April 2023

Econometric base cost models for PR24

Ofwat

About this document

This document presents our proposed set of econometric models that we intend to use to help set efficient base expenditure allowances at PR24. It includes wholesale water, wastewater network plus, bioresources and residential retail models. This allows water companies to:

- account for early efficiency information in their PR24 business plans;
- focus more on long-term challenges; and
- submit high quality cost adjustment claims in June 2023.

We invite responses to this consultation by **12th May 2023**. Please complete the consultation responses template available on our website.[1] We will review responses ahead of our PR24 draft determinations, and consider making changes to our proposed cost models where appropriate.

Alongside this consultation we publish an independent report commissioned from CEPA on econometric models for wholesale water, wastewater network plus and bioresources, as well as cost models suggested by water companies.[2]

[1] Available here: https://www.ofwat.gov.uk/wp-content/uploads/2023/04/Econometric-base-cost-models-for-PR24-response-template.xlsx
[2] Available here: https://www.ofwat.gov.uk/econometric-base-cost-models-for-pr24/

Executive summary

This document presents our proposed set of econometric models that we intend to use to help set efficient base expenditure allowances at PR24.

Base expenditure is routine, year-on-year expenditure, which companies incur in the normal running of their businesses to provide a base level of good service to customers and the environment. It includes expenditure to maintain the long-term capability of assets, as well as expenditure to improve efficiency.

Water companies are monopoly providers of most water and wastewater services. We cannot rely on competition to deliver efficient costs. We therefore use regulatory tools to incentivise companies to reveal efficient costs and reduce information asymmetry between ourselves and water companies. This ensures that customers do not overpay.

We use econometric benchmarking models to help to set efficient base cost allowances. These use statistical methods to compare costs between companies on a like-for-like basis by considering multiple factors that drive differences in costs between companies and over time. For example, company size, population density, treatment complexity, etc. They allow us to identify an efficiency 'benchmark' that all companies should achieve. 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 complement our econometric benchmarking models with the cost adjustment claim process. Our models capture the key drivers of base expenditure. But companies may face other exogenous factors that make it more or less expensive to deliver water and wastewater services. Companies can submit a cost adjustment claim if they face specific circumstances that have a material impact on costs. To reflect more of a forward-looking approach, companies can also submit cost adjustment claims for exogenous factors that require a step change in efficient base expenditure compared to the past.

Our PR19 approach to assessing base costs received broad support from the sector. We therefore set a high bar for any changes. We worked with the sector through the Cost Assessment Working Group to explore potential areas of improvement for PR24. We subsequently considered cost models suggested by water companies, our independent consultants – CEPA - recommended models,[3] and our own internal analysis to arrive at our set of proposed PR24 base cost models.

We propose the following improvements to our PR19 base cost models informed by company suggestions. These improvements are largely consistent with CEPA's independent

[3] CEPA, 'PR24 Wholesale Base Cost Modelling', March 2023.

recommendations. Our proposed models perform well against our model selection criteria and are sufficiently robust to set efficient expenditure allowances at PR24.

We seek views on our proposed models by **12th May 2023** using the response template on our website.[4] We also invite water companies to submit base cost adjustment claims to us by **9th June 2023** for factors not sufficiently captured in our proposed models.[5]

Wholesale water econometric cost models

We are consulting on **6 water resources plus models**; **6 treated water distribution models**; and **12 wholesale water models**. Water resources plus is made up of water resources, raw water distribution, and water treatment base expenditure. Wholesale water is made up of water resources plus and treated water distribution base expenditure.

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 base 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.

Wastewater network plus econometric cost models

We are consulting on **6 sewage collection models**; **3 sewage treatment models**; and **8 wastewater network plus models**. Wastewater network plus is made up of sewage collection and sewage treatment base expenditure.

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

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

- **Include two alternative economies of scale at sewage treatment works variables** alongside the percentage of load treated in sewage treatment works serving up to 2,000 resident population equivalent (ie size bands 1 to 3) variable used at PR19:

[4] Available here: https://www.ofwat.gov.uk/wp-content/uploads/2023/04/Econometric-base-cost-models-for-PR24-response-template.xlsx
[5] Cost adjustment claim template is available here: https://www.ofwat.gov.uk/wp-content/uploads/2023/04/Early-cost-adjustment-claim-template-v1.xlsx

    - Percentage of load treated in sewage treatment works serving more than 100,000 people.
    - Weighted average sewage treatment works size.
- **Include alternative weighted average population density variables** in sewage collection models based on granular population density data from the Office for National Statistics.
- **Include urban rainfall in a subset of sewage collection and wastewater network plus models**, which controls for differences in the volume of inflows into drainage and sewerage networks.
- **Add top-down wastewater network plus models** to the modelling suite.

Bioresources econometric cost models

We are consulting on **6 bioresources total cost models** and **4 bioresources unit cost models**.

The key exogenous drivers of bioresources expenditure are **scale**; **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:

- **sludge produced** to control for scale; and
- **weighted average population density, sewage treatment works per property, and percentage of load treated at sewage treatment works serving up to 2,000 resident population (ie size bands 1 to 3)** to control for economies of scale in sludge treatment and the location of sewage treatment works relative to sludge treatment centres.

Residential retail econometric cost models

We are consulting on **3 bad debt cost models**; **2 other cost models**; and **6 total cost models**. In each model, the dependent variable is specified as cost per household.

Our analysis found that our PR19 residential retail models are significantly impacted by Covid-19, largely attributable to an increase in companies' bad debt provisions that is not explained by the explanatory variables.

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 and the proportion of metered households variables**; and
- **inclusion of a third deprivation variable capturing the average number of county court judgements/partial insight accounts per household.**

Responding to this consultation

Please complete the consultation response template available on our website.[6] Email the completed response template alongside any other supporting documents to CostAssessment@ofwat.gov.uk or post them to: Daniel Mitchell, Ofwat, 11 Westferry Circus, Canary Wharf, London E14 4HD.

The closing date for the consultation is **12th May 2023**. If you wish to discuss any aspect of this consultation, please contact Daniel Mitchell by email at CostAssessment@ofwat.gov.uk.

We intend to publish responses to this consultation on our website at www.ofwat.gov.uk. Subject to the following, by providing a response to this consultation you are deemed to consent to its publication.

If you think that any of the information in your response should not be disclosed (for example, because you consider it to be commercially sensitive), an automatic or generalised confidentiality disclaimer will not, of itself, be regarded as sufficient. You should identify specific information and explain in each case why it should not be disclosed [and provide a redacted version of your response], which we will consider when deciding what information to publish. At a minimum, we would expect to publish the name of all organisations that provide a written response, even where there are legitimate reasons why the contents of those written responses remain confidential.

In relation to personal data, you have the right to object to our publication of the personal information that you disclose to us in submitting your response (for example, your name or contact details). If you do not want us to publish specific personal information that would enable you to be identified, our privacy policy explains the basis on which you can object to its processing and provides further information on how we process personal data.

In addition to our ability to disclose information pursuant to the Water Industry Act 1991, information provided in response to this consultation, including personal data, may be published or disclosed in accordance with legislation on access to information – primarily the Freedom of Information Act 2000 (FoIA), the Environmental Information Regulations 2004 (EIR) and applicable data protection laws.

Please be aware that, under the FoIA and the EIR, there are statutory Codes of Practice which deal, among other things, with obligations of confidence. If we receive a request for disclosure of information which you have asked us not to disclose, we will take full account of your explanation, but we cannot give an assurance that we can maintain confidentiality in all circumstances.

[6] Available here: https://www.ofwat.gov.uk/wp-content/uploads/2023/04/Econometric-base-cost-models-for-PR24-response-template.xlsx

Contents

Glossary

Acronym	Term
AFW	Affinity Water
ANH	Anglian Water
AMP	Asset management plan
APH	Average pumping head
BOD	Biochemical Oxygen Demand
BGS	British Geological Survey
BRL	Bristol Water
Capex	Capital expenditure
CMA	Competition and Markets Authority
WSH	Dŵr Cymru
EIR	Environment information regulations
HDD	Hafren Dyfrdwy
IED	Industrial Emissions Directive
LAD	Local authority district
MSOA	Middle super output area
NES	Northumbrian Water
ONS	Office for National Statistics
Opex	Operating expenditure
OLS	Ordinary least squares
P-permit	Phosphorus-permit
PRT	Portsmouth Water
RE	Random effects estimation
RESET	Regression Equation Specification Error Test
RDC	Residential retail bad debt cost model
ROC	Residential retail other cost model
RTC	Residential retail total cost model
SVE	Severn Trent Water
SES	SES Water
SEW	South East Water
SRN	Southern Water
SWC	Sewage collection
SWT	Sewage treatment
STWs	Sewage treatment works
STC	Sludge treatment centre
SSC	South Staffs Water
SWB	South West Water
TMS	Thames Water

TWD	Treated water distribution
UV	Ultra-violet
UUW	United Utilities
WWNP	Wastewater network plus
WOC	Water only company
WaSC	Water and sewerage company
WRP	Water resources plus
WAB	Weighted average band size
WATS	Weighted average sewage treatment works size
WAWS	Weighted average work size
WSX	Wessex Water
WW	Wholesale water
YKY	Yorkshire Water

1. Introduction

1.1 Aims of this document

This document presents our proposed set of econometric models that we intend to use to help set efficient base expenditure allowances at PR24. It includes wholesale water, wastewater network plus, bioresources and residential retail models. This allows water companies to:

- account for early efficiency information in their PR24 business plans;
- focus more on long-term challenges; and
- submit high quality cost adjustment claims in June 2023.

1.2 Context

Base expenditure is routine, year-on-year expenditure, which companies incur in the normal running of their businesses to provide a base level of good service to customers and the environment. It includes expenditure to maintain the long-term capability of assets, as well as expenditure to improve efficiency.

Water companies are monopoly providers of most water and wastewater services. We cannot rely on competition to deliver efficient costs. We therefore use regulatory tools to incentivise companies to reveal efficient costs and reduce information asymmetry between ourselves and water companies. This ensures that customers do not overpay.

We use econometric benchmarking models to help to set efficient base cost allowances. These use statistical methods to compare costs between companies on a like-for-like basis by considering multiple factors that drive differences in costs between companies and over time. For example, company size, population density, treatment complexity, etc. They allow us to identify an efficiency 'benchmark' that all companies should achieve. 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 complement our econometric benchmarking models with the cost adjustment claim process. Our models capture the key drivers of base expenditure. But companies may face other exogenous factors that make it more or less expensive to deliver water and wastewater services. Companies can submit a cost adjustment claim if they face specific circumstances that have a material impact on costs. To reflect more of a forward-looking approach, companies can also submit cost adjustment claims for exogenous factors that require a step change in efficient base expenditure compared to the past.

We have confidence in our PR19 base cost econometric models, developed through an extensive consultation process, which began in 2016.[7] We had extensive input from the sector and the models are consistent with engineering insight. Our approach to assessing wholesale base costs was largely supported in the Competition and Markets Authority's (CMA's) PR19 redeterminations.[8] In our PR24 final methodology, we therefore set out our intention to build on our PR19 econometric models, making improvements where appropriate.[9]

We have worked collaboratively with the sector to identify potential areas of improvement through the Cost Assessment Working Group since early 2021, and consulted on our approach to assessing base costs at PR24 in December 2021.[10] We then collected additional data to inform the assessment of base costs at PR24 in July and August 2022, which was based on feedback received from water companies.[11]

We published updated base cost modelling datasets in October and November 2022, which included historical data up to 2021-22 and the additional data collected in July and August 2022. We subsequently invited water companies to develop their own base cost econometric models and submit them to us for our consideration ahead of this consultation. We published a template and guidance note to support companies in the model development process, and to ensure that models can be compared on a like-for-like basis.[12]

Since publishing our updated base cost modelling datasets, we commissioned CEPA to independently develop wholesale base cost models for PR24. We also conducted our own econometric analysis, supported by our econometric advisor, Professor Andrew Smith.[13]

14 water companies submitted around 400 models for consideration for inclusion in this consultation, which are available on our website.[14] Each company tended to suggest changes to the PR19 base cost models that would benefit them in terms of higher base expenditure allowances. We have arrived at our proposed econometric cost models in this document after carefully considering cost models suggested by water companies, CEPA's recommended models,[15] and our own internal analysis.

Overall, we have made a limited number of improvements to our PR19 base cost models informed by company suggestions. These improvements are largely consistent with CEPA's

[7] Ofwat, 'Cost assessment for PR19: a consultation on econometric cost modelling', March 2018.
[8] 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.
[9] Ofwat, 'Creating tomorrow, together: Our final methodology for PR24. Appendix 9 Setting expenditure allowances', December 2022, pp.8-9.
[10] Ofwat, 'Assessing base costs at PR24', December 2021.
[11] Ofwat, 'Information notice 22/02 Cost assessment data requests', April 2022.
[12] Ofwat, 'Template and guidance for the submission of base econometric cost models ahead of the spring 2023 consultation', November 2022.
[13] See Appendix A5 for Professor Andrew Smith's review statement.
[14] Available here: https://www.ofwat.gov.uk/econometric-base-cost-models-for-pr24/
[15] CEPA, 'PR24 Wholesale Base Cost Modelling', March 2023.

independent recommendations. Our proposed models perform well against our model selection criteria and are sufficiently robust to set efficient 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 developing and selecting the econometric cost models presented in this document.
- Chapter 3 presents our proposed wholesale water econometric cost models.
- Chapter 4 presents our proposed wastewater network plus econometric cost models.
- Chapter 5 presents our proposed bioresources econometric cost models.
- Chapter 6 presents our proposed residential retail econometric cost models.
- Chapter 7 presents a consolidated list of consultation questions.

All the accompanying data sets and Stata do files that were used to produce the econometric model results presented in this document are available on our website.[16]

1.4 Next steps and early cost adjustment claim submission

We invite responses to this consultation by **12th May 2023**. Please complete the consultation response template available on our website.[17]

We also invite water companies to submit base cost adjustment claims to CostAssessment@ofwat.gov.uk based on our proposed econometric models included in this document by close of play on **9th June 2023**.

We have uploaded a cost adjustment claim template on our website that companies must complete for each cost adjustment claim, which is informed by our PR24 final methodology.[18] The template includes additional guidance companies should follow for their submission.

We will aim to publish all cost adjustment claims shortly after, which will provide companies with an opportunity to comment on other companies proposed cost adjustment claims alongside their PR24 business plans. But we will not provide feedback to companies on their cost claims until our PR24 draft determinations.

[16] Available here: https://www.ofwat.gov.uk/econometric-base-cost-models-for-pr24/
[17] Available here: https://www.ofwat.gov.uk/wp-content/uploads/2023/04/Econometric-base-cost-models-for-PR24-response-template.xlsx
[18] Available here: https://www.ofwat.gov.uk/wp-content/uploads/2023/04/Early-cost-adjustment-claim-template-v1.xlsx

2. Approach to model development and selection

This chapter outlines our approach to developing and selecting the econometric cost models presented in this document.

2.1 Base cost modelling suite

We intend to set efficient base expenditure allowances at PR24 by triangulating across a range of models with different cost drivers and levels of cost aggregation. This mitigates the risk of error and bias in any one model.

The levels of cost aggregation for base cost modelling at PR24 are 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.

Table 2.1: levels of cost aggregation for base cost modelling at PR24

	High level of aggregation	Medium level of 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**
Wholesale wastewater	N/A	**Wastewater network plus**: sewage collection + sewage treatment	• **Sewage collection** • **Sewage treatment** • **Bioresources**
Residential retail	**Residential retail**: bad debt + other retail costs	N/A	• **Bad debt** • **Other retail costs**

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 modelling suite. As stated in our PR24 final methodology, we intend to 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.

2.2 Scope of modelled base costs

The scope of modelled base costs we used to develop the models presented in this document is described below. Further details are also provided in Chapters 3 to 6.

Table 2.2: scope of modelled base costs

Modelling area	Modelled base cost definition
Wholesale water	• Operating expenditure (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 opex (including customer services, meter reading, and depreciation)

The main differences from PR19 are the exclusion of the following growth related costs from the base cost models at PR24:[19]

- **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 models.[20] This has been facilitated through improved cost reporting in this area.
- **Growth at sewage treatment works costs** - Arup concluded that a standalone econometric model may be a viable option for assessing these costs.[21] We will continue to assess this. If a robust standalone cost model is not feasible, we may revert to including growth at sewage treatment works costs in the base cost models.

As detailed in our final methodology, the models in this document have been developed before the deduction of grants and contributions. We also made several pre-modelling adjustments to facilitate accurate cost comparisons between companies and over time (eg different treatment of atypical expenditure reporting), as described in Appendix A1.

[19] More details can be found in: Ofwat, 'Creating tomorrow, together: Our final methodology for PR24. Appendix 9 Setting expenditure allowances', December 2022, section 2.4.1.
[20] Wastewater site-specific developer services are removed from the price control at PR24 for Welsh companies. But water site-specific developer services remains in the price control for Welsh companies, and will be assessed as part of unmodelled base costs.
[21] Arup, 'Assessment of growth-related costs at PR24', May 2022.

2.3 Panel data structure and sample period

We have access to 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. 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. This also ensures we capture the cyclical nature of capital maintenance expenditure.

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

Table 2.3: 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 2021-22 (11 years)	187	• 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 2021-22 (11 years)	110	• 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 2021-22 (11 years)	110	• As above for wholesale wastewater network plus.
Residential retail	17	2013-14 to 2021-22 (9 years)	153	• As above for wholesale water.

