WATER PR24 REFERENCES

Base Costs Modelling – Working Paper

18 December 2025

Website: www.gov.uk/cma

The Competition and Markets Authority has excluded from this published version of the working paper information which the group considers should be excluded having regard to section 206 of the Water Industry Act 1991.

Any omissions are indicated by [✂]. Any non-sensitive replacement content is indicated in square brackets.

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1. Introduction

Purpose and scope

1.1 On 9 October 2025 we issued our provisional determinations on the PR24 water references (**PR24 PD**).[1] Our PR24 PD outlined, among other things, our provisional decision on wholesale water and wastewater base cost allowances. The allowances for these modelled base costs in the PR24 PD reflected an econometric modelling approach that differed from the approach adopted in Ofwat's PR24 FD. We have received detailed submissions on this aspect of our PR24 PD, and several Disputing Companies requested additional engagement on this matter before we issue our final determinations.

1.2 While some stakeholders expressed qualified support for our approach, other respondents raised concerns that include:

(a) the technical implementation of the model;

(b) the model stability and interpretability associated with the input selection technique; and

(c) the lack of transparency of statistical robustness checks that the CMA performed.

1.3 This working paper outlines our latest thinking to enable interested parties and their advisers to comment on the technical aspects of our approach. We do not intend in this document to respond to every point raised in response to our PR24 PD. We focus on the key points where we seek further input.

1.4 Further, the scope of this consultation is limited to the implementation of wholesale water and wastewater base cost benchmark models and a subset of claims related to those models.[2]

Current position

1.5 We have adopted a targeted and proportionate approach to base cost modelling in response to the concerns raised by Disputing Companies at the outset of this process. Those concerns largely focused on matters such as the selection of cost drivers, the accuracy of predicted costs, the appropriateness of the upper quartile (**UQ**) 'catch-up' efficiency challenge and abnormalities in efficiency challenges set

[1] CMA (2025) Water PR24 References Provisional Determination report (**PR24 PD**).
[2] These include South East's claim for a cost adjustment to reflect the physical constraints that limit its ability to fully access economies of scale at its water treatment works; and Southern's claim for a cost adjustment for the effect that serving a large coastal population has on efficient costs.

by Ofwat's models.[3] In response to those concerns, we considered it appropriate and in line with our overriding objective to develop a simple suite of econometric benchmarking models designed to select economic and engineering cost drivers that most accurately predict routine, year-on-year costs, which companies incur in the normal running of the business. This would allow us to both set base cost allowances and to assess the Disputing Companies' requests in relation to specific cost drivers.

1.6 Since publication of our PR24 PD, we have improved and refined our approach in response to the concerns raised by some stakeholders. Having made those changes, our proposed updated approach has a number of important benefits that should outweigh any residual concerns. These include improved predictive accuracy, simpler cost models, and a transparent data-driven approach to select cost drivers that have an engineering and economic rationale.

1.7 At its most basic level, econometric benchmarking is designed to predict efficient costs so companies can fund their day-to-day activities, without customers overpaying where companies are inefficient. No econometric model will perfectly capture the complexities of the industry and regulators must therefore use judgement to pick a model that in the round performs best. We find that our updated models perform better than Ofwat's with this basic task in mind.

1.8 As part of our updated approach, we have:

(a) addressed technical implementation issues identified following publication of our PR24 PD;

(b) taken steps to mitigate the concerns raised around model stability and conducted extensive stability and robustness checks. This includes checking results against a suite of statistical tests, carrying out stability tests through the use of repeated sampling analysis and updating the technical implementation of our methodology; and

(c) taken steps to mitigate the concerns raised around model treatment of correlation between cost drivers. The result is a modified list of cost drivers that improves the performance of our updated econometric modelling approach.

1.9 Our updated models produce wholesale water and wastewater allowances that are 1.5% lower sector-wide and 1.0% higher for Disputing Companies than those in

[3] For an explanation of catch-up efficiency and how it applies in the context of PR24, see Ofwat (2024) PR24 final determinations: Expenditure allowances, pp25–27.

Ofwat's PR24 FD before applying modelled efficiency challenges.[4] Our models do, however, result in a stronger efficiency challenge. Once this stronger efficiency challenge is applied, our models produce allowances that are 7.1% lower sector-wide and 4.8% lower for Disputing Companies than Ofwat's PR24 FD.[5] [6]

Structure of working paper

1.10 The remainder of this paper is structured as follows:

(a) section 2 outlines our proposed revised methodology to setting base costs;

(b) section 3 presents a summary of the key methodological changes to cost drivers, new modelled allowances, efficiency scores and updated cost allowances for wholesale water;

(c) section 4 presents the revised base cost model for wastewater;

(d) section 5 explains our current thinking on true-ups and a subset of claims; and

(e) section 6 sets out next steps.

1.11 In addition, we include the following annexes:

(a) Appendix A provides a technical description of our revised approach and the bootstrap method used to analyse the robustness of our revised base models; and

(b) Appendix B and Appendix C provide more detail on the set of cost drivers and model results for wholesale water and wastewater models, respectively.

Invitation to comment

1.12 We invite comments on this working paper, which should be sent to waterpr24references@cma.gov.uk, **no later than 5:30pm (UK time) on Wednesday 7 January 2026**. The statutory deadline for our final determinations is 17 March 2026.

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[4] Calculated by combining wholesale water and wastewater cost allowances from Table 3.4 and Table 4.4, and computing combined percentage change for Disputing Companies. For each Disputing Company the changes are: Anglian 0.4%; Northumbrian -2.6%; South East 4.5%; Southern 3.9%; and Wessex 0.6%.

[5] Calculated by combining wholesale water and wastewater cost allowances from Table 3.3 and Table 4.3, and computing overall percentage change for Disputing Companies. For each Disputing Company the changes are: Anglian -5.3%; Northumbrian -8.3%; South East -1.8%; Southern -1.9%; and Wessex -5.1%.

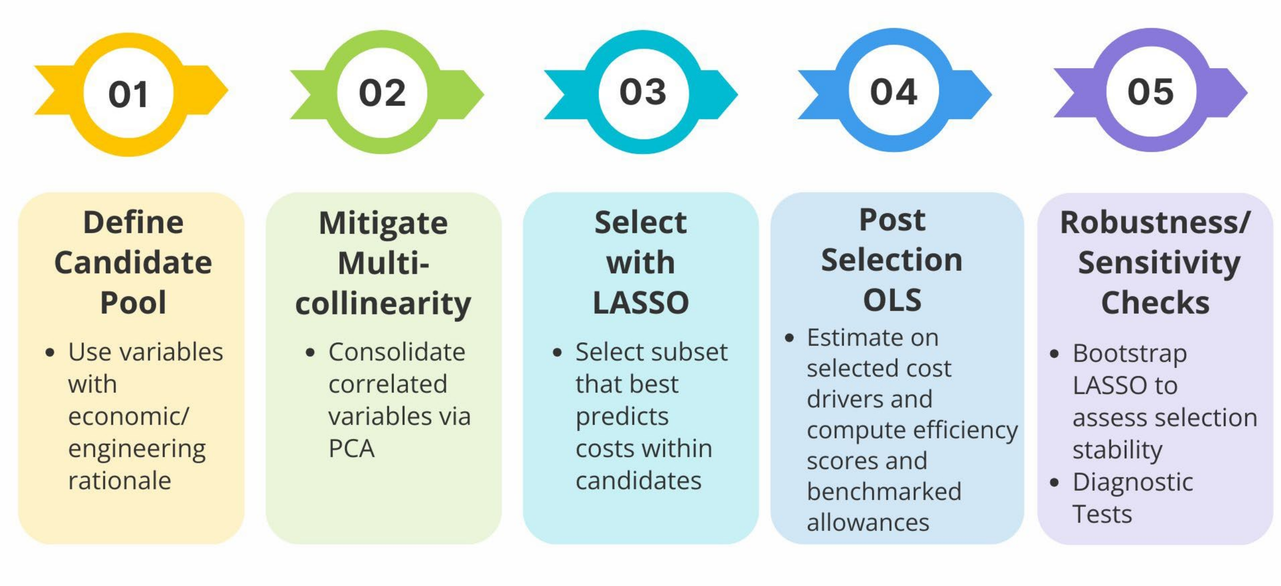
[6] The wholesale water and wastewater allowances described in this working paper do not equate to overall base cost allowances: they do not include retail or bioresources, nor have we applied any frontier shift.

