Robustness tests	Adjusted R-squared	0.256	0.172	0.145	0.166
	RESET test	0.37	0.002	0.041	0.497
	VIF (max)	0	0	0	0
	Pooling / Chow Test	0.000	0.000	0.000	0.000
	LM test (Pooled OLS vs RE)	0	0	0	0
	Normality of model residuals	0	0	0	0
	Heteroskedasticity of model residuals	0	0	0	0
Model information	Estimation method	RE	RE	RE	RE
	Observations	120	120	120	120
	Dependent variable	Bioresources modelled base costs divided by sludge produced			
Efficiency score distribution	Minimum	0.59	0.55	0.55	0.54
	Maximum	1.36	1.25	1.29	1.31
	Range	0.77	0.70	0.74	0.77
Sensitivity checks	Removal most efficient company	G	G	G	G
	Removal least efficient company	G	A	A	G
	Removal first year	G	G	G	G
	Removal last year	G	G	G	G

A2.4 Residential retail

Table 25: Residential retail models

Cost driver	Explanatory variable	RDC1	RDC2	ROC1	ROC2	RTC1	RTC2	RTC3	RTC4
Revenue at risk	Average bill size (£ per/household) (log)	1.086*** {0.000}	1.014*** {0.000}			0.665*** {0.000}	0.686*** {0.000}	0.548*** {0.000}	0.558*** {0.000}
Deprivation	Equifax - Percentage of households with payment default (%)	0.046*** {0.007}				0.021*** {0.003}		0.021*** {0.002}	
	ONS - Income deprivation score (interpolated) (%)		0.075*** {0.002}				0.025* {0.079}		0.028* {0.079}
Type of customer	Proportion of dual households (%)			0.002** {0.026}	0.004*** {0.000}				
Economies of scale	Total number of households (log)				-0.069* {0.054}	-0.092*** {0.001}	-0.092*** {0.005}		
Covid-19 dummies	Covid-19 dummy for 2019-20 (nr)	0.379*** {0.000}	0.396*** {0.000}			0.166*** {0.000}	0.167*** {0.000}	0.166*** {0.000}	0.169*** {0.000}
	Covid-19 dummy for 2020-21 (nr)	0.201** {0.012}	0.210*** {0.008}			0.048 {0.103}	0.045* {0.097}	0.044 {0.129}	0.044 {0.112}
Constant	Constant	-4.933*** {0.000}	-4.399*** {0.000}	2.900*** {0.000}	3.793*** {0.000}	0.442 {0.196}	0.495 {0.219}	-0.175 {0.694}	-0.092 {0.829}

Table 26: Residential retail models – model robustness and additional information

Model robustness tests and additional information		RDC1	RDC2	ROC1	ROC2	RTC1	RTC2	RTC3	RTC4
Robustness tests	Adjusted R-squared	0.664	0.668	0.143	0.152	0.711	0.656	0.672	0.651
	RESET test	0.165	0.179	0.989	0.099	0.689	0.502	0.418	0.283
	VIF (max)	1.036	1.209	1	2.091	2.424	1.931	1.036	1.209
	Pooling / Chow Test	0.998	0.973	0.419	0.754	1.000	1	1.000	1.000
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0	0	0
	Normality of model residuals	0	0	0.087	0.158	0.034	0.045	0.011	0.029
	Heteroskedasticity of model residuals	0.000	0.000	0.021	0.074	0.056	0.049	0.300	0.145
Model information	Estimation method	RE	RE	RE	RE	RE	RE	RE	RE
	Observations	170	170	170	170	170	170	170	170
	Dependent variable	Bad debt related costs per household		Other costs per household		Total costs per household			
Efficiency score distribution	Minimum	0.71	0.65	0.80	0.80	0.80	0.73	0.82	0.79
	Maximum	1.70	1.44	1.53	1.49	1.27	1.34	1.38	1.45
	Range	0.99	0.80	0.74	0.69	0.47	0.60	0.55	0.66
Sensitivity checks	Removal most efficient company	G	G	G	G	G	A	G	A
	Removal least efficient company	G	A	G	A	G	A	G	G
	Removal first year	A	G	G	G	G	G	G	G
	Removal last year	A	G	G	A	G	A	G	A

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