2.4 Model estimation method

We use random effects to estimate the base cost econometric models, which was used by all companies to estimate their suggested 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.

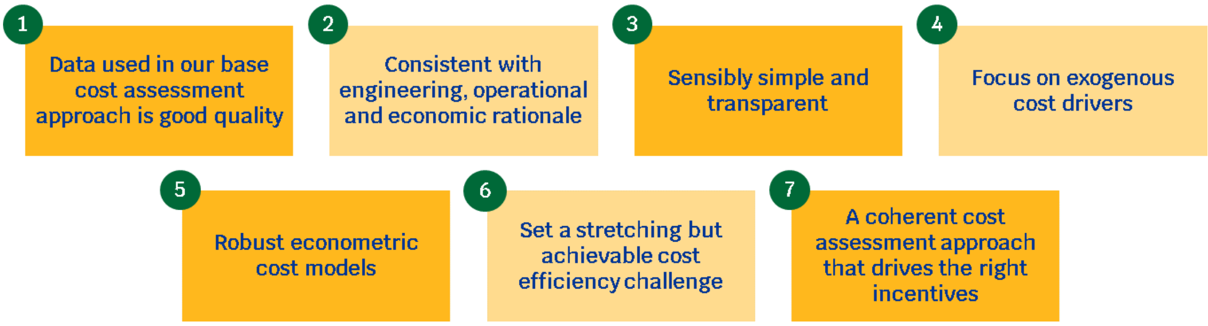
We set out reasons for not adopting alternative estimation methods such as fixed effects and stochastic frontier analysis in our assessing base costs at PR24 consultation.[22]

2.5 Model selection process

In our PR24 final methodology, we set out our intention to build on our PR19 base cost models, making improvements where appropriate.[23] Our model selection process reflects this, and we set ourselves a high bar for making changes to our PR19 base cost models.

Our principles of PR24 base cost assessment are summarised below.

Figure 2.1: 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 have made sure that the data used in the model development process 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. Any remaining data issues are discussed in the relevant areas of Chapters 3 to 6 below.

Our emphasis has been to develop and select sensibly simple and transparent cost models that are consistent with engineering, operational and economic rationale. This ensures that the models 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 ensure the independence of our efficient base cost allowance and avoid the risk of perverse incentives. For example, inflating cost driver forecasts and/or causing suboptimal investment decisions.

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

Our cost models should accurately 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**?
- Can the models **accurately predict** the efficient expenditure of companies?
- 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)?

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 ourselves and water companies.

Appendix A2 includes the model robustness tests that we used to assess each model, with its relative degree of importance. We considered the relevant importance of each test result when developing and selecting the base cost models included in this consultation. But the results of these robustness tests should not be interpreted as a mechanistic rule for the rejection or acceptance of the models. **Statistical robustness tests can provide useful guidance as we develop models, but they should not alone drive our model selection.** For example, it may be appropriate to include variables that are not statistically significant if they produce results that are consistent with engineering, operational and/or economic logic.

We assess how our selected base cost models perform against the model robustness tests in Chapters 3 to 6.

3. Cost models for wholesale water activities

Summary

We are consulting on **6 water resources plus (WRP) models**; **6 treated water distribution (TWD) models**; and **12 wholesale water (WW) models**.[24]

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 propose to include **average pumping head** in a subset of TWD and WW models to capture network topography. We also propose models that include booster pumping stations per length of mains, which was the topography variable used at PR19.
- We propose 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 also seek views on the need to **collect data on the number of reservoirs that have been designated as high-risk** and are subject to the inspection and maintenance requirements under the Reservoirs Act 1975, which would ensure consistency in reporting.

This section presents our proposed econometric models we intend to use to help set efficient wholesale water base expenditure allowances at PR24. It is structured as follows:

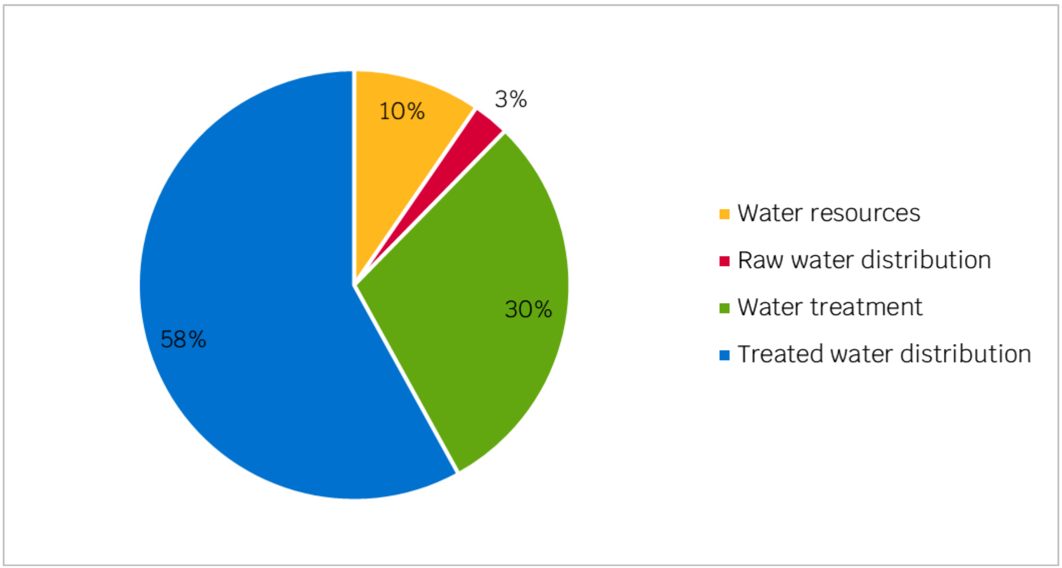
- defining the dependent variable;
- selected cost drivers;
- cost drivers not included in our proposed models; and
- proposed wholesale water base cost econometric models.

[24] Water resources plus = water resources + raw water distribution + water treatment. Wholesale water = water resources plus + treated water distribution.

3.1 Defining the dependent variable

Wholesale water modelled base costs across the sector equalled £3.6bn in 2021-22. Figure 3.1 below shows the share of expenditure of each activity. Treated water distribution expenditure typically makes up over half of wholesale water modelled base expenditure.

Figure 3.1: share of expenditure of wholesale water activities in 2021-22



Our dependent variable for wholesale water modelled base costs includes operating, capital maintenance, network reinforcement, and addressing low pressure enhancement expenditure. Further details are provided in section 2.2.[25] Most companies used this definition in their January 2023 submissions.

In line with PR19, we have developed models at different levels of cost aggregation. That is, **water resources plus (water resources plus raw water distribution plus water treatment), treated water distribution,** and **wholesale water**. Most companies submitted models at these levels of aggregation in their January 2023 submissions.

United Utilities proposed water resources and water network plus models. As we found at PR19,[26] it is challenging to develop robust water resources models because of the interactions and trade-offs with water treatment. The quality of raw water influences the level of treatment complexity required. We therefore consider it is proportionate to focus attention on the development of water resources plus and wholesale water models that can capture these interactions. Most companies agreed with this view in their responses to our 'Assessing base costs at PR24' consultation in December 2021.[27]

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[25] We made several pre-modelled adjustments to modelled base costs, as detailed in Appendix A1.
[26] Ofwat, 'Supplementary technical appendix: Econometric approach', January 2019, p. 11.
[27] Ofwat, 'Assessing base costs at PR24', December 2021.

3.2 Selected cost drivers

As in PR19, we consider the key wholesale water base cost drivers are:

- **Scale**
- **Treatment complexity**
- **Network topography**
- **Population density**

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

3.2.1 Scale

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

We maintain the same explanatory variables we used at PR19 to capture the company's scale of operations. This aligns with the variables CEPA recommended in its main set of models, and the variables most companies used in their January 2023 submissions.

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).

Water resources plus (WRP) models

In WRP models, we use the **number of properties** (household plus non-household) as the measure of company scale. We consider this to be an intuitive driver in WRP models, which include expenditure for sourcing and treating water. We expect the amount of water to be related to the number of properties served.

Treated water distribution (TWD) models

In TWD models, we use the **length of the potable water mains** as the measure of company scale. This is the most intuitive scale driver because TWD costs are associated with running a distribution network consisting mainly of water mains. We recognise that companies have a degree of control over the length of mains. But we consider that it remains substantially determined by exogenous factors (eg location of properties in the company's region).

Wholesale water (WW) models

In WW models, we use the **number of properties** as the measure of company scale. This is an intuitive driver of costs at the aggregate wholesale water level. The length of mains is not an intuitive driver of water resources and water treatment costs, which are mainly driven by the quantity and quality of water sourced and treated, rather than the length of the network.

We note CEPA used the length of mains as an alternative scale driver in its WW models, to capture both scale variables from the WRP and TWD models. On balance we decided not to apply CEPA's recommendation. The number of properties is the most intuitive scale driver of wholesale water base costs. We did not consider the large increase in the number of proposed models that would be caused by an additional scale driver would be proportionate or add much value given properties and network length are highly correlated. In addition, models using properties per length of mains as the density driver would lead to the same result irrespective of whether we use properties or length of mains as the scale driver.

Other company suggestions

Anglian Water used the volume of surface water and the volume of ground water as scale drivers in its WRP models. As we noted at PR19 and the Competition and Markets Authority (CMA) noted in its PR19 redeterminations, the volume of water is endogenous due to companies' influence on leakage and water demand.[28] [29] This would not align with our incentive on reducing per capita consumption.

Severn Trent Water, Yorkshire Water and South East Water used the number of properties as an alternative scale driver to the length of mains in their TWD models. We recognise the number of properties may be more exogenous as any variation is driven by new developments, which are outside companies' control. But we consider the length of the network to be a more intuitive driver of TWD base costs.[30]

Anglian Water used distribution input as the scale driver in its TWD models. As noted above, this variable is endogenous due to companies' influence on leakage and water demand and would not align with our incentive on reducing per capita consumption.

Thames Water used a composite scale variable in its WW models, capturing both the number of properties and the length of the network. We do not include a composite scale variable in our proposed WW models because (i) it does not materially increase the predictive power of the models; and (ii) we do not consider the additional complexity is warranted given properties and network length are highly correlated.

[28] Ofwat, 'Supplementary technical appendix: Econometric approach', January 2019, p. 12.
[29] 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, p. 148.
[30] We note that both Yorkshire Water and South East Water used the length of mains as their preferred driver.

3.2.2 Treatment complexity

Water treatment works complexity can reflect both the quality of the raw water source(s) supplying the works, and any requirements for the quality of the treated output. Where 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.

We propose to maintain the same explanatory variables we used at PR19 to capture the complexity of treatment, ie the proportion of **water treated at complexity levels from 3 to 6**, and the **weighted average treatment complexity**.

The first variable is the proportion of **water treated at complexity levels 3 to 6**. Based on engineering and statistical evidence, we consider there is a step change in treatment costs between works of complexity level 2 or less and works at higher levels of complexity. Levels 0, 1 and 2 include relatively simple works, such as those treating good quality groundwater sources, while level 3 will introduce works with multiple treatment stages treating lower quality 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, as illustrated below.

Table 3.1: 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 addition, almost all companies proposed it in their January 2023 modelling submissions.

CEPA used the same variables to capture treatment complexity in its recommended models. They also considered several alternative treatment complexity drivers as part of their work, following suggestions from water companies in responses to our December 2021 base cost consultation.[31] These included alternative weights when calculating the weighted average complexity variable. But CEPA did not consider that any of the options were an improvement over the PR19 approach.

Other company suggestions

Most companies support the same treatment complexity variables that are included in our proposed models. But there was a small number of alternative suggestions.

Severn Trent Water argued that average pumping head (APH) is the most appropriate proxy for treatment complexity. We disagree. The complexity bands are the closest approximation of water treatment complexity available in companies' annual reporting, and are well established and understood in the sector. The quality of disaggregated APH data in water treatment is also too poor to consider including in the models, based on the findings from the Turner and Townsend APH study.[32] CEPA considered APH in WRP models as an additional variable to treatment complexity, but found it was not a significant driver of costs.

Yorkshire Water and Thames Water suggested alternative weights when calculating the weighted average treatment complexity variable. Yorkshire Water suggested taking the log of the current weights. While Thames Water suggested to assign a weight of 2 to the simple band, band 1 and band 2, and a weight of 5.5 to the higher bands.[33] We remain with the current weights as they are simple and intuitive. In addition, Yorkshire Water's weights imply that lower levels of complexity are more expensive than higher levels of complexity, which does not align with engineering rationale.

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 propose to use two measures at PR24 to capture network topography:

- **booster pumping stations per length of mains**; and
- **treated water distribution (TWD) average pumping head (APH).**

At PR19, we used the **number of booster pumping stations per length of mains** to proxy differences in network topography. The CMA supported its use in its PR19 redeterminations.[34]

[31] Severn Trent Water, 'Ofwat's consultation on assessing base costs at PR24: Severn Trent Water response', February 2022, pp. 31-32.
[32] Turner & Townsend and WRc, 'Average Pumping Head: data quality improvement', 2022.
[33] Thames Water derives the alternative weights as follows: average(1+2+3)=2 and average(4+5+6+7)=5.5.
[34] 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.

The estimated coefficient on this variable is consistently positive and statistically significant across specifications. We therefore propose to maintain it for PR24.[35]

APH is a direct measure of pumping requirements. It captures the volume of water pumped and the pressure at which it is pumped. It therefore has a clear underlying engineering rationale. APH was considered at PR19, but was not adopted 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.[36]

Since PR19, we have worked with the industry to review reporting practices and improve consistency of reporting across companies.[37] We subsequently tested APH in WRP, TWD and WW models. We tested WRP APH (water resources plus raw water distribution plus water treatment APH) in WRP models, but found it is not a significant driver of WRP costs. TWD APH appears to be a significant driver of TWD base costs, and improves the explanatory power of the TWD and WW models. This is consistent with the findings in CEPA's report. These results are supported by Turner and Townsend's finding that TWD APH is by far the largest contributor to wholesale water APH (57.7%). Turner and Townsend also considered TWD APH data to be of better quality than other components of APH, such as APH in water treatment.

We are still concerned about the quality of APH data. Turner and Townsend found significant variation between companies of the proportion of measured and estimated data in TWD for both volume and lift. It noted this is often due to distribution networks having smaller pump sets which are needed for localised boosting of smaller volumes, which are less likely to have flow and pressure monitoring. Reliance on estimated data means the variable is less objective than other variables, and Turner and Townsend found that estimated data may overestimate pumping head. Inaccurate APH data could lead to bias in the estimated relationship between costs and APH.

On balance, we include TWD APH in a subset of our proposed TWD and WW models to proxy network topography.[38] This aligns with CEPA's recommendation. APH data quality is improving, and steps are in place to reduce the reliance on estimated data. In addition, APH has a strong engineering rationale, and TWD APH performs well in the TWD and WW models.

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[35] Booster pumping stations per length of mains was included in models proposed by Anglian Water, Northumbrian Water, Severn Trent Water, Southern Water, United Utilities, Welsh Water, Wessex Water, Yorkshire Water, Affinity Water, and South East Water.
[36] 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.
[37] Turner and Townsend, 'Average Pumping Head: data quality improvement Ofwat. Final report', March 2022.
[38] Average pumping head was included in models proposed by Anglian Water, Severn Trent Water, South West Water, Thames Water, SES Water, South East Water, and South Staffs Water.

Other company suggestions

Anglian Water, Severn Trent Water and South East Water suggested including booster pumping stations per length of mains and APH in the same model. We do not adopt this approach as both variables proxy for network topography.

Thames Water suggested using capacity of booster pumping stations per length of mains if APH was not included. Wessex Water suggested using the average capacity of booster pumping stations. We decided not to progress these suggestions given our decision to adopt APH in our TWD and WW models at PR24.

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 PR19 wholesale water base cost models included a density variable and a quadratic density variable to allow for the opposing effects of population density on costs described above (ie u-shape relationship between costs and density). We also apply this approach in our proposed PR24 wholesale water models.[39]

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 moved away from the simpler measure used at PR14 (properties per length of

[39] Severn Trent Water suggested the density squared term should be removed from water resources plus models. But we consider the argument for a non-linear relationship between wholesale water costs and population density is clear based on this rationale set out above.

mains). It was also more exogenous than the PR14 measure (given it relied on ONS data), and better reflected density within company regions because it used more granular data.

Since PR19, we found that changes in the ONS LAD boundaries (for example, mergers of LADs) can impact the measured density of a company. We also found errors in the allocation of LADs to company boundaries, which was prepared and reviewed by water companies at PR19. For example, the LAD "Poole" was erroneously left out of the PR19 mapping file.

For PR24, we have developed two new weighted average density measures, which aim to map geographical units to company boundaries in a more accurate way. Both measures are calculated using the same approach as the PR19 measure. But they are based on population density data from the ONS at Middle Super Output Area (MSOA) level, which is more granular than LAD level. There are more than 7,000 MSOA areas in England and Wales. But only around 350 LADs. MSOA data can be mapped to company boundaries using a shape file published under the Open Government Licence.[40] This removes the need for companies to identify the percentage allocation of LADs to their boundaries. The use of more granular density data can also better reflect density within company regions.

Using MSOA data, we have developed the following two population density measures:

- **Weighted average density – LAD from MSOA**. This measure uses MSOA level data, mapped first to LADs, and then from LADs to company boundaries. Population density data is weighted by the population of the LAD, as in PR19.
- **Weighted average density - MSOA**. This measure uses MSOA level data, mapped directly to company boundaries. Population density data is weighted directly by the population of the MSOA.