2. Revised base cost modelling approach: updated methodology and key issues

Updated methodology

2.1 Following feedback on our PR24 PD, we have reviewed and updated our approach to base cost modelling.[7] This has resulted in an updated methodology.

Figure 2.1: Updated methodology



2.2 As shown in Figure 2.1 above, the steps in our updated methodology can be summarised as follows:

(a) define the candidate pool: variables with economic/engineering rationale;

(b) mitigate multicollinearity ex-ante: consolidate correlated variables via principal component analysis (**PCA**);

(c) select with Least Absolute Shrinkage and Selection Operator (**LASSO**): choose the subset that best predicts costs within the candidate pool;

(d) re-estimate on the selected set (post-selection ordinary least squares regression (**OLS**) to compute efficiency scores and benchmarked allowances); and then

(e) conduct robustness and further sensitivity checks:

[7] We continue to use the same data as at our PR24 PD. That is, we use yearly data for 12 financial years (2011/12-2023/24) to then predict allowances for AMP8.

(i) bootstrap LASSO to assess driver selection stability; and

(ii) diagnostic tests (heteroskedasticity, residual structure etc).

2.3 Later in this paper, we apply this updated methodology to wholesale water and wastewater base cost models, and present the new modelled efficiency scores, and cost allowances both before and after application of an UQ efficiency challenge for each of these updated models. We also provide the results of the sensitivity and robustness checks.

2.4 We describe below how we have sought to address the challenges of developing an interpretable benchmark modelling approach that is grounded in economic and engineering rationale, mitigates multicollinearity, and is robust to plausible changes to the underlying data and statistical testing. To the extent that a trade-off exists in simultaneously meeting these challenges, we consider that our updated modelling approach strikes the appropriate balance between developing a readily interpretable benchmarking model and one that accurately and robustly predicts costs.

2.5 We first consider key issues that we have addressed within our updated methodology.

Key issues we have considered

2.6 We recognise that a broad set of concerns were raised by stakeholders in addition to some specific technical points which we have addressed. Our review highlighted that, while our approach delivered simpler models with improved predictive accuracy, four issues persisted to varying degrees:

(a) **economic framework and cost driver selection:** difficulties translating selected variables into intuitive, economic and engineering-consistent narratives;

(b) **multicollinearity**: strong correlation between variables poses challenges for model selection, prediction for individual firms, and interpretation;

(c) **stability**: the implementation used in our PR24 PD led to stability issues where small data perturbations or the ordering of cost drivers could lead to meaningful shifts in selected drivers and company allowances; and

(d) **sensitivity analysis and statistical testing**: detailed sensitivity analysis and statistical tests were not presented at the PR24 PD stage.

2.7 To address these issues, we have developed a modified version of our previous econometric approach. In summary, consistent with our earlier methodology, we first estimate both bottom-up and top-down base cost models for wholesale water and wastewater. We then select whether to rely on the bottom-up or top-down model for the purpose of setting allowances. As part of this, we retain an updated LASSO-based variable selection as a transparent, data-driven tool, but re-anchor specifications in established economic rationale and undertake additional stability checks. Following these steps, we select a top-down model for each of wholesale water and wastewater.

2.8 The remainder of this section discusses changes we have made to address the points listed above.

Economic framework and cost driver selection

2.9 Responses to the PR24 PD raised difficulties translating selected variables into intuitive, economic and engineering-consistent narratives.

2.10 In developing our models, we have taken steps to ensure that the candidate variable set comprises only those variables supported by robust economic and engineering rationale. We continue to regard it as central to our approach in developing cost models that they reflect standard economic theory of costs. This involves including the following groups of cost drivers, and controlling for them:

(a) scale: a measure of quantity produced (eg number of properties, load, length of mains, etc);

(b) input prices: such as unit costs of raw water inputs, regional labour costs, energy prices; and

(c) engineering controls: in order to make different cost processes across firms more similar (eg population density and topological factors).

2.11 After controlling for these factors, the differences between predicted and actual costs are intended to reflect relative efficiencies – the key for benchmarking. For this to work well we need to control for the most influential variables (for which we use the LASSO technique) and, as far as possible, avoid statistical problems linked to the nature of the data (for which we use PCA – described below).

2.12 An important element of this approach is the inclusion of energy prices in the model. Not only does this have a strong economic justification in a cost model but we view it as essential in order to allow the model to capture the energy cost shock of the early 2020s. The failure of Ofwat's econometric model to account for this led to firms appearing more inefficient and as such resulted in a reduced UQ challenge. As in our PR24 PD, we consider that this was flawed and largely explains the difference in post-UQ efficiency allowances between our updated models and Ofwat's.

2.13 The inclusion of input prices, scale and engineering controls was also a feature of our PR24 PD modelling. We have since reflected on the most appropriate way of including these. We have revised the treatment of certain variables – such as energy and wages – by removing interactions with scale. While this type of interaction variable often forms part of the popular Translog cost function, we consider that the additional flexibility it can provide does not outweigh the complexity it introduces.[8] Further details of these specification changes are provided in section 3 and section 4 below.

2.14 In our PR24 PD, we showed that the inclusion of input prices was an important factor in capturing observed cost increases and led to recovery of stable efficiency scores over time.[9] In turn, this led to a more stringent UQ efficiency challenge and therefore lower cost allowances than permitted by Ofwat in its PR24 FD.

2.15 We consider that by developing our model framework in line with the standard economic theory of costs, ensuring that the cost drivers it uses have an economic and engineering rationale, and retaining the cost driver groupings used by Ofwat in its PR24 FD, we maximise the opportunity to give causal interpretation to the resulting model's output. However, we also emphasise that, while interpretability can provide a useful sense check, we consider that it is not the primary objective of benchmarking.[10] The primary objective is to deliver accurate cost predictions and to identify relative efficiency across companies. As such, we consider that the primary test is whether the model, using cost drivers grounded in economic and engineering rationale, provides accurate predictions useful for economic benchmarking. As noted in section 3 and section 4 below, we find that our updated models achieve this primary objective more effectively than Ofwat's models.

Multicollinearity

2.16 As in our PR24 PD: (i) only cost drivers that are of sufficiently high data quality are included in the set of variables considered by our new LASSO estimator; and (ii) in accordance with best practice for estimating cost functions, we identify a subset of

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[8] The CMA took a similar view on the use of Translog in its evaluation of Ofwat's PR14 Translog base cost model. CMA (2015) Bristol Water plc price determinations Final Report, paragraph 4.50(c).
[9] CMA (2025) Water PR24 References Provisional Determinations Volume 1: Introduction, Background, Approach and prioritisation, Base costs – Chapters 1–4 (**PR24 PD Volume 1**), p57, Figure 4.1 and Figure 4.2.
[10] Causal interpretations of coefficients may, all else equal, enhance confidence in a model's predictive ability. However, the models employed by Ofwat are predominantly statistical in nature and we consider that caution should be applied when attributing a causal interpretation to their models' coefficients. Moreover, all base cost models are, to differing degrees, affected by multicollinearity across cost driver categories. As we explain in more detail below, this can further complicate the interpretation of coefficients.

additional cost drivers that meet engineering and economic rationales. The inclusion of this set of variables aims to control for differences in production processes across companies.

2.17 A key challenge, however, arises where cost drivers are highly correlated. In such cases, both the interpretability of the model and the stability of variable selection may be adversely affected. We recognise that the LASSO technique can be sensitive to multicollinearity among input variables, which may in turn impact the robustness of the resulting cost allowances. To help address this, we systematically assess correlations within groups of candidate variables, including scale indicators and population density measures.

2.18 Where appropriate, we consider the application of PCA can help mitigate some of the problems linked to underlying multicollinearity. This approach enables us to consolidate highly correlated variables into composite indices and can help reduce instability in model results.

2.19 PCA is a statistical technique that transforms a set of potentially correlated variables into a smaller number of uncorrelated components, known as principal components. In the context of our modelling, we apply PCA to groups of cost drivers – such as scale or population density measures – that exhibit high degrees of correlation.

2.20 By consolidating these variables into components, PCA captures the majority of the variation that they contain into a composite index. Using the composite index in the econometric model reduces the risk that the cost allowances for companies with outlier values in any of the variables in the composite index are unduly affected.

2.21 This approach not only improves the stability and reliability of the model selection process but also supports clearer interpretation of the resulting coefficients. This is because each principal component reflects the underlying variation in the original data set. Where it can be applied, the use of PCA therefore helps to retain the economic and engineering rationale for including key drivers, while ensuring that the statistical properties of the model are robust.

2.22 It is however important to recognise that, in the presence of potential multicollinearity between sets of variables, limited weight should be placed on the interpretation of individual model coefficients. While the use of PCA helps to mitigate some of the issues associated with highly correlated variables, it does not fully eliminate the underlying dependencies within the data. As a result, the estimated coefficients may not always provide a clear or unique economic interpretation. For this reason, our modelling approach places greater emphasis on the overall predictive performance and robustness of the model, rather than on the interpretation of specific parameter estimates. We have not gone further in using statistical techniques such as PCA to remove more dependencies within the data. This is in order to retain clearer interpretability and simplicity.

Stability

2.23 Stakeholders raised concerns regarding aspects of the stability of our modelling approach in response to the PR24 PD and focused on the implementation of the LASSO estimator. Where technical implementation issues were identified, we have taken steps to address these.

2.24 We have introduced the following two key changes to address these concerns.

(a) **Algorithm refinement:** We have adopted Least Angle Regression (**LAR**) in place of coordinate descent for LASSO estimation.[11] We consider that this addresses the concern that the ordering of candidate variables in the code can influence results. Further details are provided in Appendix A.

(b) **Cross-validation procedure**: To reduce sensitivity to random variation and given the limited sample size, we now employ Leave-One-Out Cross-Validation (**LOOCV**). The associated trade-offs between this approach and the approach taken in our PR24 PD are discussed in Appendix A.[12]

2.25 Taken together, these changes – alongside our addressing of technical implementation issues – substantially improve the specific stability concerns of the modelling framework. We have also conducted additional robustness checks, as described below, to ensure that the resulting cost allowances are not unduly influenced by the distribution of the data or by model specification.

Sensitivity analysis and statistical testing

2.26 To assess the sensitivity and robustness of our updated base cost modelling, we have undertaken a series of diagnostic exercises.

2.27 First, we perform a repeated sampling analysis using a bootstrapping approach. This involves resampling the data many times with replacement to generate a distribution of efficiency scores and modelled allowances. The rationale for this method is to mimic the inherent uncertainty in the data by constructing alternative

[11] Efron, B. et al (2004), 'Least angle regression', *The Annals of Statistics*, 32(2).
[12] We have also completed robustness checks using alternative choices for the number of cross-validation folds.

samples. This allows us to observe the stability of the model's predictions under different data realisations.

2.28 It is important that the baseline model's predictions do not lie at the extremes of the resulting distribution. This would indicate that the model's results are unstable and unduly sensitive. Ideally the baseline modelled efficiency scores and cost allowances would be close to the middle of the set of their predictions.

2.29 Some responses to our PR24 PD pointed to tests in which an entire company had been removed from the sample. We do not think that this test is useful for checking the appropriateness of a benchmarking model.[13] Indeed, the special water regime may in fact prohibit an equivalent loss of company data from that available for benchmarking in the event of a merger.[14] [15]

2.30 Second, we subject our models to the suite of statistical tests routinely applied by Ofwat to its own cost models. This enables us to verify the statistical properties of our models and to ensure that they perform appropriately against established sector standards. The suite of tests includes the following:

(a) misspecification test (ie RESET) to check for omitted variable bias and functional form;

(b) test for heteroskedasticity (ie Breusch-Pagan) to ensure that the variance of residuals is stable across observations;

(c) test for multicollinearity (ie using Variance Inflation Factors (**VIF**)) to identify excessive correlation among explanatory variables; and

(d) residual analysis to check for normality and independence of errors.

2.31 While this suite of statistical tests provides a framework for assessing model validity, as also noted by Ofwat, it is not necessary for a model to pass every individual test in order to be considered robust and fit for purpose. This is because the tests are designed to highlight a range of potential issues – such as functional form, heteroskedasticity, or multicollinearity – that may arise in complex, real-world datasets.

2.32 In practice, some degree of departure from ideal statistical properties is common, particularly when working with real world data. The key consideration is whether

[13] A test cannot be selective in which parts of the data are held out of the sample. Any tests in our view should be systematic in its approach to holding out data. For example, in our implementation of cross-validation and bootstrap we take a systematic approach.
[14] Ofwat (2025) Base cost modelling response, paragraph 1.9.
[15] See Ofwat, Investigations – Mergers (accessed 15 December 2025), for a brief explanation of that regime.

any identified issues materially affect the reliability of the model's predictions or its suitability for regulatory benchmarking.

2.33 It is not possible to fully evaluate the predictive performance of a model ex-ante. However, where a model demonstrates strong predictive performance in the data available, is grounded in sound economic rationale, and passes the majority of diagnostic checks, it can be considered appropriate for use.

3. Wholesale water

3.1 This section presents the results of the updated base cost modelling for wholesale water, following the methodological refinements described above. Wholesale water covers 'water resources plus' (**WRP**) (broadly treatment operations) and 'treated water distribution' (**TWD**) (broadly network operations).

3.2 As in our PR24 PD we estimate these two bottom-up models and a single top-down model for wholesale water, then select the model with the best in-sample predictive performance. In this case (ie our updated modelling), we therefore select the top-down model. Further technical detail and supporting analysis are provided in Appendix B.

Cost drivers

3.3 As in our PR24 PD, our candidate set of cost drivers is grounded in economic and engineering rationale, comprising scale variables, controls for production process differences and network topology, and input prices linked to water treatment complexity, labour and wages. Below we discuss each category of cost driver and how we have included these in our modelling.

Scale

3.4 In line with the approach taken by Ofwat in its PR24 FD: (i) the number of properties served is included in the set of candidate variables in our bottom-up water resources plus model; and (ii) the length of potable mains is used in our TWD model.

3.5 Recognising that both scale variables used in the bottom-up models are highly correlated (around 96.7%: see Appendix B, Figure B1) and have roles in the different parts of the value chain of wholesale water, we include a composite measure of scale constructed using the first principal component from the PCA applied to both scale variables in our top-down model.[16] Using the weights that define the first principal component, its estimated coefficient can be transformed back into the original constituent scale variables.

Population density

3.6 Due to high levels of correlation between the three density cost drivers, in our updated modelling we use PCA to calculate a composite measure of population

[16] The first principal component is our composite measure of scale. It captures 98.3% of the variance of the logarithm of the number of connected properties and the logarithm of the length of potable mains.

density. The first principal component of PCA on the three density measures captures over 93.5% of the variance of the logarithm of the population density variables.[17] We include it in the modelling in its level and square. The square term allows for a 'U-shaped' relationship between population density and wholesale water costs.[18]

Network topology

3.7 To control for differences in cost due to network topology, we include average pumping head (**APH**) in our updated bottom-up TWD model and our top-down model. Since our PR24 PD, we have not seen sufficient evidence to change our view on the data quality of the APH cost driver, so include this in our updated bottom-up TWD model and our top-down wholesale model. We also include booster pumping stations per length of mains in our updated bottom-up TWD model and our top-down wholesale model. As in our PR24 PD, we continue to allow the LASSO technique to select one, both or neither of these cost drivers in these models. In contrast, Ofwat only permits one of the network topology cost drivers in each of its TWD models and top-down wholesale water cost models.

Water treatment complexity

3.8 Ofwat used two variables to measure water treatment complexity in its PR24 FD:[19]

(a) **Weighted average treatment complexity measure** (**WAC**), where each level of complexity, as defined in Ofwat's annual reporting tables (ie levels 0 to 6), is weighted by the proportion of water treated at that level; and

(b) **Proportion of water treated at complexity levels 3 to 6.** 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.

3.9 These water treatment complexity cost drivers differ conceptually from those that are used in PCA to measure the scale and population density. The variables that measure scale and population density used in our PCA measure different aspects of their respective cost driver category (ie number of properties vs length of mains)

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[17] The first principal component is our composite measure of population density. It captures 93.5% of the variance of logarithm of properties per length of mains, 96.4% of the logarithm of the Middle-layer Super Output Area (**MSOA**) weighted average density, and 95.9% of the logarithm of the Local Authority District (**LAD**) from MSOA weighted averaged density.

[18] Ofwat's PR24 FD notes the potential existence of opposing forces that can lead to increased costs when serving populations that are particularly sparse or very dense. If so, the relationship between cost and population density may be 'U-shaped'. If the squared term on population density has a positive coefficient, then the shape of this relationship in the estimated model is U-shaped. Ofwat (2025) PR24 Final Determinations: Expenditure Allowances – Base cost modelling appendix, p25.