The **LAD from MSOA** measure is closest to the PR19 LAD measure. Compared to the PR19 LAD measure, it applies a more consistent and accurate approach to the mapping of LADs to company boundaries. It may still be sensitive to changes in LAD boundaries over time, but the availability of population density at MSOA level should reduce this sensitivity. It also captures population density better for LADs that are shared between companies. For the PR19 LAD measure, we determine the average density per LAD and then apportion to each company. The LAD from MSOA density improves on this averaging assumption as it uses the information on the company's unique population density within the share of the LAD it serves. This can be more or less dense than the average LAD density. LAD from MSOA is therefore a more accurate representation of the density in shared LADs compared to the PR19 measure.

The **MSOA** measure uses more granular population density, which may better reflect differences in population density within a company's operating area. It also has the advantage of being less sensitive to changes in geographical boundaries over time given

[40] House of Commons Library, "Constituency information: Water companies", October 2022.

MSOAs are less likely to change over time than LADs. But we have found the MSOA measure leads to larger changes in efficiency scores and rankings.

We also include a third density measure in our proposed wholesale water base cost models for consultation. The PR14 measure of population density – **properties per length of mains**. At PR19, we used a similar measure in our wastewater sewage collection models (properties per length of sewers) alongside the weighted average density variable. 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 density measures and may not capture the differences in population density within a company's operating region as well.

We seek views on all three selected population density measures in response to this consultation:

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

CEPA included all three density measures (including a squared term) in its set of recommended models, and suggested exploring them further.

Most companies included a weighted average density measure in at least some of their wholesale water models. But there was more support for a measure based on LAD level population density data than MSOA level population density data. Yorkshire Water and South East Water included properties per length of mains in their models.

Other company suggestions

Severn Trent Water included population per area as an alternative density measure in their suggested wholesale water models. But we found this variable to be less statistically robust than the population density measures included in our proposed models.

3.3 Cost drivers not included in our proposed models

We considered alternative cost drivers that are not included in our proposed models. These were based on company suggestions, CEPA's suggestions, and our own internal analysis. The reasons why we decided not to include these alternative cost drivers are set out below.[41]

[41] In no particular order.

3.3.1 Reservoir maintenance under the Reservoirs Act 1975

United Utilities and Thames Water both suggested a variable to capture costs related to reservoir maintenance requirements under the Reservoirs Act 1975 in WRP models. A large raised reservoir in England and Wales designated as a “high-risk reservoir” by the Environment Agency or Natural Resources Wales is subject to regular inspections and maintenance standards under the Reservoirs Act 1975. 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.[42]

United Utilities and Thames Water argue that this leads to substantially higher maintenance expenditure. To control for this cost driver, United Utilities proposed a variable for impounding reservoirs normalised by the number of properties, while Thames Water proposed a variable for capacity of total reservoirs per property.

Engineering rationale indicates that the number of high-risk reservoirs is a more appropriate variable than the capacity of reservoirs, and that a variable for reservoir maintenance should capture all relevant impounding, pumped and balancing reservoirs (rather than impounding reservoirs only) that fall under the Reservoirs Act 1975.

We seek views on the appropriateness of capturing a variable for reservoir maintenance requirements under the Reservoirs Act 1975, and on the materiality of the costs. The relative cost of different water sources is unclear. Different water sources will bring differing levels of operating and capital maintenance expenditure, and factors could balance out in the round. For example, impounding reservoirs may require less pumping than boreholes. CEPA found that the water resources variables they tested were either not significant or produced results not in line with engineering expectations.

We are also concerned about the quality and consistency of historical reporting of reservoir numbers (in particular, pumped and balancing reservoirs), and the sensitivity of model results. We tested the number of reservoirs per property as an additional variable in the WRP models. We found the model results to be sensitive to minor changes in the number of reservoirs. We also note that the number of reservoirs per property is correlated with the treatment complexity variables and leads to both complexity variables losing statistical significance. This may be because water from reservoirs is treated in more complex water treatment works. CEPA found similar results in their testing of water resources drivers.

We seek views on the need to collect data on the number of reservoirs that have been designated as high-risk and are subject to the inspection and maintenance requirements under the Reservoirs Act 1975, which would ensure consistency in reporting.

[42] See the definition in section A1 of the Reservoirs Act 1975.

3.3.2 Economies of scale in water resources

CEPA explored drivers to capture economies of scale in water resources. Companies with larger water sources may be able to benefit from lower unit costs of sourcing water. CEPA tested two variables for this, ie the number of water sources and distribution input per water sources. It found that both variables were insignificant in WRP models. This may be because of interactions with water treatment. For example, the impact of many small sources could be mitigated if they are linked to one, or few, water treatment works. Smaller water sources also tend to be ground water sources, which typically require less complex treatment.

3.3.3 Economies of scale at water treatment works

Severn Trent Water states that population density captures the opportunity to benefit from treatment economies of scale. But population density does not explain the impact geography (availability/quality of surface water) and geology (availability/quality of ground water) has on the optimal selection of how and where to source and treat water.

Severn Trent Water suggests using population density in conjunction with a variable that captures the ground water asset base (ie % of distribution input from groundwater sources) in WRP and WW models. The company argues, based on analysis of internal cost data, that economies of scale are more present at groundwater than surface water treatment works.

We do not adopt Severn Trent Water's suggestion in our proposed models. We tested Severn Trent Water's suggested variable. We found it was statistically insignificant in our proposed models, which may be because it is correlated with our water treatment complexity variables. We also find the rationale of the variable unclear, and think it may capture a treatment complexity effect instead of economies of scale effect.

CEPA explored several variables to capture economies of scale at water treatment works in WRP models. But found they produced either insignificant or counterintuitive results. CEPA did not include any variables to directly capture economies of scale at water treatment works in its recommended models. This may be because the population density variables already capture economies of scale in water treatment works. Another reason may be that inefficient small water treatment works have been decommissioned over time, meaning the remaining small works are not very expensive to operate and maintain.

3.3.4 Network reinforcement drivers

Differences in population growth rate can lead to differing levels of network reinforcement expenditure between companies and over time. CEPA explored a number of variables that may explain differences in network reinforcement spend. These included the % of new properties, the % increase in new properties, and annual population growth.

We do not include any of the network reinforcement variables tested by CEPA in our proposed models. CEPA found the statistical results were poor. This may be because we excluded site specific developer services expenditure from modelled base costs at PR24, and network reinforcement spend alone may not be sufficiently material. In addition, other cost drivers captured in the models may be sufficient to explain differences in network reinforcement expenditure requirements, such as scale and population density.

3.3.5 Water mains condition

Affinity Water suggested including a soil aggressiveness variable in its proposed models. It argues that soil aggressiveness is a key driver of burst pipes, leaks and subsequent repair activity, and maintenance requirements. Affinity Water built the variable using data from the British Geological Survey (BGS) on soil susceptibility to shrink and swell.

We have not included soil aggressiveness in our proposed models. A range of factors can impact mains condition that are not reflected in the proposed soil aggressiveness variable. These include soil corrosivity and water hardness. The proposed variable only captures one factor that impacts mains condition and could lead to biased results.

There is also a risk that the variable is endogenous and could lead to perverse incentives. Pipe material and age of mains can impact mains condition and bursts rate, which are within company control and reflect past investment decisions. Affinity Water's soil aggressiveness variable weights the soil aggressiveness index with the percentage of mains laid or substantially refurbished prior to 1961. It argues the use of cast and ductile iron for water mains, which the company thinks is most at risk from exposure to shrink/swell effects, was in decline after this point. This would give a perverse incentive not to replace pre-1961 mains.

Thames Water suggested including age of mains and proportion of mains renewed or relined as drivers of capital maintenance requirements. These variables produced statistically significant results. But as we noted at PR19, both variables are under company control and could lead to perverse incentives.[43] We therefore do not include them in our proposed models as they do not meet our base cost assessment principles.

3.3.6 Leakage

Thames Water suggested the inclusion of leakage per distribution input. It acknowledges this is under management control but argues that with a negative sign (ie reducing leakage leads to higher costs) it would incentivise companies to reduce leakage.

We do not include leakage per distribution input in our proposed models. Even with a negative sign, inclusion of this variable could lead to perverse incentives. For example,

[43] Ofwat, 'Supplementary technical appendix: Econometric approach', January 2019, p. 16.

incentives to allocate water to per capita consumption to reduce leakage; and neglecting other performance commitments to focus on leakage reduction (as no other performance measures would be included in the models).

3.3.7 Weather impacts

Severn Trent Water suggested a variable that captures the impact of higher temperatures on water treatment base costs. Severn Trent Water argued that high temperatures drive high demand, and this in turn increases the marginal cost of operating water treatment works at maximum rather than optimum capacity, increasing operational stress on assets. The variable is built using Met Office data and is defined as the number of days per year where the company weighted average maximum temperature is greater than 25 degrees.

We have considered the relationship between Severn Trent Water's proposed variable and power costs / treatment costs but found no evidence of a relationship. Weather can have a range of effects on costs, for example driven by hot temperatures, cold temperatures and rainfall. These effects could lead to both positive and negative impacts on costs. Only capturing high temperatures would risk cherry picking the impacts we would capture on costs. We also note that temperature effects could be picked up by APH, because APH captures the volume of water distributed. We will consider exploring the impact of extreme weather on base costs in more detail for PR29.

CEPA considered several variables to proxy for the impact of weather. These included Potential Evapotranspiration, annual rainfall, and peak distribution input. CEPA found them to be statistically insignificant in most models. CEPA considered that the link between the variables tested and base costs was unclear, especially over a short period of time.

3.3.8 Regional wages

Affinity Water suggested including a variable that captures differences in regional wages. The estimated coefficient is above one in all models and is above seven in the treated water distribution model. This would indicate that a 1% increase in wages would lead to a more than 1% increase in costs (up to 7% increase). We do not consider an estimated coefficient of this magnitude is sensible. The CMA also noted that the estimated coefficient on regional wages should be below one in its PR14 redetermination.[44] We consider that the inclusion of population density in our proposed models captures the effect of regional wage differentials on wholesale water base costs as the two are correlated, as we noted at PR19.[45]

[44] Competition and Markets Authority, 'Bristol Water plc: A reference under section 12(3)(a) of the Water Industry Act 1991. Appendices 1.1 – 4.3', October 2015, Appendix 4.1, pp. 14-15, paragraphs 62-65.
[45] Ofwat, 'Supplementary technical appendix: Econometric approach', January 2019, pp. 15-16.

3.3.9 Time trend, year dummies and other dynamic factors

Wessex Water and South West Water suggested including a time trend to pick-up long-term trends not explained by the other explanatory variables, such as ongoing efficiency, real price effects, and costs associated with delivering better service levels. A time trend can capture multiple factors, which means the expected sign of the estimated coefficient is ambiguous.

The estimated coefficient of time trend in companies' models is positive. This likely reflects higher company wholesale water base costs in recent years. We have not seen clear evidence to explain the increase in expenditure, and there is a risk that a time trend captures factors that are inside of company control. There is also a risk that the increase in wholesale water base expenditure in recent years is not permanent or will 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 base cost assessment.[46]

CEPA considered the inclusion of a time trend in water models. But did not include it in its final set of recommended models for similar reasons.

Wessex Water suggested including Covid-19 dummy variables for the years 2020-21 and 2021-22. It found the two dummies had a negative sign, which it says is consistent with its expectation of a slowdown in capital expenditure seen in those years due to reductions in planned work. We consider the decision to reduce planned work was under company control and should not be controlled for in the models. For example, Severn Trent Water noted that they took advantage of reduced traffic resulting from Covid-19 lockdowns to pull forward network renewal.[47] This is also reflected in reported wholesale water base expenditure, which shows that several companies increased spend in 2020-21 and 2021-22.

Severn Trent Water suggested additional dynamic variables in its set of 'more sophisticated but complex models':

- The inclusion of dummy variables for AMP years 2, 3, 4 and 5 to control for AMP cyclical effects on capital expenditure. The dummy variables are statistically significant in some models submitted by Severn Trent Water. But this could introduce a distortive incentive on companies' expenditure patterns. We use a long time series to estimate the models and calculate efficiency scores on a five-year basis, which mitigate for any AMP cyclical effects on expenditure.
- Using spatial lag variables to correct for spatial autocorrelation of residuals between neighbouring companies in TWD models. The variables are statistically significant in the models submitted by Severn Trent Water. But we consider their inclusion would lead to unnecessary additional complexity and overfitting. There is also not a clear economic or

[46] Severn Trent Water proposed to include a dummy for AMP5 and a dummy for AMP6, to correct for structural changes between AMPs. We do not adopt this suggestion in our proposed models for the same reasons behind our decision not to include a time trend in our proposed models.
[47] Severn Trent Water, 'Investor roadshow presentation 2020', May 2020, page 9.

engineering rationale. It is more appropriate to focus on cost drivers that have a clear engineering, operational and economic rationale and are simple to interpret.

SES Water proposed the inclusion of a lagged dependent variable, which the company says is to correct for autocorrelation in the residuals. We use cluster robust standard errors, which means our model estimation results are robust to autocorrelation in the residuals. This proposal would therefore add unnecessary complexity to our modelling approach and would make the interpretation of model results more difficult.

3.4 Proposed wholesale water cost models

We are consulting on 6 water resources plus (WRP) models; 6 treated water distribution (TWD) models; and 12 wholesale water (WW) models. The model specifications are summarised below, and model estimation results are in Appendix A4.

Table 3.2: Summary of proposed wholesale water cost models

Level of cost aggregation	No. models	Cost drivers	Explanatory variables
Water resources plus	6	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	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	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.

Our selected models align with CEPA's recommendations.[48] 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 also statistically significant at the 10 percent significance level apart from weighted average treatment complexity in WRP2, WRP4, WRP6 and WW10. We do not consider the marginal statistical insignificance of the weighted average treatment complexity variable a reason to exclude this variable, given it is supported by strong engineering and operational rationale and produces sensible results that are consistent across model specifications. CEPA included weighted average treatment complexity in its recommended models, and the variable is also supported by water companies.

The models perform well against all other model robustness tests of medium and high importance. A few models have an amber rating to the removal of the most and/or least efficient company. The weighted average treatment complexity variable appears to be the most sensitive variable in these instances. But we include it in our proposed models for the reasons set out above.

We note that the range of efficiency scores is higher than at PR19, particularly in WRP models. This is driven by an increasing trend in expenditure for some of the most inefficient companies in the last few years (eg Southern Water in WRP models), rather than because the models are no longer as good at predicting costs. We consider this increase in spend is driven by management decisions to catch-up with the rest of the sector rather than exogenous factors, which we do not consider should be explained by the models.

Please see the CEPA report for further details on how the models perform against model robustness tests.[49]

[48] With the exceptions of length of mains as a scale driver in wholesale water models, which we do not adopt for the reasons explained in section 3.2.1.
[49] CEPA, 'PR24 Wholesale Base Cost Modelling', March 2023.

4. Cost models for wastewater network plus activities

Summary

We are consulting on **6 sewage collection (SWC) models**, **3 sewage treatment (SWT) models**, and **8 wastewater network plus (WWNP) models**.[50]

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 potentially **urban rainfall**.

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

- **Include two alternative economies of scale at STWs variables** to better capture economies of scale at large STWs, alongside the percentage of load treated in STWs bands 1 to 3 variable used at PR19:
  - Percentage of load treated in STWs serving more than 100,000 people
  - Weighted average sewage treatment works size (WATS).
- **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 a subset of SWC and WWNP models**. 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 and discharges of wastewater from storm overflows, and maintain good asset health. It can also help account for climate change impacts.
- **Add top-down WWNP models** to the modelling suite, which allows us to triangulate between models of different levels of cost aggregation.

We also seek views on whether we should **capture the percentage of population living in coastal areas** in the SWT models. The variable can account for additional sewage treatment costs associated with operating in a coastal environment. But model results are sensitive to the underlying data. Hence, we do not include in our proposed models.

We are also exploring alternative options to ensure that our cost assessment approach funds efficient ongoing P removal costs, which we welcome company views on. Including (i) consideration of models with a P-driver; (ii) estimating a post-modelling adjustment; or (iii) using the cost adjustment claims process.

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

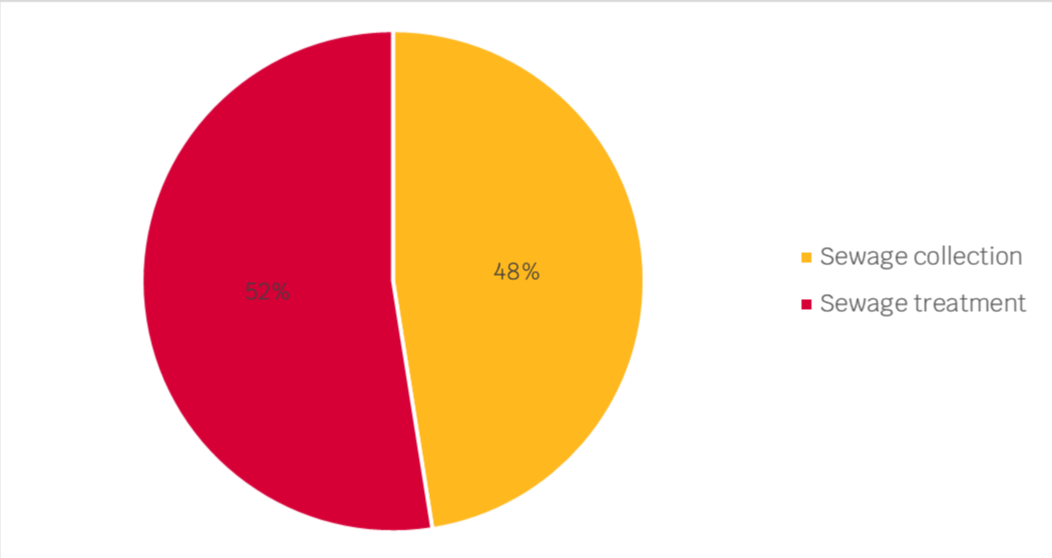
This section presents our proposed econometric models we intend to use to help set efficient wastewater network plus base expenditure allowances at PR24. It is structured as follows:

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

4.1 Defining the dependent variable

Wastewater network plus modelled base costs across the sector equalled £3.1bn in 2021-22. Figure 4.1 below shows the share of expenditure made up by each activity. Sewage collection and sewage treatment expenditure typically both make up around half of wastewater network plus modelled base expenditure.

Figure 4.1: share of expenditure of wastewater network plus activities in 2021-22



Our dependent variable for wastewater network plus modelled base costs includes operating, capital maintenance, network reinforcement, transferred private sewers and pumping stations enhancement, and **reduce flooding risk for properties enhancement expenditure**. We also include **enhancement operating expenditure 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). Further details are provided in section 2.2.[51] Most companies used this definition in their January 2023 submissions.

[51] We made several pre-modelled adjustments to modelled base costs, as detailed in Appendix A1.

We have developed models at different levels of cost aggregation. Granular "bottom up" models are based on modelling the two business units of wastewater network plus separately – sewage collection (SWC) and sewage treatment (SWT). Aggregate "top down" models assess SWC and SWT expenditure together in wastewater network plus (WWNP) models. Most companies submitted models at this level of aggregation in their January 2023 submissions.

Anglian Water also developed models at a wholesale wastewater level. And Southern Water and United Utilities submitted bioresources plus models. But we have not explored these suggestions given our intention to assess bioresources expenditure separately from wastewater network plus expenditure at PR24, as discussed in section 2.2.

4.2 Selected cost drivers

For PR24, we build on the PR19 set of cost drivers for wastewater network plus activities by proposing to include urban rainfall:

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

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

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 propose to maintain the same explanatory variables we used at PR19 to capture the company's scale of operations.

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).

Sewage treatment (SWT) models

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

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.

Other company suggestions

Dŵr Cymru, Severn Trent Water and Yorkshire Water suggested using the number of properties instead of sewer length in sewage collection models. Thames Water suggested a sewage collection model with a composite scale variable combining properties and sewer length. We consider that sewer length continues to be the most appropriate sewage collection scale driver from an engineering perspective. 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.[52]

There was universal support for retaining load as the sewage treatment scale variable. Only Wessex Water suggested using population equivalent which can be used to estimate load with companies required to use an assumption that each population equivalent is equal to 60 grams of load in kg BOD_5/day in annual regulatory reporting.

Companies suggested several different scale variables in their wastewater network plus models. Thames Water and Severn Trent Water suggested load, Dŵr Cymru and United Utilities suggested properties, and Yorkshire Water suggested sewer length. Anglian Water suggested using the volume of wastewater received at treatment works, distinguishing between indigenous and non-indigenous volume depending on whether the STWs is co-located with a sludge treatment centre (STC). We consider load is the most appropriate scale variable for wastewater network plus models from an engineering perspective and has better statistical performance than sewer length or properties. We do not think it is appropriate to use volume of wastewater received at sewage treatment works as the scale variable because of the risk of perverse incentives (ie companies should aim to minimise the volume of inflows into drainage and sewerage networks).

[52] This is due to properties of logarithmic functions.

Dŵr Cymru and Yorkshire Water also suggested having more than one scale driver in the wastewater network plus model by using additional normalised scale drivers (eg load per sewer length). Both variables were statistically significant in the models submitted by Dŵr Cymru and Yorkshire Water. But we do not include in our proposed models as it does not increase the overall the predictive power of the models, and it would make it more challenging to interpret the impact of scale on efficient costs.

4.2.2 Economies of scale at sewage treatment works

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

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.

We found that the PR19 economies of scale variables have lost statistical significance with the inclusion of additional outturn data in the models. Some companies, including Anglian Water, argued in a Cost Assessment Working Group discussion that band 6 (STWs serving more than 25,000 people) is too broad and does not explain the cost savings associated with operating very large works (eg STWs serving more than 100,000 people).[53]

To address some of these issues, we collected additional data from companies. That has enabled us to develop alternative variables. Our proposed economies of scale at sewage treatment works explanatory variables are considered in turn below.

We retain **the percentage of load treated in STWs serving less than 2,000 people** (bands 1 to 3) used in PR19. This variable has lost statistical significance since PR19. However, it still has a strong engineering rationale, is supported by companies, and is statistically significant in the bioresources cost models (see section 5).

We 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. Using a threshold of 100,000 people is supported by engineering rationale as we expect stronger economies of scale due to the adoption of different treatment processes around that threshold. Data analysis shows that unit costs continue to fall as the size of STWs increase. There is also a sufficiently large number of STWs that fall under this category. This reduces the risk of the results being driven by a small sample of STWs (eg

[53] See [Cost Claims CAWG Nov2021 (ofwat.gov.uk)](#) for an overview of a Cost Assessment Working Group (CAWG) discussion on economies of scale in sewage treatment in the November 2021 CAWG

there is a relatively low number of STWs serving more than 500,000 people). CEPA considered several size thresholds and concluded the percentage of load in STWs serving more than 100,000 people was the most robust threshold variable.

We also 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 BOD_5/day. It uses information on the distribution of all STWs sizes rather than focussing on the largest or smallest STWs as our other two economies of scale variables do. This can help explain the overall economies of scale the company faces across its sewage treatment unit more accurately. WATS allows for a more continuous relationship with sewage treatment costs. This is different from the size threshold variables which model step-like changes in sewage treatment costs beyond a certain threshold. It has strong statistical performance, and several companies suggested some sort of a weighted average STWs variable. CEPA included WATS in its model recommendations. Appendix A3 shows how we calculated WATS.[54]

Other company suggestions

Companies mostly supported the PR19 measures of economies of scale at sewage treatment works or a weighted average treatment size variable. A few other suggestions were raised.

Anglian Water suggested a model that splits the scale driver into two variables to capture total load in STWs that serve more or less than 125,000 people. Both variables were statistically significant in Anglian Water's proposed models. But we do not adopt this approach as it would make the interpretation of results more challenging and less transparent due to the difficulty to separate the distinct scale and economies of scale impacts. We also apply a threshold of 100,000 people in our proposed models for the reasons set out above, which is consistent with CEPA's recommendations.

Southern Water suggested a weighted average works size (WAWS) variable. That measure is like the WATS measure we are proposing as it captures the weighted average treatment works size in kg BOD_5/day. However, when calculating the measure, Southern Water assumed the average size of STWs in each band from 1-5 is at the mid-point. For example, the average STWs size in band 5 was assumed to be 1050 (mid-point between 600kg and 1500kg) BOD_5/day. Our WATS measure uses the same formula to calculate the weighted average but replaces the mid-point assumption with the actual average STWs size for bands 1-5 by dividing the total load in each band by the number of STWs in that band (eg 'total band 5 load' / 'number of band 5 STWs'). We consider this is an improvement on the Southern Water variable. Please refer to Appendix A3 for a full explanation of how we calculated the WATS.

Severn Trent Water and Yorkshire Water proposed weighted average band sizes measures akin to CEPA's recommendation to consider using a Weighted Average Band sizes (WAB)

[54] We have also published the derivation of the percentage of load in STWs serving more than 100,000 people and WATS on our website - https://www.ofwat.gov.uk/wp-content/uploads/2023/04/Economies-of-scale-at-sewage-treatment-works-variables-derivation-v1.xlsx

measure. These measures use the bands 1-5 sizes and disaggregate band 6 further using the large STWs dataset we published. The weighted average band size is calculated by summing the percentage of load treated in each band multiplied by the band number (1, 2, 3, etc.). This approach is like the calculation of weighted average water treatment complexity in wholesale water base cost models (see section 3). The weighted average band size variables produce statistically significant results. But we do not include in our proposed models because WATS is strongly statistically significant and has two favourable properties:[55]

- WATS does not depend on defining different bands and the value is not sensitive to how many bands are defined; and
- WATS does not implicitly impose a pre-modelling assumption on the relationship between cost and STW size via the number of size bands.

Dŵr Cymru suggested using population density in sewage treatment models to proxy economies of scale at sewage treatment works. We do not support this as our three economies of scale explanatory variables directly account for economies of scale at STWs.

4.2.3 Treatment complexity

Treatment complexity is a key cost 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 proposed models retain the PR19 treatment complexity variable. This is the **percentage of load with ammonia permit <= 3mg/l**. We include this explanatory variable in sewage treatment (SWT) and wastewater network plus (WWNP) models.

We considered alternative treatment complexity variables:

- percentage of load with a Total Phosphorus (P) permit <= 0.5mg/l or <= 1mg/l;
- percentage of load with a Biochemical Oxygen Demand (BOD) permit <= 7mg/l or <= 10mg/l; and
- percentage of load with an Ultra-Violet (UV) treatment permit.

None of the alternative variables improved on the PR19 complexity variable. They did not generate statistically significant results. The coefficient on the UV variable was also found to be of the wrong sign, predicting that tight permits have a negative impact on costs. For BOD <= 7 mg/l, we found that the data does not have a sufficient variation across the sector with a very limited proportion of load subject to these permits. This could lead to spurious results.

[55] We note that this approach cannot be applied in the wholesale water models due to data limitations.

CEPA included percentage of load with ammonia permit <= 3mg/l in its recommended models and did not recommend any other sewage treatment complexity variables.

Accounting for additional ongoing cost associated with P-removal

We recognise that the additional ongoing cost associated with more stringent phosphorus removal programmes across the sector may not be fully captured in our proposed base cost models. We are exploring alternative options to ensure that our cost assessment approach funds efficient ongoing P removal costs, which we welcome company views on:

- We will continue to consider models with a P-driver (eg percentage of load with a P-permit <= 0.5mg/l) fixed at the 2024-25 level. This will have the impact of funding the additional base expenditure associated with phosphorus removal enhancement schemes funded at PR19 and completed by the end of AMP7.
- We are considering whether we can calculate an accurate post-modelling adjustment that funds efficient ongoing opex associated with P-removal using data provided by companies in annual performance reports (APRs).
- The cost adjustment claim process.

Other company suggestions

Anglian Water, Southern Water, Severn Trent Water, Thames Water, Dŵr Cymru and Yorkshire Water all submitted models that included the PR19 measure of treatment complexity – percentage of load with ammonia permit <= 3mg/l. But companies also suggested several alternative sewage treatment complexity variables.

Anglian Water suggested the inclusion of the percentage of load subject to a BOD permit <= 10mg/l and trade effluent load. United Utilities suggested using the number of UV permit days total or number of UV permit days over 30mW/s/cm, arguing that works subject to UV permits exhibit higher costs. But our analysis suggests that the estimated coefficients on alternative sewage treatment complexity explanatory variables are statistically insignificant.

Severn Trent Water, Southern Water, South West Water and Yorkshire Water considered composite treatment permit variables. These explanatory variables combine two or more relevant tight treatment permits from data on ammonia, phosphorus, BOD and UV. We found composite treatment variables to be statistically significant. But they are less transparent and are harder to interpret than the PR19 ammonia variable. There is also a risk that the resulting expenditure allowances become non-sensical when P-permits is captured in a composite driver due to the relatively small number of sewage treatment works currently operating at tight permits (eg <= 0.5mg/l). This may change when additional outturn data becomes available. So we will keep open the option of models with a P-permits variable alongside post-modelling adjustments discussed above.

4.2.4 Network topography

We use **pumping capacity per sewer length** to capture the effect of network topography on sewage collection costs in our proposed 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. All companies used pumping capacity per sewer length as a proxy for network topography.

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.

We have developed alternative weighted average density measures using more granular Middle Super Output Area (MSOA) population density data from the ONS. We seek views on three measures of population density for PR24:

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

We set out the advantages and disadvantages of each population density variable in section 3.2.4 above. The LAD from MSOA weighted average density measure is the closest to the PR19 LAD weighted average density measure. But it applies a more consistent and accurate approach to the mapping of LADs to company boundaries and should be a more accurate representation of population density of LADs shared between companies. CEPA included models with all three measures in its model recommendations.

Most companies included the weighted average density measure in at least some of their suggested models, but there was more support for the PR19 measure based on LAD level population density data than MSOA population density data. Severn Trent Water, South West Water and Yorkshire Water also suggested models with properties per sewer length.[56]

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

Severn Trent Water and United Utilities suggested models that do not include a squared weighted average density term in the sewage collection models. This proposal is consistent with our PR19 models which only included a linear density term in sewage collection models. The squared density term was added by the CMA in the PR19 redeterminations.[57] Severn Trent Water and United Utilities argued that sewerage networks tend to be a lot more localised than water networks and are more of a passive asset, reducing travel and intervention costs compared to water networks. Therefore, companies serving sparsely populated areas should not face relatively higher costs.

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:

- Gravity sewers tend to be deeper than water mains. As such, heavy traffic loading in urban areas, which may result in greater ground movement and stresses on the pipework, would be expected to affect water mains to a greater degree.
- Gravity sewers are unpressurised and 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. These factors mean that sewers generally last longer than water mains and so require less maintenance.

For these reasons, we do not consider the non-linear relationship between population density and sewage collection base costs is as strong as in water from an engineering perspective. This is supported by empirical evidence, which shows that the squared density term is strongly insignificant when properties per sewer length is used as the density variable.

Our proposed sewage collection models therefore assume a linear relationship between population density and sewage collection base costs, which is consistent with our PR19 sewage collection models. This also ensures our sewage collection models are internally

[56] Yorkshire Water did not propose models with weighted average density.
[57] The CMA appear to have assumed the impact of having larger, more efficient sewage treatment works was relevant for the sewage collection models. If so, this is an impact that might warrant the use of a squared density term. But it does not apply to sewage collection as all cost incurred within sewage treatment works fall in the sewage treatment unit.

consistent as they all assume a linear relationship between population density and costs.[58] We welcome views on this approach. But we welcome company evidence on the engineering rationale that may justify a non-linear relationship between population density and sewage collection costs.

Other company suggestions

Severn Trent Water considered alternative density variables that normalise weighted average density with network length. It also considered a transformed density variable for sewage collection models which does not allow for higher unit costs in sparse areas and allows for increasing unit costs in dense areas. These variables are statistically significant in Severn Trent Water's suggested models. But we do not include in our proposed models as they do not improve model performance overall and unnecessarily add complexity.

4.2.6 Urban rainfall

Urban rainfall is defined as the **average rainfall falling in a company area (mm) multiplied by the urban company area (squared kms)**. 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 to account for climate change impacts where periods of extreme rainfall could become more prevalent over time.

We considered the use of urban rainfall in the sewage collection models at PR19. However, the measure did not perform well in the models. There were also concerns around data quality and transparency. For PR24, we have collected and constructed the data ourselves using rainfall data provided by the Environment Agency.

To derive our proposed urban rainfall measure we:

[58] Unlike the sewage collection models adopted by the CMA in its PR19 redeterminations, which had one model assuming a linear relationship between density and costs, and another assuming a non-linear relationship between density and costs.

- use granular rainfall data provided by the Environment Agency mapped to geographical company boundaries to determine total annual rainfall;
- use urbanisation data derived using data at the MSOA level of granularity; [59] and
- normalise by sewer length when including in proposed models.

The urban rainfall variable has some limitations. Forecasting urban rainfall is likely to be challenging despite having a long time series of historical data going back to 2000. And the variable does not take into account that the volume of rainfall may differ within a company's operating area. But, on balance, we include urban rainfall per sewer length in a subset of our proposed sewage collection and wastewater network plus models because it has a clear engineering rationale, is exogenous, and produces good statistical results.

Thames Water, United Utilities and Severn Trent Water included urban rainfall in their proposed sewage collection and wastewater network plus models. CEPA also included models with urban rainfall per sewer length in its model recommendations.

Other company suggestions

United Utilities and Severn Trent Water captured soil permeability in their urban rainfall variables. We decided not to capture soil permeability in our urban rainfall variable. The data is not sufficiently transparent, and we do not have any means to validate the soil permeability data provided by United Utilities. In addition, our early model testing suggested that adding soil permeability does not result in a material difference in model performance.

South West Water and Thames Water both suggested models that include total annual rainfall. We disagree with this approach as rainfall in more rural areas is less likely to drain into the sewerage network.

Severn Trent Water and United Utilities also suggested including the percentage of combined sewers in sewage collection models. We consider this variable is endogenous and including in the models might perversely incentivise companies not to separate sewers into surface water and foul. We also consider urban rainfall captures a similar impact and is more exogenous.

4.3 Cost drivers not included in our proposed models

We considered alternative cost drivers that are not included in our proposed models. These were based on company suggestions, CEPA's suggestions, and our own internal analysis. The reasons why we decided not to include these alternative cost drivers are set out below.[60]

[59] We use the MSOA urbanisation data to align to our proposed weighted average density approach which depends on the same mapping of geographical data on company boundaries and MSOAs. In practice, the difference between urbanisation data using LADs and MSOAs is very small.
[60] In no particular order.

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 UV 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 STWs 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, which it proposed in its January 2023 submission.

This variable is exogenous to the extent that 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.

We have 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.