[19] Ofwat (2025) Response to common issues on expenditure allowances, paragraph 2.76.

and typically draw on different underlying data. In contrast, both water treatment complexity cost drivers are calculated from the same data and only differ by the weighting assigned to percentage of water treated in each band.[20] Therefore, even though water treatment complexity variables are highly correlated (more than 90%), we do not consider that PCA would add any insight over well-understood differences in the way these variables are calculated. As such, we consider that only one of these cost drivers is needed to capture costs associated with water treatment complexity.

3.10 We consider that unit cost proxies should be included as logs in a cost model with log of total cost as a dependent variable. Since in this instance they are nearly mathematically identical and use the same data, we consider that there is a strong case to avoid the multicollinearity that including both in the model in their logarithm would create and instead to include only one. Given its prior use (in Ofwat's PR24 FD model, our PR24 PD, and at PR19), and that it is already included in its log, in our judgement we consider it appropriate to use the logarithm of WAC. [21]

Input prices

3.11 As in our PR24 PD, regional hourly construction wages (ONS ASHE) are included as a measure of the unit cost of labour. Further, and in line with the commonly used Cobb-Douglas cost function, we include its logarithm in our set of cost drivers for our updated model.[22] Likewise, the logarithm of the Department for Energy Security and Net Zero (**DESNZ**) energy price index captures typical industrial energy prices faced by water companies.

3.12 As outlined in section 2 (paragraph 2.13) above, for input prices, we diverge from the approach taken in our PR24 PD and do not interact it with the logarithm of scale.

Summary

3.13 Table 3.1 below summarises the resulting cost drivers included in bottom-up (WRP and TWD) and top-down wholesale water models. This structure ensures the model captures key cost drivers while minimising redundancy and multicollinearity.

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[20] The weighted average treatment $WAC = \sum_{b=0}^{6}(b+1) \times \%\, water\ treated\ in\ band\ b$. The percentage water treated in bands 3 to 6 is calculated as: $\%\, treated\ in\ bands\ 3\ to\ 6 = \sum_{b=0}^{6} \mathbf{1}[3 \leq b \leq 6] \times \%\, water\ treated\ in\ band\ b$.
[21] Ofwat (2025) Response to common issues on expenditure allowances, paragraph 2.80.
[22] Charles W. Cobb and Paul H. Douglas (1928), 'A theory of production', *The American Economic Review*, 18(1):139–165.

Table 3.1: Cost drivers included in our updated approach: wholesale water models

	Bottom-up models		*Top-down model*
Cost drivers	WRP	TWD	WW
Number of Properties (log)	✓		
Length of Mains (log)		✓	
(log) Scale combined			✓
(log) Density combined	✓	✓	✓
Squared (log) density combined	✓	✓	✓
Average Pumping Head TWD (log)		✓	✓
Booster Stations per length of mains (log)		✓	✓
Weighted Average Complexity (WAC) (log)	✓		✓
Hourly regional construction wages (log)	✓	✓	✓
DESNZ energy price index (log)	✓	✓	✓

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.[23]

Model selection

3.14 To choose the level of aggregation we estimate the fit of the updated (i) bottom-up WRP and TWD models and (ii) top-down model.[24] Both deliver a strong fit overall and a materially improved fit compared to Ofwat's FD models: an 11% better root mean squared error (**RMSE**).[25] [26]

3.15 While the RMSE is similar for the bottom-up models (33.1) and top-down model (33.0), the top-down model performs slightly better. Since the top-down model resulted in a lower RMSE and our primary consideration is predictive power we have used this model as the basis for our final allowances.[27] [28] We discuss below that we consider that our top-down model performs sufficiently well in statistical tests.

Model results

3.16 In this subsection, we discuss the interpretation of the top-down wholesale water model, its efficiency score and resulting benchmarked cost allowances.

[23] See PR24 PD Volume 1, pp51–52, paragraph 4.51(a) –(b).
[24] Wholesale water allowances under the bottom-up are the sum of allowances in the WRP and TWD models.
[25] The CMA top-down RMSE (33.0) and bottom-up RMSE (33.1) both perform 11% better than the RMSE of Ofwat's triangulated model (37.2) for wholesale water. PR24 PD Volume 1, pp50–51, paragraph 4.57.
[26] Note the RMSE is measuring in-sample performance. As such it is expected that both our and Ofwat's model should perform well as the fit is part of the model selection procedure (via cross-validation in our model and through R-Squared in Ofwat's approach).
[27] The CMA top-down RMSE performs (RMSE 33.0) 0.4% better than the CMA bottom-up model with RMSE 33.1.
[28] An additional advantage of the top-down model is that it has coefficients on wages of the correct sign and of plausible magnitude.

Coefficients

3.17 Table 3.2 shows the coefficients on the cost drivers in the top-down wholesale water model. However, as explained in paragraph 2.22, estimated coefficients may not always provide a clear or unique economic interpretation and are also not the goal of the modelling. Given that multicollinearity is relatively low, as measured by the maximum VIF score in Table 3.5, we consider that we can interpret the model coefficients. The results show that for this model coefficients are either of intuitively expected signs or as (in the case of scale) are of the expected sign when the PCA weighting is taken into account.

3.18 For example, we see that the squared term on density is positive. Meanwhile, the coefficient of scale appears to be of a negative sign. However, this is due to the weighting applied by the PCA to the coefficients, which can often be negative (see section A2). When we consider the underlying coefficients of the component parts after removing the weightings, we find that they are both of positive signs and sum to just above 1, indicating some economies of scale. In addition, we note both the coefficients on unit energy and labour costs have the expected sign and are both of plausible magnitude.

Table 3.2: Coefficients in the CMA's top-down wholesale water model

Cost Drivers	Top-down wholesale water model (WW)		
	Coefficient	Standard Error	Significance
Intercept	3.804	0.528	***
(log) Scale combined	-0.683	0.009	***
(log) Density combined	0.050	0.010	***
Squared (log) density combined	0.026	0.003	***
Weighted average complexity (log)	0.450	0.080	***
Average pumping head TWD (log)	0.096	0.045	**
Booster pumping stations per length of mains (log)	0.318	0.058	***
Energy index (log)	0.116	0.054	**
Construction wages (log)	0.303	0.189	

*Note: *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level*
Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

Efficiency scores

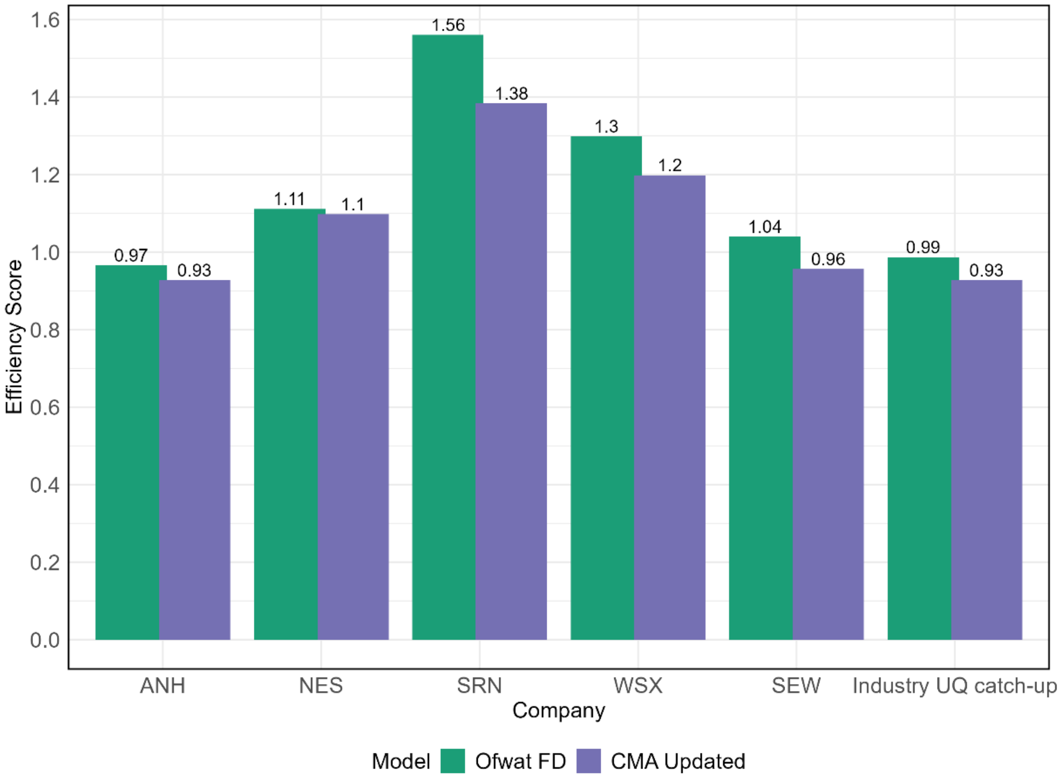
3.19 Efficiency scores are calculated as the ratio between actual costs and modelled costs in the final five years of the sample (ie financial years 2019/20 to 2023/24).[29] Therefore, efficient firms have efficiency score below 1. For example, an efficiency score of 0.8 would indicate that a company spent 20% less than the model would

[29] The efficiency score is the sum of observed expenditure over the last 5 years of the sample divided by the corresponding sum of model predicted costs.

predict and therefore was efficient. The UQ catch-up challenge is calculated as the 25th percentile of the efficiency scores.