CEPA also considered including pumping capacity in the sewage treatment models as it is highly correlated with Southern Water's coastal variable. But it concluded the correlation may be spurious as the pumping capacity variable does not include pumping to sea outfalls.[61]

We do not include the coastal variable in our proposed sewage treatment models due to these concerns. We ask for company views before making a final decision.

[61] See RAG-4.10–––Guideline-for-the-table-definitions-in-the-annual-performance-report.pdf (ofwat.gov.uk), line 7C.3

4.3.2 Sewer condition

South West Water and Yorkshire Water suggested including the percentage of sewer assets constructed after 2001 as a measure of the age of the network in sewage collection models. Yorkshire Water also suggested including it in wastewater network plus models. These variables are statistically significant in the models submitted by South West Water and Yorkshire Water. But we do not include in our proposed models because age-related variables are endogenous and can create perverse incentives not to replace older assets.

4.3.3 Time trend, year dummies and other dynamic factors

CEPA considered a time trend but did not include it in its final set of recommended models. 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 base cost assessment. No company suggested including a time trend in wastewater network plus models.

Severn Trent Water also suggested additional dynamic variables in its set of 'more sophisticated but complex models'. But we do not include these in our proposed models for the reasons set out in section 3.3.

4.3.4 Network reinforcement drivers

Differences in population growth rate can lead to differing levels of network reinforcement expenditure between companies and over time. CEPA explored a number of variables that may explain differences in network reinforcement spend. These included the percentage of new properties, the percentage increase in properties, and annual population growth.

We do not include any of the network reinforcement variables tested by CEPA in our proposed models. They produced poor statistical results. The estimated coefficients were statistically insignificant and of the wrong sign (ie negative). CEPA concluded that network reinforcement may not be a sufficiently material component of modelled base costs, particularly now that site specific developer services and growth at sewage treatment works are excluded. Other cost drivers in the models, such as scale and population density, may be sufficient to explain network reinforcement expenditure requirements.

4.4 Proposed wastewater network plus cost models

We are consulting on **6 sewage collection (SWC) models**, **3 sewage treatment (SWT) models**, and **8 wastewater network plus (WWNP) models**. The model specifications are summarised below, and model estimation results are in Appendix A4.

4.4.1 Summary of proposed wastewater network plus cost models

Level of cost aggregation	No. models	Cost drivers	Explanatory variables
Sewage collection	6	Scale	• Sewer length - included in 6 models.
		Network topography	• Pumping capacity per sewer length - included in 6 models.
		Population density	• Properties per sewer length – included in 2 models. • Weighted average density – LAD from MSOA - included in 2 models. • Weighted average density - MSOA– included in 2 models.
		Urban rainfall	• Urban rainfall per sewer length - included in 3 models.
Sewage treatment	3	Scale	• Load – included in 3 models.
		Treatment complexity	• Load treated with ammonia permit ≤ 3mg/l – included in 3 models.
		Economies of scale in sewage treatment	• Load treated in size bands 1 to 3 (%) – included in 1 model. • Load treated in STWs ≥ 100,000 people (%)– included in 1 model. • Weighted average treatment size – included in 1 model.
Wastewater network plus	8	Scale	• Load - included in 8 models.
		Network topography	• Pumping capacity per sewer length – included in 8 models.
		Treatment complexity	• Load treated with ammonia permit ≤ 3mg/l – included in 8 models.
		Economies of scale in sewage treatment	• Load treated in size bands 1 to 3 (%) – included in 2 models. • Load treated in STWs ≥ 100,000 people (%)– included in 2 models. • Weighted average treatment size – included in 2 models.
		Urban rainfall	• Urban rainfall per sewer length - included in 4 models.

Our selected models broadly align with CEPA's recommendations.[62]

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

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, and load treated in sewage treatment works serving more than 100,000 people in WWNP3 and WWNP7. We do not consider the marginal insignificance of these variables is a reason to exclude them given they

[62] Except for our choice of economies of scale variables, which we explain in section 4.2.2.

are supported by strong engineering and operational rationale; produce sensible results in terms of sign and magnitude of the estimated coefficient; and are 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 the CEPA report for further details on how the models perform against model robustness tests.[63]

[63] CEPA, 'PR24 Wholesale Base Cost Modelling', March 2023.

5. Cost models for bioresources activities

Summary

We are consulting on **6 bioresources total cost models** and **4 bioresources unit cost models**. We seek views on whether to use **total or unit cost models** to assess efficient bioresources expenditure at PR24.

We consider the key exogenous drivers of bioresources expenditure are **scale**; **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:

- **Sludge produced** to control for scale; and
- **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.

This section presents our proposed econometric models we intend to use to help set efficient bioresources 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
- proposed bioresources base cost econometric models.

5.1 Defining the dependent variable

Bioresources modelled costs across the sector equalled around £0.6 billion in 2021-22.[64] The main activities in the bioresources value chain are:

- **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.

[64] In 2017-18 prices.

Our dependent variable for bioresources modelled base costs includes operating, capital maintenance, bioresources growth enhancement, and quality enhancement operating expenditure. The addition of bioresources growth enhancement is new for PR24. As stated in our PR24 final methodology, 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.[65] The models will also produce an allowance for future growth enhancement costs.

Companies did not consistently use this definition of the dependent variable to develop their proposed bioresources cost models. Northumbrian Water, Severn Trent Water and United Utilities used this definition of the dependent variable. But Anglian Water, South West Water and Wessex Water excluded growth expenditure from the dependent variable.[66]

We made several pre-modelling cost adjustments to facilitate accurate cost comparisons between companies and over time, as detailed in Appendix A1. The backcasting adjustment is particularly important for bioresources as it accounts for our updated guidance on how to allocate the costs of sludge liquor treatment[67], energy generation[68] and overheads[69] between bioresources and sewage treatment. That improves comparability of bioresources costs across the industry, which helps to promote a market-based approach.

We seek views on whether to use **'total cost'** or **'unit cost'** models to assess the relative efficiency of each company's bioresources expenditure. Unit cost models divide the dependent variable defined above by sludge produced. This is like the approach taken to benchmark residential retail costs as discussed in section 6. 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. Whereas our proposed unit cost bioresources models omit the sludge produced scale variable from the explanatory variables. This imposes a constant returns to scale assumption, which is supported by the econometric model results.[70]

Unit cost models are arguably more intuitive for bioresources as they align better with the bioresources average revenue control. They also perform well against our model robustness tests. Northumbrian Water, Southwest Water, United Utilities and Wessex Water submitted total cost models. Anglian Water and Severn Trent Water submitted unit cost models.

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[65] Ofwat, 'Our final methodology for PR24. Appendix 4: Bioresources control', December 2022, page 25.
[66] Southern Water, Thames Water, Dŵr Cymru, and Yorkshire Water did not submit any bioresources cost models.
[67] Reporting-of-sludge-liquor-treatment-costs-final-decisions.pdf (ofwat.gov.uk)
[68] Bioresources_Cost_Allocation_Energy_Generation_Odour_Control_Final_Decision.pdf (ofwat.gov.uk)
[69] RAG-2.09-–-Guideline-for-classification-of-costs-across-the-price-controls.pdf (ofwat.gov.uk)
[70] The estimated coefficient on sludge produced in the unit cost models was not statistically significant.

5.2 Selected cost drivers

As in PR19, the key exogenous drivers of bioresources expenditure are **scale**; **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.

Our PR19 bioresources cost models cannot be improved using the data available. We therefore use the same explanatory variables to proxy the key cost drivers as we did in PR19.

5.2.1 Scale

Scale is a key driver of bioresources costs. Larger company operations deliver more output and incur greater costs. We have retained **sludge produced** as the scale driver. The total amount of sludge entering the bioresources business unit provides the best indication of expected efficient bioresources costs. All companies that submitted bioresources models used sludge produced as the scale driver.

We expect the estimated coefficient on sludge produced to be close to one, indicating that doubling sludge produced results in a doubling of costs (ie constant returns to scale).

We considered total sludge disposed as an alternative scale driver. We have not included in our proposed models as it is endogenous. It depends on management decisions on the sludge treatment technologies used. Companies that have decided to implement more advanced anaerobic digestion technologies can achieve a higher solids destruction and improved dewaterability leading to lower sludge disposed volumes.

5.2.2 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 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 have smaller 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 proposed 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. Please see sections 3.2.4 and 4.2.5 for more detail.

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 proposed bioresources cost models, which only include one of the explanatory variables listed above in any one model. CEPA included the proportion of load treated in bands 1 to 3 and number of STWs per property in its model recommendations. It also proposed using weighted average band sizes in its model recommendations which we do not include in our proposed models for the reasons set out in section 4.2.2.

Other company suggestions

Most companies suggested models that included the population density and size of STW variables listed above. A few other suggestions were raised.

Severn Trent Water and Thames Water suggested models with a squared weighted average density term. They argue 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. We do not include a squared density variable in our proposed bioresources models. The squared weighted average density term is statistically significant in some of our proposed bioresources models. But we think this result is spurious. 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 and South West Water suggested models with weighted average band size variables (see section 4.2.2 for more details). Wessex Water and Thames Water suggested models with the percentage of load treated in band 6.[71] We considered bioresources models with our other economies of scale at STWs variables developed for PR24 - WATS and the percentage of load treated in sewage treatment works serving more than 100,000 people. None of the variables were statistically significant with p values higher than 0.3. So, we have not included them in our proposed models.

Anglian Water and United Utilities suggested models using the percentage of sludge produced and treated at a site with sewage treatment works and sludge treatment centre co-location. The co-location variable was statistically significant in some of the models submitted by Anglian Water and United Utilities. But we do not capture co-location directly in our proposed bioresources models as the decision to co-locate is partially within company control, which is inconsistent with our cost assessment principles.

Severn Trent Water and South West Water suggested variables that capture sludge transport modes. For example, the percentage of intersiting via truck/tanker or pipeline (ie the share of sludge transportation activity using different transport modes). These variables were statistically significant in the models submitted by Severn Trent Water and South West Water. But we do not include them in our proposed models because sludge transport mode is within company control, which is against our cost assessment principles.

5.3 Cost drivers not included in our proposed models

We considered alternative cost drivers that are not included in our proposed models. These were based on company suggestions, CEPA's suggestions, and our own internal analysis. The reasons why we decided not to include these alternative cost drivers are set out below.[72]

[71] Band 6 include STWs that serve more than 25,000 people.
[72] In no particular order.

5.3.1 Sludge treatment technologies

Anglian Water, Severn Trent Water, South West Water and Thames Water included variables that capture sludge treatment technologies in its submitted models. For example, the percentage of sludge treated via anaerobic digestion or liming. Thames Water suggested using the ratio of sludge disposed to sludge treated (sludge disposal rate) which is a proxy for the level of solids destruction during treatment which is higher under more advanced treatment technologies. These explanatory variables were often statistically significant. But we do not include in our proposed models as companies have control over the treatment technology used, which is inconsistent with our cost assessment principles.

5.3.2 Sludge disposal route

Severn Trent Water included the percentage of sludge disposed to farmland in its suggested models to capture differences in sludge disposal routes. Thames Water included the total measure of 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). These variables were statistically significant in the companies' models. But we do not include them in our proposed models as they are inconsistent with our cost assessment principles as companies have control over the sludge disposal route and the distance travelled to disposal sites (through the location of their sludge treatment centres).

5.3.3 Impact of sewage treatment complexity on bioresources costs

United Utilities and Wessex Water considered the impact of sewage treatment complexity on bioresources costs. United Utilities suggested using the percentage of load with a P permit <= 1mg/l. Wessex Water included the total load received at STWs subject to Secondary Activated sludge treatment.

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. But these variables are not included in our proposed models as they did not perform well against our model assessment criteria.

5.3.4 Time trend

CEPA considered the inclusion of a time trend but did not include it in its final set of recommended models.

5.4 Proposed bioresources cost models

We are consulting on **6 bioresources total cost models** and **4 bioresources unit cost models**. The model specifications are summarised below, and model estimation results are in Appendix A4.

Table 5.1: Summary of proposed bioresources cost models

Level of cost aggregation	No. models	Cost drivers	Explanatory variables
Total cost	6	Scale	• Sludge produced - included in 6 models.
		Economies of scale in sludge treatment, and location of STWs relative to sludge treatment centres	• Load treated in bands 1-3 - included in 3 models. • Weighted average density – LAD from MSOA – included in 2 models. • Weighted average density – MSOA – included in 2 models. • Number of STWs per property – included in 1 model.
Unit cost	4	Economies of scale in sludge treatment, and location of STWs relative to sludge treatment centres	• Load treated in bands 1-3 - included in 1 model. • Weighted average density – LAD from MSOA – included in 1 model. • Weighted average density – MSOA – included in 1 model. • Number of 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 models generally perform well against all other model robustness tests of medium and high importance. But the unit cost bioresources models perform better overall.[73] They appear less sensitive to changes in the underlying data, and the variables that proxy for economies of scale in sludge treatment and the location of STWs relative to sludge treatment centres are all statistically significant at the 10 percent level. BR8 and BR9 do fail the RESET test, but this is not overly concerning because the models perform well against all other tests.

Please see the CEPA report for further details on how the models perform against model robustness tests.[74]

[73] We did not include sludge produced in the unit cost models as the estimated coefficient was not statistically different from zero. This means the unit cost models impose a constant returns to scale assumption.
[74] CEPA, 'PR24 Wholesale Base Cost Modelling', March 2023.

6. Cost models for residential retail activities

Summary

We are consulting on **3 bad debt cost models**, **2 other cost models**, and **6 total cost models**. In each model, the dependent variable is specified as cost per household.

The PR19 models captured the following cost drivers: the **amount of revenue at risk** if a customer does not pay its water bill; a customer's **propensity to default**; **transience**; **type of customer**; and **economies of scale**.

Our analysis found that our PR19 residential retail models are impacted by Covid-19, largely attributable to the increase in companies' bad debt provisions that are not explained by the explanatory variables.

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 and the proportion of metered households variables; and**
- **inclusion of a third deprivation variable capturing the average number of county court judgements/partial insight accounts per household.**

This section presents our proposed econometric models we intend to use to help set efficient residential retail expenditure allowances at PR24. It is structured as follows:

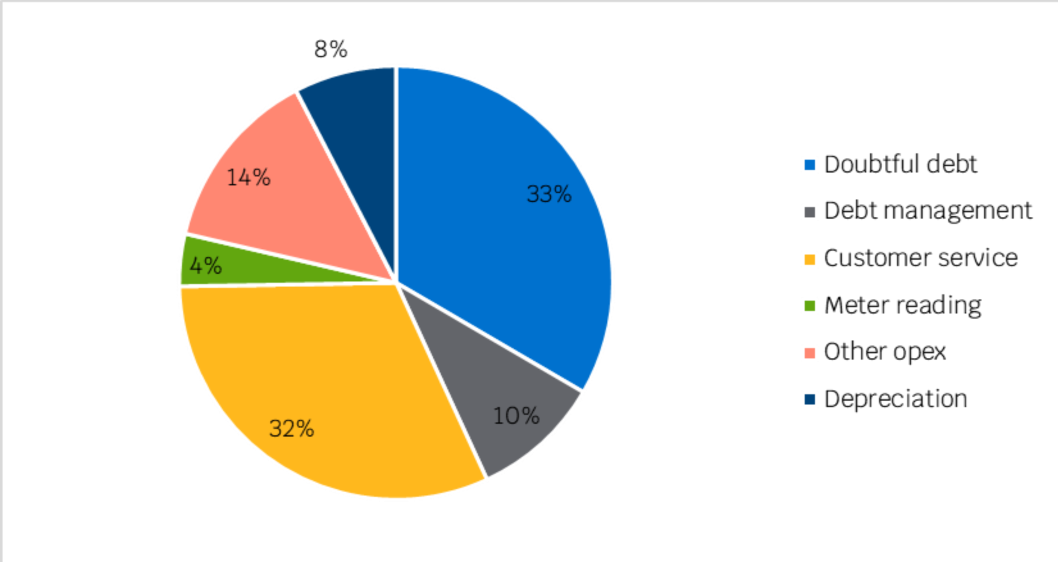
- defining the dependent variable;
- selected cost drivers;
- cost drivers not included in our proposed models; and
- proposed residential retail cost models.

6.1 Defining the dependent variable

Residential retail expenditure across the sector equalled £0.8bn in 2021-22.[75] Figure 6.1 sets out the relative share of different types of costs included in the residential retail cost models. The dependent variable includes all residential retail costs. Bad debt related costs typically account for just under half of total retail costs.

[75] In 2017-18 prices.

Figure 6.1: share of expenditure of residential retail services in 2021-22



In line with PR19, we have developed granular "bottom up" bad debt and other retail costs models, and aggregate "top down" total retail costs models.

In each model, the dependent variable is specified as retail cost per connected household, aligning to the unit cost approach we took at PR19. We have chosen to maintain a unit cost approach at PR24 as the total number of customers is the main driver of retail costs.

A unit cost approach allows us to decide whether to impose a constant return to scale assumption based on analysis and engineering, operational and economic rationale. Constant returns to scale (ie costs vary in the same proportion to the number of households) are assumed if we do not include the number of households as an explanatory factor in the models. As in PR19, we include the number of households in one of the other retail costs models, and a subset of the total cost models. This relaxes the constant returns to scale assumption. We assume constant returns to scale in the bad debt and a subset of the total retail costs models. For these models, we free up one degree of freedom for the estimation of model parameters in the models. This improves the ability of the models to capture the impact of alternative drivers on retail costs.

The unit cost models present a lower adjusted R-squared than if the dependent variable was defined as total costs. This is purely cosmetic. The number of households is the main driver of residential retail costs, with an adjusted R-squared value greater than 0.9 when included alone in a retail total cost model. A unit cost modelling approach aims to explain variations in companies' residential retail costs above and beyond the number of households, which subsequently leads to a lower adjusted R-squared.

As in PR19, we used three dependent variables to develop 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. 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 construct this variable using smoothed depreciation.[76]

6.1.1 Alternative approaches to defining the dependent variable

Bad debt related costs are based on companies' doubtful debt data reported in APRs. Doubtful debt is the bad debt charge for all customer types, forecasted by companies for the year ahead. The forecast nature of this data poses some issues, particularly in times of high uncertainty. Covid-19 is an example of this, where we observed a significant increase in doubtful debt across the sector in 2019-20 and 2020-21 as companies did not know what impact Covid-19 was going to have on customers' ability to pay their water bill. This increase is not explained by the explanatory variables included in the retail models.

Some companies tried to address this issue by using smoothed doubtful debt data to calculate the dependent variable.[77] Companies smoothed bad debt across 2019-20 and 2021-22, which when summed should equate to the unsmoothed total over the same period. We have chosen not to use this data to construct the dependent variable as:

1. using smoothed bad debt did not significantly improve the statistical performance of the models compared to using unsmoothed bad debt;
2. we have some concerns around the consistency in approach used by companies to smooth the data, which we will look to address through the query process; and
3. our proposed models include dummy variables to isolate the additional impact of Covid-19 on bad debt costs (see below), which removes the need to smooth the data.

Other alternatives proposed included South West Water modelling other retail costs on a per service basis and Wessex Water's definition of bad debt costs as a ratio of costs to total billed revenue. But it was not clear why these approaches would be better than the unit cost modelling approach applied in PR19.

[76] Smoothed depreciation is calculated by taking the company average of the historical depreciation data provided by companies over the full length of the dataset (2013/14 – 2021/22).
[77] These companies were SES Water, South East Water, United Utilities, Wessex Water, and Yorkshire Water.

6.2 Selected cost drivers

We include the following cost drivers in our proposed residential retail cost models:

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

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

The remainder of this section discusses the cost drivers and corresponding explanatory variables that are included in our proposed set of models.

6.2.1 Amount of revenue at risk

As at PR19, we include **average bill size** in bad debt and total cost models to capture the amount of revenue at risk if a customer defaults on its water bill; a key driver of bad debt and debt management costs. It has a clear rationale, and produces good statistical results.

At PR19 we expected a one-to-one relationship between bill size and the level of bad debt. At the time, we stated that a coefficient slightly above one may suggest that, after capturing the revenue at risk, this variable may also be capturing that as bill size increases, the likelihood of default increases. We retain this view at PR24.

South Staffs Water argues we should reconsider using average bill size in the retail models. It does not think that a lower bill is necessarily easier to pay and hence will have high recovery rates. South Staffs Water also argues that water only companies (WOCs) bill for wastewater services on behalf of the water and sewerage company (WaSC), meaning it is unlikely customers would only pay the water component. These arguments appear to be driven by an incorrect interpretation of average bill size. It is included in our models mainly as a proxy for the amount of revenue at risk, rather than as a propensity to default.

South Staffs Water also argues that average bill size may proxy for company type. We have tested this, but our analysis does not indicate that this is the case.

Other suggestions

Almost all companies included average bill size in their suggested retail costs models. Only SES Water presented an alternative variable to explain the amount of revenue at risk: total consumption. But we do not include this variable in our proposed models as it is not a direct proxy for the amount of revenue at risk.

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.

Our proposed models include three variables to proxy for customers' **propensity to default**:

- **income deprivation score**, sourced from the Office of National Statistics (ONS);
- **percentage of households with a payment default**, sourced from Equifax; and
- **average number of county court judgements/partial insight accounts per household**, sourced from Equifax.

Each variable captures the deprivation within the operating area of each company. The underlying data for each variable is available at a local authority district (LAD) level. This data is then mapped to each company's operating area.

We have chosen to retain the two PR19 deprivation variables, income deprivation score and percentage of households with default. Both variables performed well throughout our model development process and received support from companies. For income score we have selected the interpolated variable, which was adopted by several companies on the basis of better statistical performance.

To enhance the ability of the models to capture the impacts of deprivation on companies' costs, we propose the inclusion of a third deprivation variable – **the average number of county court judgements/partial insights accounts per household**. This variable is intuitive and performs well against our model robustness tests. The underlying data also captures the range in deprivation levels across England and Wales comparably well.

We also considered including council tax collection rates and credit risk score to explain propensity to default. We decided not to include them in our proposed models due to the lower statistical performance of the variables. We also have doubts on how well the credit risk scores explains differences in deprivation across England and Wales.

Other company suggestions

Yorkshire Water, South East Water, and South West Water suggested composite deprivation metrics. These combine multiple deprivation variables into one variable. The composite deprivation variables tended to produce statistically significant results. But we do not include in our proposed models as it would not materially increase the predictive power of the models; add unnecessary complexity; and make it more difficult to interpret model outputs.

Wessex Water proposed including a squared income deprivation score variable to allow more weight to be placed on more deprived areas. The estimated coefficient on the squared term was large in the bad debt models. This produced non-sensical elasticities. The data in our proposed deprivation variables have a wide enough variation between companies to sufficiently capture the differences in deprivation across England and Wales.

Thames Water and SES Water suggested including deprivation variables in other retail costs models. Other retail costs are predominantly driven by customer service costs, which we do not expect to vary with deprivation. Therefore, the underlying economic or operational rationale to support including them is unclear.

6.2.3 Type of customer

Type of customer defines the customer based upon the services received. This influences the amount of contact and enquiries a company is likely to receive from its customers, which in turn drives customer services costs.

We include the PR19 **proportion of dual customers** variable in our proposed other retail costs models. Dual service customers receive both water and wastewater services from the same company. Dual customers may generate more contact and enquiries relative to single service customers, which in turn drives customer service costs. The variable is statistically significant, positive, and small in magnitude as expected.

The proportion of dual customers is not included in total retail costs models due to its high correlation with average bill size.

We do not to include the proportion of metered customers in our proposed residential retail cost models. While we included this variable at PR19, it performed poorly throughout model development, producing highly statistically insignificant results, and often presenting an estimated coefficient close to zero. This indicates that meter reading does not have a material impact on retailers' costs. This may be reflected in the drop in metering costs since Covid-19, the decreasing share of total expenditure attributable to meter reading costs over time, and increased smart metering.

Other company suggestions

South West Water submitted models that capture the proportion of wastewater only customers, but the economic, engineering, and operational rationale was not clear.

6.2.4 Economies of scale

Economies of scale are when the cost per household decreases with the total number of households served.

Economies of scale can be an important factor in explaining other retail costs. But total number of households, which aims to capture economies of scale, is not statistically significant at the 10 percent significance level.

We do not consider economies of scale are a key driver of bad debt costs given the wide availability of third-party providers for bad debt management services. Controlling for economies of scale in the bad debt models could also disincentivise efficient procurement of third-party services.

Our proposed models therefore include the total number of households in one other retail costs model (RO2), and a subset of total retail costs models (RTC1 to RTC3), to capture economies of scale in other retail costs. As in PR19, we do not include the variable in our bad debt models for the reasons set out above. See Appendix A4 for the model estimation results.

6.2.5 Covid-19 dummy variables

As acknowledged by several companies, the statistical performance of the PR19 residential retail cost models worsened because of the spike in bad debt costs between 2019-21. Several explanatory variables were no longer statistically significant and the estimated coefficients on some variables switched signs. The spike was caused by companies increasing bad debt provisions because of Covid-19, which was not explained by the PR19 residential retail explanatory variables.

We have addressed this issue by including two Covid-19 dummy variables in the residential retail bad debt and total costs models. The 2019-20 dummy variable is set equal to one in 2019-20 and zero for all other years of the sample. The 2020-21 dummy variable is set equal to one in 2020-21 and zero for all other years of the sample.

The Covid-19 dummy variables allow us to isolate the additional impact of Covid-19 on companies' bad debt costs that is not explained by the other explanatory variables in the models. This allows us to estimate the relationship more accurately between retail costs and the other explanatory variables. This approach was suggested by South West Water and Wessex Water in their January 2023 model submissions.[78]

Overall, we consider the use of Covid-19 dummy variables is the best option to mitigate the impact of Covid-19 on the residential retail cost models. We also considered using (i) companies smoothed bad debt data; and (ii) companies' debt written off data instead of bad debt provisions. We decided not to use smoothed bad debt data for the reasons set out in section 6.1.1 above. And decided not to use debt written off due to the varying nature of companies' debt write off policies, which can lead to bad debt to be written off many years

[78] In addition, South Staffs Water, Thames Water and Welsh Water each provide commentary on dummy variables in their submissions.

after it is incurred. We will revisit the use of Covid-19 dummy variables when we receive 2022-23 and 2023-24 outturn data.

6.3 Cost drivers not included in our proposed models

We considered alternative cost drivers that are not included in our proposed models. These were based on company suggestions and our own internal analysis. The reasons why we decided not to include these alternative cost drivers are set out below.

6.3.1 Transience

We included total migration (internal plus international inflows and outflows) in two out of seven PR19 residential retail models, to capture the impact of higher transience levels on retailers' bad debt costs.

We exclude transience from our proposed PR24 residential retail models.

The transience variable is highly unstable, often presenting a counterintuitive, negative estimated coefficient, and is highly statistically insignificant in almost all models. Irrespective of sign, the size of the coefficient was also significantly smaller than in the PR19 models. This suggests that transience does not have a material impact on bad debt costs.

In addition, the ONS has discontinued the international migration dataset that we use to construct this variable. No companies suggested an alternative transience variable despite its relatively poor performance.[79]

6.3.2 Density

Severn Trent Water and Hafren Dyfrdwy suggested the inclusion of a density variable as a proxy for multiple retail cost drivers, including deprivation, meter reading costs and transience. We do not include density in our proposed residential retail models because of unclear economic, operational, and engineering rationale. It would also introduce transparency and interpretability issues as including a variable that proxies for several different factors would make it difficult to understand the underlying drivers of change.

6.3.3 Time trends and year dummies

Wessex Water suggested the inclusion of year dummies for every year of the sample in the other retail cost models, and a time trend variable in the bad debt and other retail costs

[79] Thames Water suggested a smoothed transience variable, however this relies on the same ONS dataset.

models. It argues the year dummies and time trend aim to capture 'dynamic' factors, such as persistent and year-specific effects not captured by the other explanatory variables.

We have included two Covid-19 dummies for 2019-20 and 2020-21 in our bad debt and total cost models to isolate the impact of Covid-19 on bad debt costs. Additional year dummies are unnecessary and use up degrees of freedom which can reduce model precision.

We have not included a time trend in our proposed models. We prefer to include variables that directly capture a certain cost driver, rather than a time trend that can capture multiple factors and therefore can be difficult to explain.

6.4 Proposed residential retail cost models

We are consulting on 3 bad debt costs models; 2 other retail costs models; and 6 total retail costs models. The model specifications are summarised below, and model estimation results are in Appendix A4.

Table 6.1: Summary of proposed wholesale water cost models

<table>
<tr><th>Level of cost aggregation</th><th>No. models</th><th>Cost drivers</th><th>Explanatory variables</th></tr>
<tr><td rowspan="3">Bad debt costs</td><td rowspan="3">3</td><td>Amount of revenue at risk</td><td>• Average bill size – included in 3 models.</td></tr>
<tr><td>Deprivation</td><td>• Proportion of households with default– included in 1 model.
• Number of county court judgements/partial insight accounts per household– included in 1 model.
• Income deprivation score (interpolated) – included in 1 model.</td></tr>
<tr><td>Covid-19 dummies</td><td>• 2019-20 dummy variable – included in 3 models.
• 2020-21 dummy variable – included in 3 models.</td></tr>
<tr><td rowspan="2">Other retail costs</td><td rowspan="2">2</td><td>Type of customer</td><td>• Proportion of dual customers – included in 2 models.</td></tr>
<tr><td>Economies of scale</td><td>• Total number of households – included in 1 model.</td></tr>
<tr><td rowspan="4">Total retail costs</td><td rowspan="4">6</td><td>Amount of revenue at risk</td><td>• Average bill size – included in 6 models.</td></tr>
<tr><td>Deprivation</td><td>• Proportion of households with default– included in 2 models.
• Number of county court judgements/partial insight accounts per household– included in 2 models.
• Income deprivation score (interpolated) – included in 2 models.</td></tr>
<tr><td>Economies of scale</td><td>• Total number of households – included in 3 models.</td></tr>
<tr><td>Covid-19 dummies</td><td>• 2019-20 dummy variable – included in 6 models.
• 2020-21 dummy variable – included in 6 models.</td></tr>
</table>

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

The inclusion of the Covid-19 dummy variables for 2019-20 and 2020-21 improves model performance and allowes us to estimate an accurate cost function by isolating the impact of Covid-19 on bad debt provisions.

All estimated coefficients in the bottom-up retail models are statistically significant at the 10 percent level, except for total households which is only statistically significant at the 15 percent level in ROC2. The bottom-up retail models generally perform well against all other model robustness tests of medium and high importance. The bad debt models fail the RESET. This does not concern us because the models perform well against all other tests. The RESET also failed in companies' submissions of bad debt unit cost models.[80]

The top-down total retail cost models generally perform well against the model robustness tests. The deprivation variables are not as statistically significant as they are in the bad debt models. This is expected as bad debt costs, which deprivation helps to explain, only make up around half of total retail costs. Sensitivity testing shows the top-down total retail cost models to be more sensitive to changes in the underlying data, ie removal of companies and the final year. This does not concern us as these ratings are largely attributable to changes in the estimated coefficient on the second Covid-19 dummy, which we do not intend to use to set allowances given this will be set equal to zero in future years. We will also revisit the need for inclusion of the Covid-19 dummy variables in the residential retail models when 2022-23 and 2023-24 outturn data becomes available.

[80] We have tested the inclusion of an average bill size quadratic term in the models. The term was statistically insignificant and did not improve the RESET results.

7. Consultation questions

Please respond to the questions below using the responses template available on our website: https://www.ofwat.gov.uk/wp-content/uploads/2023/04/Econometric-base-cost-models-for-PR24-response-template.xlsx

7.1 Wholesale water

Q3.1) Do you agree with our proposed set of wholesale water base cost models?

Q3.2) Do you agree with the inclusion of average pumping head in a sub-set of treated water distribution and wholesale water models?

Q3.3) Do you agree with our approach to modelling population density?

Which of the three proposed population density variables do you support?

a. Weighted average density – LAD from MSOA
b. Weighted average density - MSOA
c. Properties per length of mains

Q3.4) Do you agree we should collect additional data on the number of reservoirs that are designed as high-risk by the Environment Agency and Natural Resources Wales?

Do you have a view on the appropriateness of capturing a variable for reservoir inspection and maintenance requirements under the Reservoir Act 1975 in the water resources plus models?

7.2 Wastewater network plus

Q4.1) Do you agree with our proposed set of wastewater network plus base cost models?

Q4.2) Do you agree with our approach to modelling economies of scale at sewage treatment works? Which of the three proposed explanatory variables do you support?

a. Percentage of load treated in STWs bands 1 to 3
b. Percentage of load treated in STWs serving more than 100,000 people
c. Weighted average sewage treatment works size

Q4.3) Do you agree with our approach to modelling population density?

Which of the three proposed explanatory variables do you support?

d. Weighted average density – LAD from MSOA
e. Weighted average density - MSOA
f. Properties per sewer length

Q4.4) Do you agree with our proposal to assume a linear relationship between population density and sewage collection base costs?

Q4.5) Do you agree with the inclusion of urban rainfall in our sewage collection and wastewater network plus models?

Q4.6) Do you agree with our approach to capturing sewage treatment complexity in our proposed wastewater network plus base cost models?

What are your views on our proposed options to account for additional ongoing cost associated with P-removal?

g. Models with a P-driver (eg percentage of load with a P-permit <= 0.5mg/l) fixed at the 2024/25 level.
h. A post-modelling adjustment that funds efficient ongoing opex associated with P-removal using data provided by companies in APRs.
i. Cost adjustment claims.

Q4.7) Do you agree with Southern Water's proposal to include the percentage of population living in coastal areas in sewage treatment models?

7.3 Bioresources

Q5.1) Do you agree with our proposed set of bioresources cost models?

Q5.2) Do you agree we should use unit cost models to assess bioresources expenditure?

7.4 Residential retail

Q6.1) Do you agree with our proposed set of residential retail cost models?

Q6.2) Do you agree with our approach to modelling deprivation, and/or have any views on the selected variables?

Q6.3) Do you agree with the inclusion of Covid-19 dummy variables in the residential retail cost models?

Q6.4) Do you agree with the removal of transience from the residential retail cost models?

Q6.5) Do you agree with the removal of 'proportion of metered customers' from the residential retail cost models?