3.20 Figure 3.1 below shows the wholesale water efficiency scores for each of the Disputing Companies and the industry UQ catch-up challenge in our model. In our revised model the UQ challenge for the industry is more stretching (at 7%) than in Ofwat's PR24 FD (at 1%) and in our PR24 PD (at 6%). [30]

Figure 3.1: Efficiency scores in the wholesale water model



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

3.21 We consider that the more stretching catch-up challenge produced by our model compared to Ofwat's model is largely due to the inclusion in our model of energy and other input prices. Specifically, through this mechanism, our model can account for the effect of the sustained shock to energy and other input prices from 2020/21 onwards that contributed to water companies overspending their PR19 allowances.

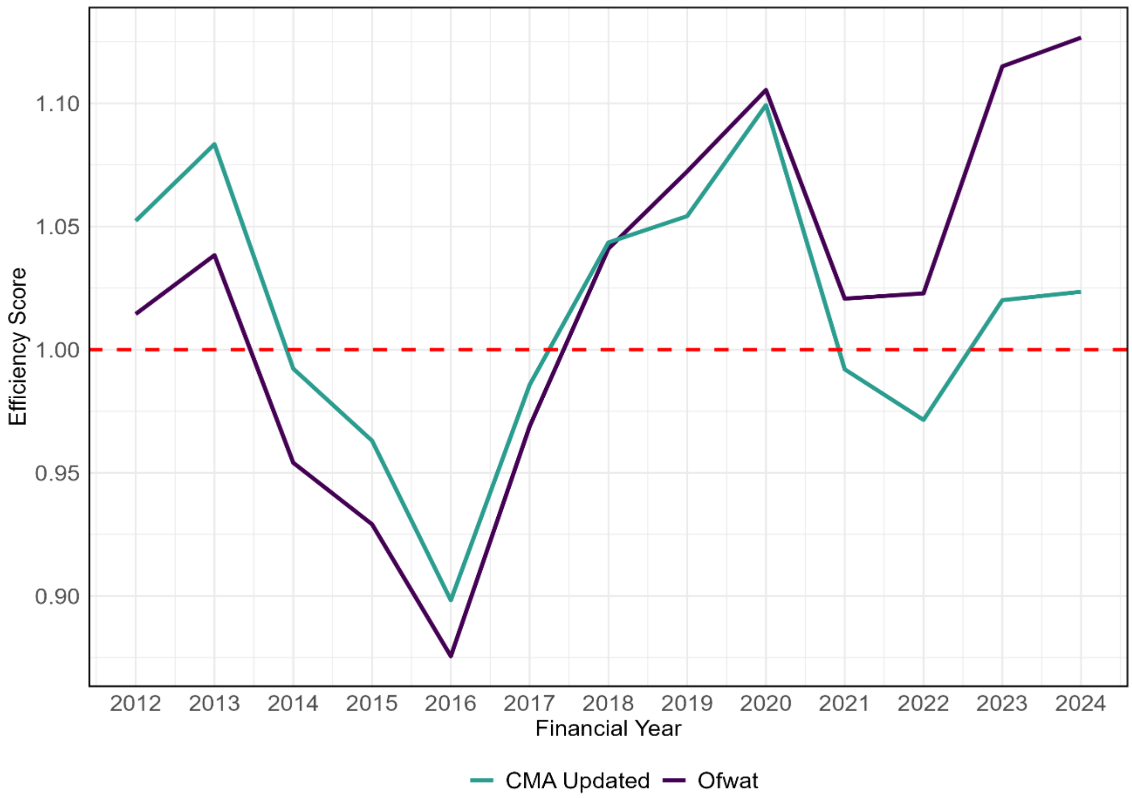
3.22 In contrast, because energy and other input prices are not directly included in Ofwat's econometric model it is likely that their effect on expenditure over AMP7 is

[30] PR24 PD Volume 1, p53, paragraph 4.57.

not as well captured in its modelled predictions.[31] Instead, we consider it likely that Ofwat's models attribute the increased expenditure across the sector to inefficiency in those years. The result is a less stretching (reduced) catch-up challenge.[32]

3.23 Figure 3.2 below shows the average efficiency score in both Ofwat's and the CMA's models from 2011/12 to 2023/24. Consistent with the explanation above, both the CMA and Ofwat models follow a similar path over time up until the early 2020s. From 2021 onwards, the distribution of efficiency scores increases in Ofwat's model, its average efficiency score increases to over 1.10, and the 25th percentile efficiency score is 0.99 (see the green bar for Industry catch-up in Figure 3.1).

Figure 3.2: Average modelled efficiency scores over time (financial years ending in March) – wholesale water



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

[31] See Figure B1 in Appendix B. It shows that the DESNZ energy price index included our model and used by Ofwat outside of econometric model to provide a cost uplift for energy over AMP8 is uncorrelated with all the other cost drivers that Ofwat included in its wholesale water models.
[32] In Ofwat's PR24 FD models, given that Figure B1 shows that wages and energy are largely uncorrelated with their other included regressors, an industry-wide energy cost shock in the last 5 years of the sample period may result in the model assigning a positive error to those years. Furthermore, a balancing negative error may result in the earlier years in the sample period. Absent included regressors that are correlated with the cost shock, the model is likely to have a worse fit in all years and not just those impacted by the shock. This may also explain why Ofwat's modelling approach leads to a higher RMSE than our updated approach.

3.24 In contrast, because our modelling directly incorporates input prices, the average efficiency scores remain stable around 1 from 2020/21 until 2023/24. Further, the 25th percentile efficiency score is 0.93, which gives a UQ challenge (of 7%) that is comparable to those set at PR14 (of 7%) and PR19 (of 5%).[33] As such, we do not currently view the UQ challenge produced by our model to be necessarily overly stringent.

Cost allowances

3.25 Table 3.3 below shows the resulting costs allowances under our updated approach. For all Disputing Companies other than Anglian our results in wholesale water leads to lower allowances compared to our PR24 PD. Compared to Ofwat's PR24 FD, all Disputing Companies except Southern receive reduced allowances.

Table 3.3: Wholesale water cost allowances comparison – after UQ catch-up challenge applied (£m, 2022-23 prices)

Company	Ofwat PR24 FD (including RPEs) (£m)	CMA PR24 PD (£m)	CMA Updated (£m)	CMA Updated vs Ofwat PR24 FD (including RPEs)	CMA Updated vs CMA PR24 PD
Anglian	1,837	1,722	1,734	-5.6%	0.7%
Northumbrian	1,484	1,403	1,366	-7.9%	-2.6%
South East	840	867	825	-1.8%	-4.9%
Southern	858	888	876	2.1%	-1.4%
Wessex	530	634	529	-0.2%	-16.5%
All Disputing Companies	5,549	5,515	5,330	-3.9%	-3.4%
Industry	22,906	21,616	21,246	-7.2%	-1.7%

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

3.26 The resulting allowances for (i) the five Disputing Companies and (ii) (for the purposes of benchmarking) the industry, are lower than Ofwat's PR24 FD. As discussed in paragraphs 3.19-3.24 this is largely due to the increased UQ challenge.

3.27 Table 3.4 below compares Ofwat and CMA wholesale water cost allowances before and after the efficiency challenge, including RPEs. Before applying efficiency adjustments, our allowances for the Disputing Companies are around 2.2% higher than Ofwat's. This suggests that our modelling approach awards slightly higher pre-efficiency allowances to these firms. However, at the industry level, our allowances are 1.3% lower than Ofwat's.

3.28 Overall, pre-efficiency differences between Ofwat and our updated modelled allowances exhibit only a modest divergence in baseline cost allowances. The more substantial impact arises post-efficiency: the model applies a substantial UQ

[33] PR24 PD Volume 1, p56, Table 4.3: UQ challenge was 6.5% and 4.6% at PR14 and PR19 respectively.

catch-up challenge, leaving Disputing Companies cost allowances around 3.9% lower than their pre-efficiency position. This pattern is consistent with the analysis presented above, highlighting that efficiency scores – and by extension input prices – are likely to be the primary drivers of cost differentials rather than the underlying cost models themselves.