A1 Pre-modelling adjustments to modelled costs

Adjustment	Description
Unmodelled costs	We excluded costs that will be treated as unmodelled base costs at PR24. Unmodelled base costs include pension deficit recovery costs, business rates, abstraction and discharge charges (water only), costs associated with the Traffic Management Act, statutory water softening costs, wastewater Industrial Emissions Directive (IED) operating costs, and third-party costs.
Atypical expenditure adjustment	We include atypical expenditure in modelled base costs by default at PR24. But continue to exclude atypical costs that relate to fines/penalties, accounting adjustments, costs associated with referrals to the Competition and Markets Authority (CMA), and truly one-off atypical costs that are unlikely to be repeated (eg costs incurred in preparation for the introduction of retail competition for business customers).
Principal use adjustment	Principal Use of Assets (PUA) accounting treatment was introduced in 2015-16. This means that base costs of assets used by more than one price control are allocated to the largest of the relevant price controls. Compensating accounting transactions are then made by the other price controls to recompense the price control of principal use. During investigation, we found that companies had not always made the correct principal use adjustments to recompense the price control of principal use. This adjustment applies from 2015-16 onwards to correct for this issue.
Bioresources and sewage treatment 'backcasting' adjustment	This adjustment accounts for our updated guidance on how to allocate the costs of sludge liquor treatment, energy generation and overheads between bioresources and sewage treatment.
Developer services base cost adjustment	Site-specific developer services expenditure is not included in the scope of modelled base costs at PR24. This adjustment makes sure that historical developer services costs that had been reported in opex and capital maintenance expenditure are not included in modelled base costs. The adjustment was informed by data submitted by water companies in Summer 2022.

A2 Model robustness tests

Table 7.1 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 7.1: 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 accurately the model fits the data. It measures the proportion of variation in the dependent variables (in our case, variation in costs) that can be explained by the model. The statistic ranges from 0 to 1. **The higher the value the better the model fits.** Importantly, R2 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. We expect efficiency scores to be in a sensible range. 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. In practice, the p-value indicates our confidence in the estimated coefficient. **The lower the p-value, the more confident we are in the value of the estimated coefficient.** 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 an inadequate functional form. For example, 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 test 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. **Both tests are failed for lower p-values.** If the normality test fails, it would suggest that the model residuals are not normally distributed. 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).
Heteroskedasticity test	Low	

<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 should be 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>

A3 Weighted average sewage treatment works size variable definition

The weighted average treatment size (WATS) is a measure that calculates the average size of every company's sewage treatment works in kg BOD_5/day. It uses data from APR tables 7B (compiled in the Large STWs dataset) and table 7D (contained in the wastewater cost assessment dataset). The following equation sets out the definition of WATS:

$$
\begin{aligned}
WATS_{it} = {} & \frac{Load\ received\ by\ STWs\ in\ size\ band\ 1_{it}}{Number\ of\ STWs\ in\ size\ band\ 1_{it}} * (\%\ Load\ received\ at\ band\ 1_{it}) \\
& + \frac{Load\ received\ by\ STWs\ in\ size\ band\ 2_{it}}{Number\ of\ STWs\ in\ size\ band\ 2_{it}} * (\%\ Load\ received\ at\ band\ 2_{it}) \\
& + \frac{Load\ received\ by\ STWs\ in\ size\ band\ 3_{it}}{Number\ of\ STWs\ in\ size\ band\ 3_{it}} * (\%\ Load\ received\ at\ band\ 3_{it}) \\
& + \frac{Load\ received\ by\ STWs\ in\ size\ band\ 4_{it}}{Number\ of\ STWs\ in\ size\ band\ 4_{it}} * (\%\ Load\ received\ at\ band\ 4_{it}) \\
& + \frac{Load\ received\ by\ STWs\ in\ size\ band\ 5_{it}}{Number\ of\ STWs\ in\ size\ band\ 5_{it}} * (\%\ Load\ received\ at\ band\ 5_{it}) \\
& + \sum\nolimits_{ijt} \left(Load\ received\ by\ STW_{ijt}\ above\ size\ band\ 5\right) \\
& * \left(\%\ Load\ received\ at\ STW_{ijt}\right)
\end{aligned}
$$

Where i denotes the company, j denotes each STWs above band 5 and t denotes year.

For bands 1-5, WATS uses the average size of sewage treatment works multiplied by the percentage of load treated in each band. For works above band size 5, the measure calculates the contribution of each works separately using granular data on load for every works from the Large STWs dataset.

Please refer to the Economies of scale variables derivation v1.0 spreadsheet published alongside this consultation for full detail on how we derived all the economies of scale measures in this consultation and CEPA's report. [81]

[81] CEPA, 'PR24 Wholesale Base Cost Modelling', March 2023.

A4 Proposed econometric base cost models for PR24

A4.1 Wholesale water

Table 7.2: Proposed water resources plus models[82]

Cost driver	Explanatory variable	WRP1	WRP2	WRP3	WRP4	WRP5	WRP6
Scale	Connected properties (log)	1.077*** {0.000}	1.075*** {0.000}	1.054*** {0.000}	1.057*** {0.000}	1.028*** {0.000}	1.027*** {0.000}
Complexity	Water treated at complexity levels 3 to 6 (%)	0.005*** {0.002}		0.004*** {0.009}		0.005*** {0.001}	
	Weighted average treatment complexity (log)		0.343 {0.183}		0.315 {0.234}		0.365 {0.143}
Density	Weighted average density - LAD from MSOA (log)	-1.545*** {0.007}	-1.468** {0.026}				
	Weighted average density - LAD from MSOA (log) squared	0.097*** {0.008}	0.091** {0.031}				
	Weighted average density – MSOA (log)			-4.986** {0.017}	-5.048** {0.034}		
	Weighted average density – MSOA (log) squared			0.303** {0.017}	0.306** {0.033}		
	Properties per length of mains (log)					-7.815** {0.019}	-7.440** {0.030}
	Properties per length of mains (log) squared					0.858** {0.028}	0.810** {0.042}
Constant	Constant	-5.335*** {0.000}	-5.660*** {0.002}	9.416 {0.226}	9.591 {0.286}	6.988 {0.309}	6.137 {0.389}

[82] Significance levels of the p-values: *** (1%), ** (5%) and * (10%).

Table 7.3: Proposed water resources plus models – model robustness tests and additional information

Model robustness tests and additional information		WRP1	WRP2	WRP3	WRP4	WRP5	WRP6
Statistical diagnostic tests	Adjusted R-squared	0.909	0.902	0.901	0.896	0.910	0.905
	RESET test	0.436	0.367	0.765	0.729	0.324	0.203
	VIF (max)*	1.206	1.253	1.269	1.308	1.112	1.158
	Pooling / Chow Test	0.999	0.999	1	1	0.983	0.997
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.522	0.812	0.417	0.416	0.143	0.527
	Heteroskedasticity of model residuals	0	0	0	0	0	0
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	187	187	187	187	187	187
	Dependent variable	Wholesale water botex plus network reinforcement					
Efficiency score distribution	Minimum	0.53	0.50	0.49	0.47	0.51	0.48
	Maximum	2.02	1.99	2.00	1.98	1.97	1.95
	Range	1.49	1.48	1.50	1.51	1.47	1.46
Sensitivity tests	Removal most efficient company	G	A	G	A	G	A
	Removal least efficient company	G	A	G	A	A	A
	Removal first year	G	G	G	G	G	G
	Removal last year	G	G	G	G	G	G

* The reported VIF excludes the density squared term

Table 7.4: Proposed treated water distribution models

Cost driver	Explanatory variable	TWD1	TWD2	TWD3	TWD4	TWD5	TWD6
Scale	Length of mains (log)	1.070*** {0.000}	1.026*** {0.000}	1.072*** {0.000}	1.062*** {0.000}	1.017*** {0.000}	1.045*** {0.000}
Topography	Booster pumping stations per length of mains (log)	0.461*** {0.002}	0.433*** {0.001}	0.488*** {0.001}			
	Average pumping head TWD (log)				0.357*** {0.000}	0.411*** {0.000}	0.357*** {0.000}
Density	Weighted average density - LAD from MSOA (log)	-2.729*** {0.000}			-2.975*** {0.000}		
	Weighted average density - LAD from MSOA (log) squared	0.219*** {0.000}			0.229*** {0.000}		
	Weighted average density – MSOA (log)		-5.561*** {0.000}			-6.539*** {0.000}	
	Weighted average density – MSOA (log) squared		0.393*** {0.000}			0.445*** {0.000}	
	Properties per length of mains (log)			-14.921*** {0.000}			-16.623*** {0.000}
	Properties per length of mains (log) squared			1.898*** {0.000}			2.055*** {0.000}
Constant	Constant	4.155*** {0.008}	15.638*** {0.002}	25.065*** {0.000}	1.99 {0.218}	16.573*** {0.000}	26.125*** {0.000}

Table 7.5: Proposed treated water distribution models – model robustness tests and additional information

Model robustness tests and additional information		TWD1	TWD2	TWD3	TWD4	TWD5	TWD6
Statistical diagnostic tests	Adjusted R-squared	0.955	0.952	0.958	0.961	0.965	0.966
	RESET test	0.09	0.122	0.489	0.439	0.719	0.845
	VIF (max)*	1.833	1.592	1.864	1.032	1.062	1.037
	Pooling / Chow Test	0.799	0.873	0.903	0.798	0.767	0.847
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.072	0.014	0.738	0.65	0.954	0.474
	Heteroskedasticity of model residuals	0.132	0.046	0.004	0.482	0.828	0.268
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	187	187	187	187	187	187
	Dependent variable	Wholesale water botex plus network reinforcement					
Efficiency score distribution	Minimum	0.80	0.75	0.74	0.72	0.71	0.75
	Maximum	1.40	1.42	1.38	1.31	1.32	1.28
	Range	0.60	0.67	0.64	0.59	0.61	0.54
Sensitivity tests	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

* The reported VIF excludes the density squared term

Table 7.6: Proposed wholesale water models (booster pumping stations)

Cost driver	Explanatory variable	WW1	WW2	WW3	WW4	WW5	WW6
Scale	Connected properties (log)	1.072*** {0.000}	1.061*** {0.000}	1.052*** {0.000}	1.046*** {0.000}	1.044*** {0.000}	1.036*** {0.000}
Complexity	Water treated at complexity levels 3 to 6 (%)	0.003*** {0.002}		0.003** {0.011}		0.003*** {0.001}	
	Weighted average treatment complexity (log)		0.354** {0.016}		0.322** {0.030}		0.366*** {0.007}
Topography	Booster pumping stations per length of mains (log)	0.457*** {0.008}	0.444*** {0.005}	0.509*** {0.003}	0.486*** {0.003}	0.377** {0.033}	0.351** {0.033}
Density	Weighted average density - LAD from MSOA (log)	-1.849*** {0.000}	-1.648*** {0.001}				
	Weighted average density - LAD from MSOA (log) squared	0.132*** {0.000}	0.117*** {0.000}				
	Weighted average density – MSOA (log)			-4.684*** {0.001}	-4.308*** {0.002}		
	Weighted average density – MSOA (log) squared			0.301*** {0.000}	0.276*** {0.001}		
	Properties per length (log)					-11.259*** {0.000}	-10.322*** {0.000}
	Properties per length (log) squared					1.318*** {0.000}	1.201*** {0.000}
Constant	Constant	-1.958 {0.206}	-2.795* {0.064}	10.300* {0.056}	8.674 {0.108}	15.655*** {0.003}	13.516*** {0.008}

Table 7.7: Proposed wholesale water models (booster pumping stations) – model robustness tests and additional information

Model robustness tests and additional information		WW1	WW2	WW3	WW4	WW5	WW6
Statistical diagnostic tests	Adjusted R-squared	0.965	0.967	0.963	0.965	0.965	0.968
	RESET test	0.164	0.075	0.178	0.075	0.205	0.072
	VIF (max)*	1.955	1.948	1.789	1.741	1.879	1.868
	Pooling / Chow Test	0.94	0.862	0.987	0.965	0.962	0.958
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.268	0.583	0.51	0.574	0.445	0.483
	Heteroskedasticity of model residuals	0	0	0	0	0	0
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	187	187	187	187	187	187
	Dependent variable	Wholesale water botex plus network reinforcement					
Efficiency score distribution	Minimum	0.76	0.76	0.73	0.74	0.71	0.72
	Maximum	1.49	1.50	1.53	1.53	1.41	1.42
	Range	0.73	0.74	0.79	0.79	0.70	0.70
Sensitivity tests	Removal most efficient company	G	G	A	A	A	A
	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

* The reported VIF excludes the density squared term

Table 7.8: Proposed wholesale water models (average pumping head)

Cost driver	Explanatory variable	WW7	WW8	WW9	WW10	WW11	WW12
Scale	Connected properties (log)	1.066*** {0.000}	1.059*** {0.000}	1.041*** {0.000}	1.037*** {0.000}	1.025*** {0.000}	1.020*** {0.000}
Complexity	Water treated at complexity levels 3 to 6 (%)	0.003** {0.028}		0.002* {0.073}		0.003** {0.014}	
	Weighted average treatment complexity (log)		0.290* {0.075}		0.258 {0.108}		0.318** {0.036}
Topography	Average pumping head (log)	0.345*** {0.001}	0.336*** {0.002}	0.359*** {0.002}	0.351*** {0.002}	0.278** {0.022}	0.265** {0.034}
Density	Weighted average density - LAD from MSOA (log)	-2.179*** {0.000}	-2.036*** {0.000}				
	Weighted average density - LAD from MSOA (log) squared	0.148*** {0.000}	0.138*** {0.000}				
	Weighted average density – MSOA (log)			-6.145*** {0.000}	-5.895*** {0.000}		
	Weighted average density – MSOA (log) squared			0.384*** {0.000}	0.367*** {0.000}		
	Properties per length (log)					-12.767*** {0.000}	-12.007*** {0.000}
	Properties per length (log) squared					1.467*** {0.000}	1.374*** {0.000}
Constant	Constant	-3.750** {0.035}	-4.293** {0.015}	13.173** {0.010}	12.138** {0.022}	16.893*** {0.000}	15.240*** {0.000}

Table 7.9: Proposed wholesale water models (average pumping head) – model robustness tests and additional information

Model robustness tests and additional information		WW7	WW8	WW9	WW10	WW11	WW12
Statistical diagnostic tests	Adjusted R-squared	0.965	0.965	0.961	0.962	0.966	0.967
	RESET test	0.838	0.821	0.895	0.935	0.781	0.614
	VIF (max)*	1.211	1.267	1.271	1.315	1.115	1.196
	Pooling / Chow Test	0.856	0.85	0.975	0.97	0.979	0.978
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.329	0.794	0.395	0.502	0.076	0.178
	Heteroskedasticity of model residuals	0	0	0	0	0	0
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	187	187	187	187	187	187
	Dependent variable	Wholesale water botex plus network reinforcement					
Efficiency score distribution	Minimum	0.74	0.72	0.72	0.70	0.75	0.73
	Maximum	1.49	1.46	1.44	1.43	1.45	1.43
	Range	0.74	0.74	0.72	0.73	0.71	0.71
Sensitivity tests	Removal most efficient company	G	G	A	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

* The reported VIF excludes the density squared term

A4.2 Wastewater network plus

Table 7.10: Proposed sewage collection models

Cost driver	Explanatory variable	SWC1	SWC2	SWC3	SWC4	SWC5	SWC6
Scale	Sewer length (log)	0.804*** {0.000}	0.888*** {0.000}	0.861*** {0.000}	0.842*** {0.000}	0.895*** {0.000}	0.873*** {0.000}
Topography	Pumping capacity per sewer length (log)	0.344** {0.012}	0.586*** {0.000}	0.542*** {0.001}	0.360** {0.017}	0.562*** {0.000}	0.518*** {0.001}
Density	Properties per sewer length (log)	1.043*** {0.000}			0.982*** {0.000}		
	Weighted average density - LAD from MSOA (log)		0.212** {0.022}			0.239*** {0.000}	
	Weighted average density – MSOA (log)			0.354*** {0.005}			0.385*** {0.000}
Urban rainfall	Urban rainfall per sewer length (log)				0.113*** {0.000}	0.152*** {0.000}	0.149*** {0.000}
Constant	Constant	-7.956*** {0.000}	-6.609*** {0.000}	-7.572*** {0.000}	-7.809*** {0.000}	-6.424*** {0.000}	-7.492*** {0.000}

Table 7.11: Proposed sewage collection models – model robustness tests and additional information

Model robustness tests and additional information		SWC1	SWC2	SWC3	SWC4	SWC5	SWC6
Statistical diagnostic tests	Adjusted R-squared	0.917	0.889	0.889	0.919	0.909	0.908
	RESET test	0.356	0.307	0.254	0.172	0.345	0.321
	VIF (max)	2.337	1.914	1.996	2.53	1.918	2.003
	Pooling / Chow Test	0.72	0.976	0.974	0.896	0.986	0.987
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.394	0.307	0.576	0.103	0.026	0.066
	Heteroskedasticity of model residuals	0.299	0.017	0.011	0.255	0.031	0.007
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	110	110	110	110	110	110
	Dependent variable	Sewage collection botex plus					
Efficiency score distribution	Minimum	0.91	0.85	0.82	0.93	0.86	0.83
	Maximum	1.13	1.19	1.19	1.17	1.14	1.09
	Range	0.22	0.34	0.37	0.24	0.28	0.26
Sensitivity tests	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	A	G	G
	Removal last year	G	G	G	G	G	G