Table 3.4: Wholesale water cost allowances comparison – before and after UQ is applied (£m, 2022-23 prices)

	Allowances pre-efficiency challenge including RPEs (£m)			Allowances post-efficiency challenge including RPEs (£m)		
	Ofwat PR24 PD	CMA Updated	Difference: CMA Updated – Ofwat PR24 FD (%)	Ofwat PR24 PD	CMA Updated	Difference: CMA Updated – Ofwat PR24 FD (%)
Anglian	1,861	1,870	0.5%	1,837	1,734	-5.6%
Northumbrian	1,503	1,473	-2.0%	1,484	1,366	-7.9%
South East	851	889	4.5%	840	825	-1.8%
Southern	869	945	8.7%	858	876	2.1%
Wessex	537	571	6.2%	530	529	-0.2%
All Disputing Companies	5,621	5,748	2.2%	5,549	5330	-3.9%
Industry	23,207	22,912	-1.3%	22,906	21,246	-7.2%

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

Sensitivity analysis

Sensitivity tests

3.29 Table 3.5 below shows the results of Ofwat's suite of statistical tests when applied to our wholesale water model. As noted above, and by Ofwat, it is not necessary for a model to pass every individual test in order to be considered robust and fit for purpose.[34]

Table 3.5: Statistical test results of the CMA's wholesale water model

Statistical test	P-value (rounded to 2 decimal places)	Interpretation
RESET	0.08	No evidence of model misspecification
Max VIF	2.24	No serious multicollinearity (VIF > 10 would suggest severe multicollinearity).
Shapiro-Wilks	0.05	We reject the hypothesis that residuals are normally distributed
Breusch-Pagan	0.00	Heteroskedasticity present
R-Squared	0.97	Model explains ~97% of variance
Adjusted R-Squared	0.97	Adjusted R^2 confirms strong explanatory power after accounting for the number of predictors.

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

[34] Ofwat (2024) PR24 final determinations: Expenditure allowances - base cost modelling decision appendix, p16.

3.30 The test results indicate that the model passes model specification and multicollinearity checks, supporting the robustness of the modelling framework. Tests for heteroskedasticity and normality are not passed. However, we do not consider these issues sufficient to invalidate the predictions of the model.

3.31 The normality assumption primarily affects the validity of standard errors and the related inference. Since our analysis does not rely on hypothesis testing or confidence intervals, this violation is not critical. Similarly, heteroskedasticity—where error variances differ across observations—is common in regulatory models, often because smaller companies exhibit differing error variances compared to larger ones. While this affects standard errors, it does not bias coefficient estimates, so we consider that model remains appropriate for our purpose.

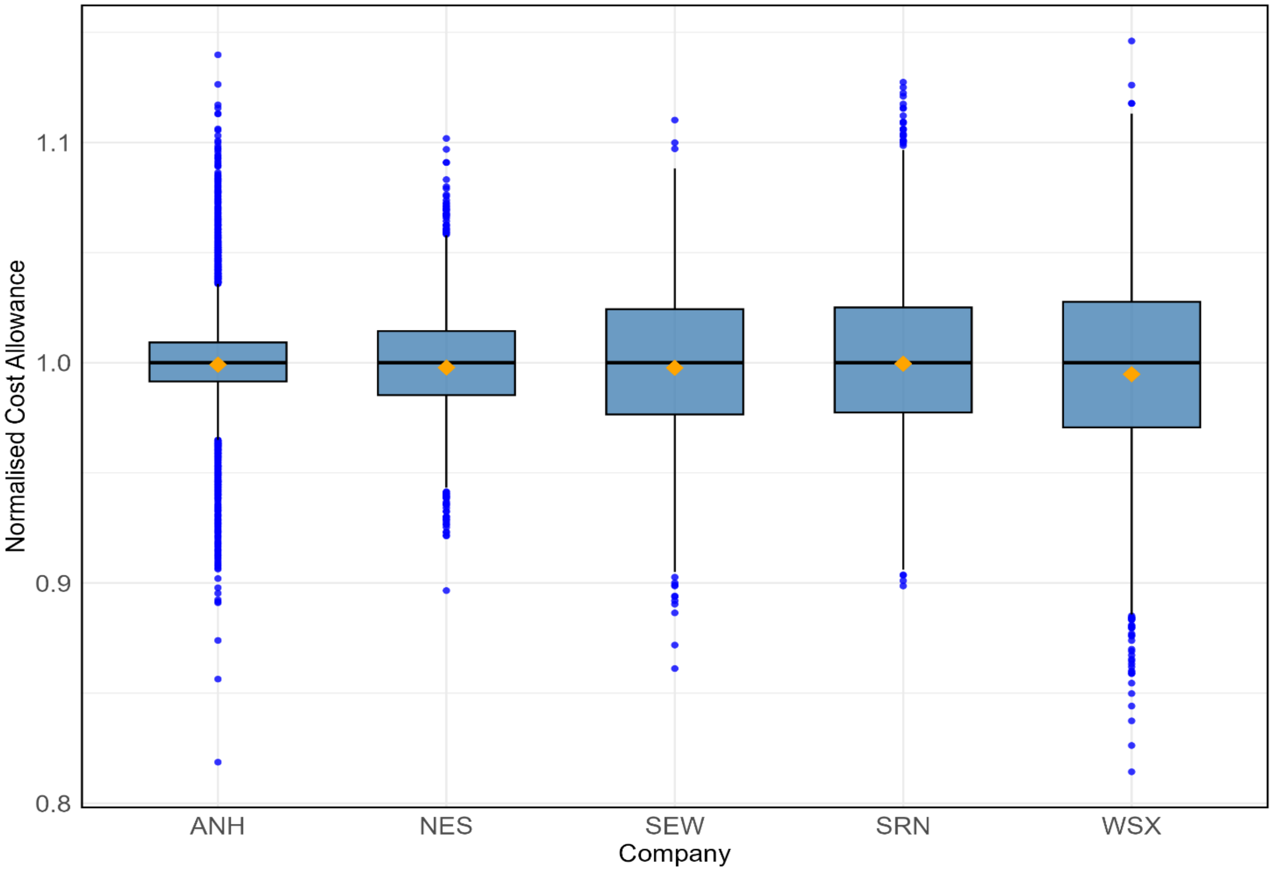
Bootstrap LASSO

3.32 As discussed in section 2, to evaluate the stability of the LASSO procedure, we use a 'bootstrap' technique on our modelled results. See Appendix A, section A3 for details.

3.33 Figure 3.3 below plots post-efficiency cost allowances for the Disputing Companies, normalised by the median cost allowance of that company. The lighter blue boxes represent the interquartile range of results across repeated runs of the model, the black line in the box represents the median, the dark blue crosses represent outliers in the data, and the orange diamond represents our modelled cost allowance after an UQ catch-up efficiency challenge is applied.

3.34 The results show that the baseline (orange diamond) is in the middle, near the median of the distribution. In addition, results show that the interquartile range is narrow (within ±5%). This indicates robust results for cost allowances of all the Disputing Companies, reinforcing the finding that the model is stable under perturbations in the data.