Table 7.12: Proposed sewage treatment models

Cost driver	Explanatory variable	SWT1	SWT2	SWT3
Scale	Load (log)	0.653*** {0.000}	0.723*** {0.000}	0.788*** {0.000}
Treatment complexity	Load treated with ammonia permit ≤ 3mg/l	0.006*** {0.000}	0.006*** {0.000}	0.006*** {0.000}
Economies of scale in sewage treatment	Load treated in size bands 1 to 3 (%)	0.029 {0.211}		
	Load treated in STWs ≥ 100,000 people (%)		-0.008*** {0.007}	
	Weighted average treatment size (log)			-0.242*** {0.000}
Constant	Constant	-3.734*** {0.004}	-4.072*** {0.000}	-3.001*** {0.000}
Model robustness tests and additional information				
Statistical diagnostic tests	Adjusted R-squared	0.854	0.869	0.911
	RESET test	0.056	0.272	0.849
	VIF (max)	5.337	5.347	4.339
	Pooling / Chow Test	0.999	1	0.997
	LM test (Pooled OLS vs RE)	0	0	0
	Normality of model residuals	0.024	0.221	0.064
	Heteroskedasticity of model residuals	0.417	0.764	0.865
Model information	Estimation method	RE	RE	RE
	Observations	110	110	110
	Dependent variable	Sewage treatment botex plus		
Efficiency score distribution	Minimum	0.82	0.87	0.91
	Maximum	1.50	1.41	1.24
	Range	0.68	0.53	0.33
Sensitivity tests	Removal most efficient company	A	G	G
	Removal least efficient company	A	G	G
	Removal first year	G	G	G
	Removal last year	G	G	G

Table 7.13: Proposed wastewater network plus models

Cost driver	Explanatory variable	WWNP1	WWNP2	WWNP3	WWNP4	WWNP5	WWNP6	WWNP7	WWNP8
Scale	Load (log)	0.646*** {0.000}	0.727*** {0.000}	0.686*** {0.000}	0.714*** {0.000}	0.651*** {0.000}	0.732*** {0.000}	0.707*** {0.000}	0.722*** {0.000}
Topography	Pumping capacity per sewer length (log)	0.367*** {0.000}	0.380*** {0.000}	0.359*** {0.000}	0.295*** {0.002}	0.357*** {0.000}	0.370*** {0.000}	0.348*** {0.000}	0.276*** {0.000}
Treatment complexity	Load treated with ammonia permit ≤ 3mg/l	0.005*** {0.000}	0.005*** {0.000}	0.005*** {0.000}	0.005*** {0.000}	0.005*** {0.000}	0.005*** {0.000}	0.005*** {0.000}	0.005*** {0.000}
Economies of scale in sewage treatment	Load treated in size bands 1 to 3 (%)		0.023* {0.073}				0.023** {0.035}		
	Load treated in STWs ≥ 100,000 people (%)			-0.002 {0.204}				-0.003 {0.102}	
	Weighted average treatment size (log)				-0.092** {0.012}				-0.096*** {0.002}
Urban rainfall	Urban rainfall per sewer length (log)					0.075** {0.016}	0.077*** {0.010}	0.080** {0.012}	0.088** {0.010}
Constant	Constant	-2.984*** {0.000}	-4.106*** {0.000}	-3.374*** {0.000}	-2.929*** {0.000}	-2.819*** {0.000}	-3.932*** {0.000}	-3.355*** {0.000}	-2.732*** {0.000}

Table 7.14: Proposed wastewater network plus models – model robustness tests and additional information

Model robustness tests and additional information		WWNP1	WWNP2	WWNP3	WWNP4	WWNP5	WWNP6	WWNP7	WWNP8
Statistical diagnostic tests	Adjusted R-squared	0.947	0.952	0.949	0.956	0.953	0.959	0.956	0.964
	RESET test	0.572	0.478	0.7	0.901	0.241	0.109	0.009	0.248
	VIF (max)	4.169	5.396	5.348	4.352	4.268	5.397	5.391	4.503
	Pooling / Chow Test	0.978	0.992	0.997	0.973	0.997	0.996	0.996	0.937
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0	0	0
	Normality of model residuals	0.435	0.044	0.352	0.102	0.683	0.223	0.879	0.255
	Heteroskedasticity of model residuals	0.515	0.603	0.333	0.167	0.206	0.7	0.054	0.051
Model information	Estimation method	RE	RE	RE	RE	RE	RE	RE	RE
	Observations	110	110	110	110	110	110	110	110
	Dependent variable	Wastewater network plus botex plus							
Efficiency score distribution	Minimum	0.92	0.91	0.92	0.95	0.93	0.93	0.93	0.96
	Maximum	1.07	1.08	1.07	1.09	1.10	1.07	1.06	1.06
	Range	0.15	0.17	0.15	0.14	0.17	0.14	0.13	0.09
Sensitivity checks	Removal most efficient company	G	G	A	G	G	G	A	G
	Removal least efficient company	G	G	A	G	G	A	A	G
	Removal first year	G	G	A	G	A	A	A	A
	Removal last year	G	G	G	G	G	G	G	G

A4.3 Bioresources

Table 7.15: Proposed bioresources total cost models

Cost driver	Explanatory variable	BR1	BR2	BR3	BR4	BR5	BR6
Scale	Sludge produced (log)	1.176*** {0.000}	1.132*** {0.000}	1.134*** {0.000}	1.119*** {0.000}	1.039*** {0.000}	1.024*** {0.000}
Economies of scale in sludge treatment, and location of STWs relative to sludge treatment centres	Load treated in bands 1-3 (%)	0.063** {0.011}	0.064** {0.016}		0.073*** {0.004}		
	Weighted average density - LAD from MSOA (log)	-0.139 {0.217}				-0.23 {0.185}	
	Weighted average density - MSOA (log)		-0.093 {0.642}				-0.305 {0.263}
	Number of STWs per property (log)			0.275 {0.174}			
Constant	Constant	-0.889 {0.312}	-0.946 {0.479}	0.808 {0.316}	-1.654** {0.014}	0.667 {0.362}	1.488 {0.301}

Table 7.16: Bioresources total cost models – model robustness tests and additional information

Model robustness tests and additional information		BR1	BR2	BR3	BR4	BR5	BR6
Statistical diagnostic tests	Adjusted R-squared	0.821	0.815	0.784	0.817	0.779	0.775
	RESET test	0.488	0.409	0.374	0.278	0.07	0.344
	VIF (max)	3.066	3.057	3.359	2.455	2.156	2.268
	Pooling / Chow Test	0.753	0.815	0.974	0.944	0.864	0.935
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.261	0.149	0.04	0.141	0.048	0.045
	Heteroskedasticity of model residuals	0.338	0.212	0.757	0.197	0.124	0.305
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	110	110	110	110	110	110
	Dependent variable	Bioresources botex including growth enhancement					
Efficiency score distribution	Minimum	0.68	0.67	0.60	0.68	0.59	0.58
	Maximum	1.44	1.50	1.47	1.53	1.43	1.47
	Range	0.75	0.83	0.87	0.85	0.84	0.89
Sensitivity tests	Removal most efficient company	A	A	A	A	A	A
	Removal least efficient company	A	A	A	G	A	A
	Removal first year	G	A	G	G	G	A
	Removal last year	G	G	G	G	G	G

Table 7.17: Bioresources unit cost models

Cost driver	Explanatory variable	BR7	BR8	BR9	BR10
Economies of scale in sludge treatment, and location of STWs relative to sludge treatment centres	Load treated in bands 1-3 (%)	0.051*** {0.000}			
	Weighted average density - LAD from MSOA (log)		-0.199* {0.073}		
	Weighted average density - MSOA (log)			-0.276* {0.086}	
	Number of STWs per property (log)				0.172* {0.061}
Constant	Constant	-0.997*** {0.000}	0.626 {0.422}	1.375 {0.273}	0.605 {0.410}
Model robustness tests and additional information					
Statistical diagnostic tests	Adjusted R-squared	0.239	0.124	0.108	0.133
	RESET test	0.508	0.000	0.005	0.445
	VIF (max)	1	1	1	1
	Pooling / Chow Test	0.875	0.626	0.75	0.881
	LM test (Pooled OLS vs RE)	0	0	0	0
	Normality of model residuals	0.051	0.040	0.046	0.021
	Heteroskedasticity of model residuals	0.252	0.790	0.835	0.955
Model information	Estimation method	RE	RE	RE	RE
	Observations	110	110	110	110
	Dependent variable	Bioresources botex including growth enhancement divided by sludge produced			
Efficiency score distribution	Minimum	0.62	0.58	0.58	0.57
	Maximum	1.52	1.44	1.48	1.49
	Range	0.90	0.86	0.90	0.92
Sensitivity tests	Removal most efficient company	G	G	G	G
	Removal least efficient company	G	G	G	G
	Removal first year	G	G	G	G
	Removal last year	G	G	G	G

A4.4 Residential retail

Table 7.18: Residential retail bottom-up models (bad debt costs and other retail costs)

Cost driver	Explanatory variable	RDC1	RDC2	RDC3	ROC1	ROC2
Revenue at risk	Average bill size (£ per/household) (log)	1.170*** {0.000}	1.207*** {0.000}	1.045*** {0.000}		
Propensity to default	Equifax – Percentage of households with payment default (%)	0.064*** {0.007}				
	Equifax – Average number of County Court Judgements/Partial Insight Accounts per household (log)		0.879** {0.017}			
	ONS – Income deprivation score (interpolated) (%)			0.089*** {0.002}		
Type of customer	Proportion of dual households (%)				0.002** {0.029}	0.003*** {0.001}
Economies of scale	Total number of households (log)					-0.045 {0.139}
Covid-19 dummies	Covid-19 dummy for 2019-20 (nr)	0.437*** {0.000}	0.395*** {0.000}	0.419*** {0.000}		
	Covid-19 dummy for 2020-21 (nr)	0.264*** {0.005}	0.193*** {0.023}	0.233*** {0.007}		
Constant	Constant	-5.861*** {0.000}	-5.101*** {0.000}	-4.767*** {0.000}	2.742*** {0.000}	3.324*** {0.000}

Table 7.19: Residential retail bottom-up models (bad debt costs and other retail costs) – model robustness tests and additional information

Model robustness tests and additional information		RDC1	RDC2	RDC3	ROC1	ROC2
Statistical diagnostic tests	Adjusted R-squared	0.662	0.661	0.677	0.118	0.131
	RESET test	0.005	0.012	0.004	0.988	0.312
	VIF (max)*	1.065	1.03	1.204	1	2.113
	Pooling / Chow Test	0.998	0.998	0.99	0.884	0.978
	LM test (Pooled OLS vs RE)	0	0	0	0	0
	Normality of model residuals	0	0	0	0.08	0.142
	Heteroskedasticity of model residuals	0	0	0	0.041	0.135
Model information	Estimation method	RE	RE	RE	RE	RE
	Observations	153	153	153	153	153
	Dependent variable	Bad debt related costs per household			Other costs per household	
Efficiency score distribution	Minimum	0.69	0.66	0.67	0.82	0.82
	Maximum	1.90	1.80	1.55	1.55	1.52
	Range	1.22	1.15	0.88	0.73	0.69
Sensitivity tests	Removal most efficient company	G	G	G	G	G
	Removal least efficient company	G	G	G	G	A
	Removal first year	G	G	G	G	G
	Removal last year	G	G	G	G	G

Table 7.20: Residential retail top-down models (total retail costs)

Cost driver	Explanatory variable	RTC1	RTC2	RTC3	RTC4	RTC5	RTC6
Revenue at risk	Average bill size (£ per/household) (log)	0.651*** {0.000}	0.659*** {0.000}	0.603*** {0.000}	0.514*** {0.000}	0.540*** {0.000}	0.491*** {0.000}
Propensity to default	Equifax – Percentage of households with payment default (%)	0.025** {0.012}			0.021** {0.022}		
	Equifax – Average number of County Court Judgements/Partial Insight Accounts per household (log)		0.229 {0.166}			0.181 {0.246}	
	ONS – Income deprivation score (interpolated) (%)			0.026* {0.093}			0.026 {0.110}
Economies of scale	Total number of households (log)	-0.096*** {0.002}	-0.082*** {0.009}	-0.072** {0.016}			
Covid-19 dummies	Covid-19 dummy for 2019-20 (nr)	0.176*** {0.000}	0.153*** {0.000}	0.161*** {0.000}	0.166*** {0.000}	0.147*** {0.000}	0.159*** {0.000}
	Covid-19 dummy for 2020-21 (nr)	0.058** {0.022}	0.026 {0.371}	0.038 {0.142}	0.044* {0.098}	0.018 {0.543}	0.033 {0.221}
Constant	Constant	0.405 {0.255}	0.626** {0.043}	0.609* {0.079}	-0.06 {0.904}	0.175 {0.664}	0.227 {0.545}

Table 7.21: Residential retail top-down models (total retail costs) – model robustness tests and additional information

Model robustness tests and additional information		RTC1	RTC2	RTC3	RTC4	RTC5	RTC6
Statistical diagnostic tests	Adjusted R-squared	0.697	0.669	0.648	0.65	0.645	0.638
	RESET test	0.103	0.054	0.128	0.092	0.023	0.176
	VIF (max)*	2.708	2.542	1.936	1.065	1.03	1.204
	Pooling / Chow Test	1	1	1	1	1	1
	LM test (Pooled OLS vs RE)	0	0	0	0	0	0
	Normality of model residuals	0.036	0.042	0.085	0.017	0.029	0.042
	Heteroskedasticity of model residuals	0.041	0.039	0.057	0.294	0.196	0.163
Model information	Estimation method	RE	RE	RE	RE	RE	RE
	Observations	153	153	153	153	153	153
	Dependent variable	Total costs per household					
Efficiency score distribution	Minimum	0.83	0.80	0.79	0.86	0.84	0.84
	Maximum	1.32	1.29	1.31	1.34	1.31	1.40
	Range	0.49	0.49	0.52	0.49	0.47	0.56
Sensitivity checks	Removal most efficient company	G	A	A	G	G	A
	Removal least efficient company	G	A	G	G	A	G
	Removal first year	G	G	G	G	G	G
	Removal last year	A	A	A	A	R	A

A5 Statement from Professor Andrew Smith

Professor Andrew Smith, University of Leeds, March 2023

This review concerns Ofwat's consultation document entitled "Econometric Base Cost Models for PR24" and covers the cost models for water, wastewater, bioresources and retail. I have acted as an independent academic advisor to OFWAT, challenging their approach (and indirectly, the underpinning work of their consultants, CEPA) to the cost modelling process at various stages of the modelling process.

My role was to question and challenge Ofwat and its consultants CEPA on the approach taken, whilst not getting involved every detail of the model selection decisions; recognising also the need for CEPA to take its own independent view and in turn then Ofwat's need to take its own view after applying appropriate regulatory judgement. Overall I consider that Ofwat and its consultants have developed a pragmatic and robust set of econometric models that are suitable to put out for consultation and take forward to the next stage of the PR24 process.

A key point to note is that considerable progress was made during PR19 to develop a robust set of models. I therefore support Ofwat's approach of seeking to improve upon those models but nevertheless setting a relatively high bar before making changes, given the model development already done at PR19. It is also positive that the consultation document does not solely put forward Ofwat's own models (built also on the work done by consultants CEPA) but also takes account of the suggestions and models put forward by the companies.

The modelling approach taken makes good use of a combination of considerations for the inclusion of variables, including whether there is engineering based support, implications for company incentives, data quality and statistical robustness (based on the model criteria set out at the outset of the process). The approach taken by Ofwat also makes appropriate application of regulatory / academic best practice, also referencing CMA determinations where applicable. Inevitably in this process some finely balanced decisions have to made which are within the scope of regulatory judgement.

In my view, the models set out therefore represent a good set of models to put out for consultation and take forward to the next stage. Potential areas for further consideration / development that I could see in due course might include:

- It is noted by Ofwat that the efficiency variation is relatively wide in some models, this being driven by increased expenditure amongst some companies in recent years. It will be important to ensure that this is not influencing the efficiency benchmark to a large extent and also to sense check the overall, triangulated efficiency targets that emerge from combining the models.

- Related to the above point, Ofwat has generally taken the view that COVID has not materially affected costs, with impacts being potentially in both directions. It will be important again to verify this point in respect of ensuring that the efficiency benchmark in particular is not greatly influenced and also any relative efficiency issues that might have arisen.

- It will be useful, if possible, to understand better the rationale for and implications of taking "threshold" approaches to dealing with treatment complexity, as opposed to utilising weighted average variables. Ultimately, however, it may be appropriate to take forward both sets of models as set out in the consultation.

- The Ofwat report makes good use of engineering understanding in interpreting results and justifying model selection. In the spirit of aiming towards continuous improvement, as has been a pattern over recent price reviews, it would be useful to consider whether there is any other empirical evidence on the expected size of the cost impact of different variables included in the cost model (beyond the scale and density variables) that could provide some further validation of the models. That said, it does need to be recognised that one of the aims of econometric modelling is to produce new evidence on how different factors influence cost where other evidence might not exist, so I recognise that this may not necessarily be feasible.

- Section 3 discusses the possibility of incorporating a quality (leakage) measure into the model, with evidence put forward that an intuitive sign on this variable had been achieved in some models, at least for the leakage variable. I understand that there are challenges of endogeneity that may be hard to overcome and also incentive compatibility issues as noted by Ofwat – and I further note that quality can be dealt with in other ways in the regulatory framework. However, to the extent that quality can successfully be incorporated into regulatory cost models it can give useful information on the cost of quality improvements and allow benchmarking to take into account a wider range of cost drivers. As a longer term objective I would therefore support continued development and consideration of these kinds of approaches going forward alongside other approaches to incentivising quality.

- It is encouraging that measures reflecting climate related variables are being reflected in the models (e.g. the rainfall measures). Section 3 discusses attempts to model the impact of temperature, but it does not seem to have a significant impact on costs when included in the water models alongside existing explanatory variables such as average pumping head. Ofwat also recognises the potential complexity needed to capture such effects. As climate effects are likely to be more important in future, I would see exploration of these areas to be a useful area for further work post PR24.

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