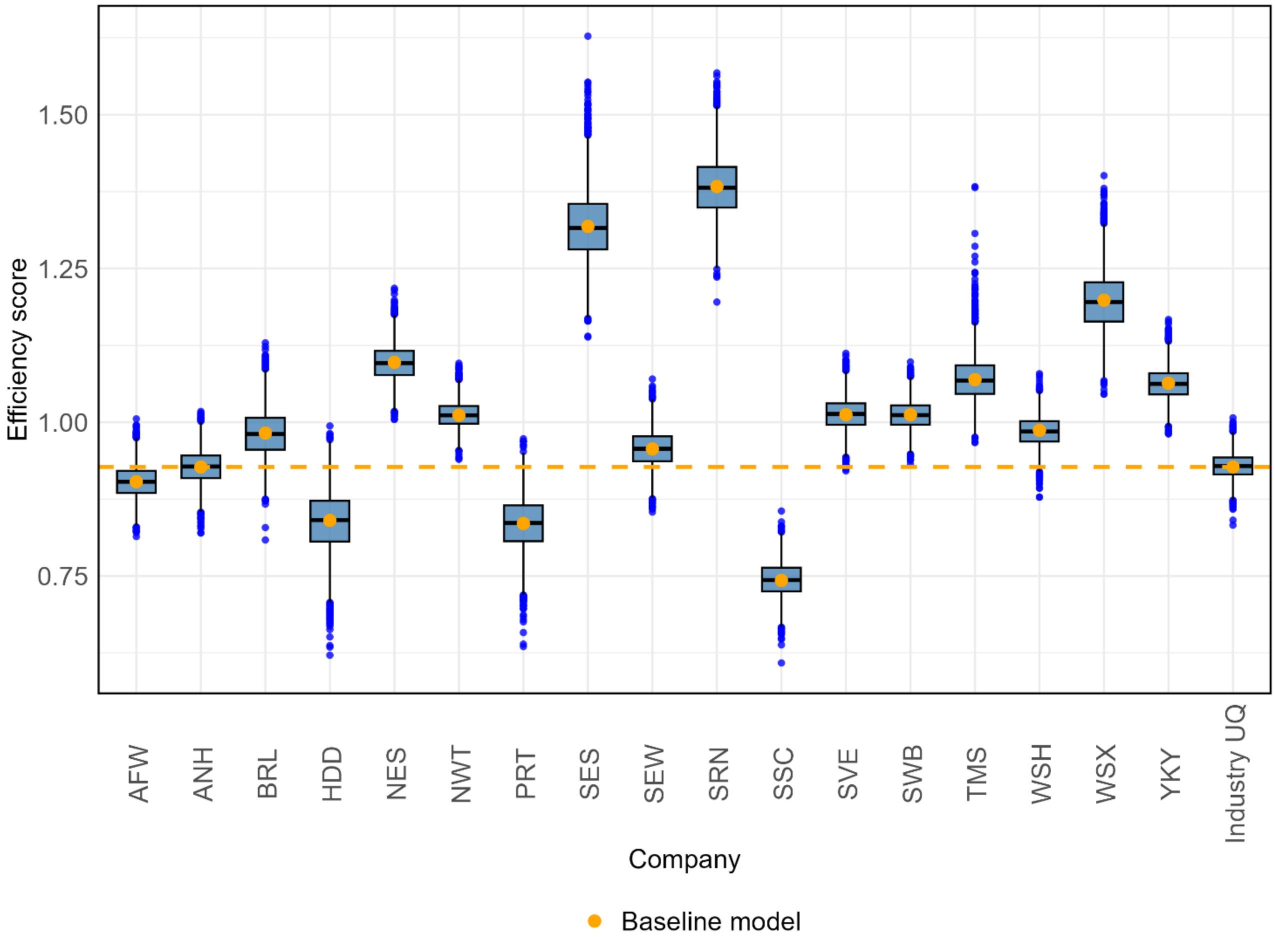
Figure 3.3: Range of Disputing Company cost allowance after UQ applied under the bootstrap LASSO – wholesale water



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

3.35 We see similarly stable results for efficiency score distributions across the industry in Figure 3.4 below. The additional dotted orange line represents the industry wholesale water UQ challenge (at 0.93). The results highlight stability in the model, with tight distribution boxes, and the baseline (orange dot) in the middle near the median for all companies.

Figure 3.4: Wholesale water company and industry-wide efficiency score distribution from bootstrap LASSO



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

3.36 Table 3.6 shows the percentage of bootstrap runs in which each cost driver is selected. The figure shows that the model selection is very stable with our chosen cost drivers each selected in at well above 50% of runs.

Table 3.6: Percentage of bootstrap runs in which costs drivers are selected – wholesale water

Cost Driver	% of runs selected
(log) Scale combined	100%
(log) Density combined	100%
Squared (log) density combined	100%
Weighted average complexity (log)	100%
Average pumping head TWD (log)	95%
Booster pumping stations per length of mains (log)	100%
Energy index (log)	99%
Construction wages (log)	92%

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

4. Wastewater

4.1 This section presents the results of the updated base cost modelling for wastewater, following the methodological refinements described above. Wastewater covers ‘sewage treatment’ and ‘sewage collection’. As in our PR24 PD, we estimate these two bottom-up models and a single top-down model for wastewater, then select the model with the best in-sample predictive performance. In this case, that is the top-down model. Further technical detail and supporting analysis are provided in Appendix C.

Cost drivers

4.2 As at PR24 PD, our candidate set of wastewater cost drivers reflects economic and engineering principles, capturing scale, density, network topology, treatment complexity, economies of scale at sewage treatment works, and input prices. Below we outline each category and how these drivers are incorporated into our modelling approach.

Scale

4.3 In line with Ofwat’s PR24 FD approach, sewer length is included as a scale variable in the bottom-up sewage collection (**SWC**) model, while load is included in the sewage treatment (**SWT**) model.

4.4 Recognising that sewer length and load are highly correlated (approximately 98%, see Figure C1) and represent different stages of the wastewater value chain, we construct a composite scale measure using the first principal component from PCA applied to these variables for the top-down wastewater (**WWW**) model. This composite measure captures the underlying scale effect while mitigating potential multicollinearity that might arise had we included both scale variables.[35]

Population density

4.5 As with wholesale water, population density influences wastewater costs through network complexity and service intensity. We use PCA to combine multiple density indicators into a single composite measure and include it in the candidate set of cost drivers for the SWC model.[36]

[35] The first principal component is our composite measure of scale. It captures 99% of the variance of both the logarithm of sewer length and logarithm of load.
[36] Ofwat only included density in its SWC model. Ofwat (2025) PR24 Final Determinations: Expenditure Allowances – Base cost modelling appendix, Section 4.2.5.

Network topology

4.6 To reflect cost differences arising from network configuration, pumping capacity per sewer length is included in the SWC and WWW models. Urban rainfall per sewer length is also incorporated to capture additional load and operational challenges in sewer systems. Both candidate variables are considered in logarithmic form, and we allow LASSO to select one or both, consistent with our PR24 PD approach.

Treatment complexity

4.7 Ofwat's PR24 FD approach for wastewater treatment complexity uses a measure of ammonia consent levels. Like Ofwat, we include the cost driver, 'load treated with ammonia consent with less than 3mg/l' in the SWT and WWW models to reflect higher treatment costs incurred in meeting more stringent discharge standards.

Economies of scale at sewage treatment plants

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

4.9 As in our PR24 PD, we include the following two candidate variables to capture economies of scale at STWs.

(a) A weighted average treatment works size (**WATS**) variable. This variable captures the weighted average sewage treatment works size for each company. It allows for a continuous relationship with sewage treatment costs.

(b) The percentage of load treated in sewage treatment works serving less than 2,000 people (bands 1 to 3). Ofwat states that this captures step-like changes in sewage treatment costs.

Input prices

4.10 As in our PR24 PD, regional hourly construction wages (ONS ASHE) are included as a measure of the unit cost of labour. Further, and in line with the commonly used Cobb-Douglas cost function, we include its logarithm in our set of cost drivers for our updated model.[37] Likewise, the logarithm of the DESNZ energy price index captures typical industrial energy prices faced by water companies.

4.11 As outlined in section 2 (paragraph 2.13) above, for input prices, we diverge from the approach taken in our PR24 PD and do not interact it with the logarithm of scale.

Summary

4.12 Table 4.1 below summarises the resulting cost drivers included in the bottom-up SWC and SWT models and the top-down WWW model. This structure ensures the model captures key cost drivers while minimising redundancy and multicollinearity.

Table 4.1: Cost drivers included in our updated approach – wastewater models

	Bottom-up models		*Top-down model*
Cost drivers	Sewage collection (SWC)	Sewage treatment (SWT)	Wastewater (WWW)
Sewer length (log)	✓		
Load (log)		✓	
Scale combined (log)			✓
Density combined (log)	✓		
Pumping capacity per sewer length (log)	✓		✓
Load treated with ammonia consent <3mg/l		✓	✓
Weighted average treatment size (log)		✓	✓
Load treated in size bands 1 to 3 (%)		✓	✓
Urban rainfall per sewer length (log)	✓		✓
Hourly regional construction wages (log)	✓	✓	✓
DESNZ energy price index (log)	✓	✓	✓

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

Model selection

4.13 We estimate the fit of the updated bottom-up SWT and SWC and top-down models. The updated top-down model delivers a good and materially improved fit compared to Ofwat's FD models (a 9% better RMSE). However, the updated bottom-up models have the same RMSE as Ofwat's.[38]

4.14 Since, the top-down model resulted in a lower RMSE and our primary consideration is predictive power, we have continued (as in our PR24 PD) to select the top-down model as a basis for our base cost allowances.

[37] Charles W. Cobb and Paul H. Douglas (1928), 'A theory of production', *The American Economic Review*, 18(1):139–165.
[38] Top-down RMSE for CMA's wastewater model is 35.7, performing 9% better than RMSEs of the CMA bottom-up and Ofwat's 'triangulated' wastewater models, both of which are 39.3.

Model results

4.15 In this subsection, we discuss the interpretation of the top-down wastewater model, its efficiency score and the resulting benchmarked cost allowances.

Coefficients

4.16 Table 4.2 below presents the estimated coefficients for the cost drivers in the top-down wastewater model. As noted previously, coefficients are not the primary goal of the modelling exercise and may not always lend themselves to unique economic interpretation, given multicollinearity (as measured by VIF scores). Overall, the signs and magnitudes of the coefficients are broadly consistent with expectations. However, due to the higher maximum VIF score in our model (of around 5, shown in Table 4.5) we do not consider that there is a clear interpretation of some cost drivers in our model where they are highly correlated across cost driver groups.

4.17 We note that in our top-down model regional hourly wages is not selected by the LASSO. This is likely caused by the correlation between it and other variables. For the reasons set out in paragraph 2.13 above, we do not, however, consider that this invalidates the model, nor does it reduce its predictive power for the purpose of benchmarking.

Table 4.2: Coefficients in the CMA's top-down wastewater model

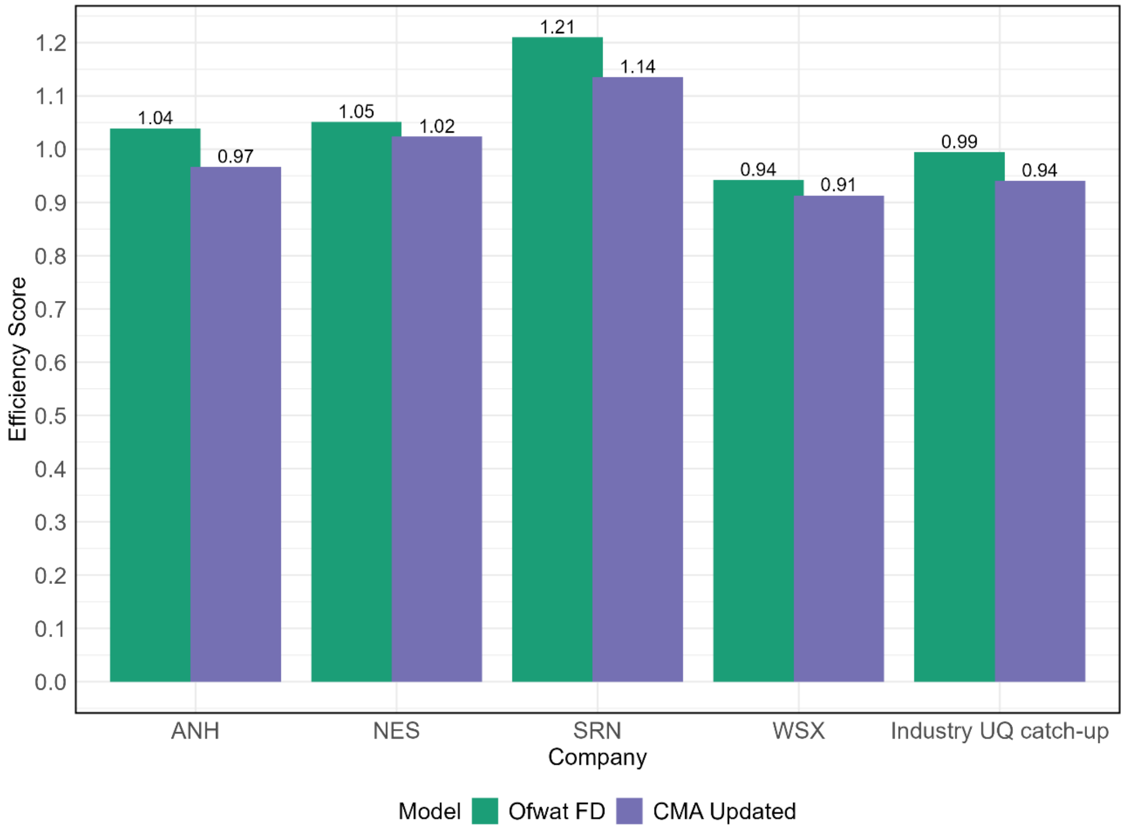
Cost drivers	Top down wastewater model		
	Estimate	Standard error	Significance
Intercept	5.013	0.368	***
Scale combined (log)	-0.307	0.016	***
Pumping capacity per sewer length (log)	0.467	0.05	***
Weighted average treatment size (log)	-0.018	0.025	
Load treated in size bands 1 to 3 (%)	0.004	0.007	
Load treated with ammonia consent <3mg/l	0.006	0.000	***
Urban rainfall per sewer length (log)	0.115	0.028	***
Energy index (log)	0.167	0.043	***

*Note: *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level*
Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

Efficiency scores

4.18 Figure 4.1 below shows the efficiency scores for each Disputing Company and the industry UQ catch-up challenge in our wastewater model. Compared to Ofwat's PR24 FD, our efficiency scores are generally lower across companies, resulting in a more stretching (increased) UQ challenge. The UQ challenge in our updated model is 6%, compared to 1% in Ofwat's PR24 FD, and 4% in our PR24 PD.

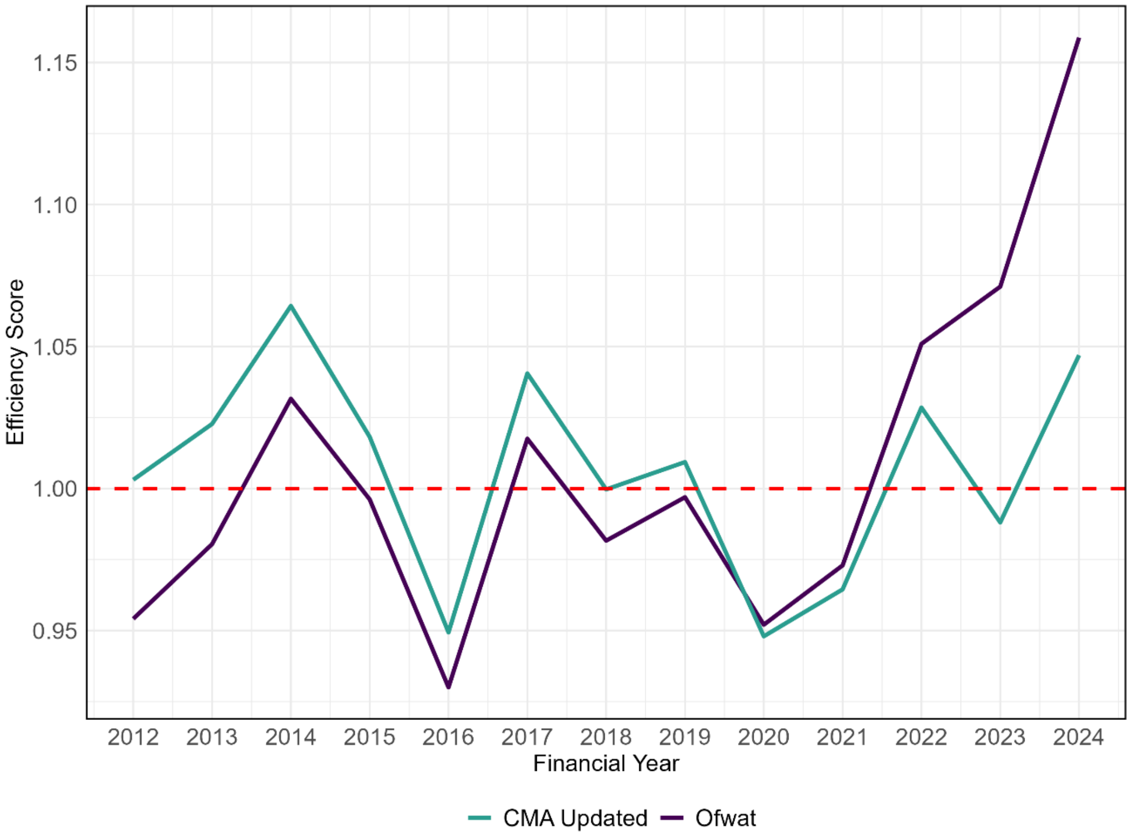
Figure 4.1: Efficiency scores by Disputing Company and industry UQ – wastewater



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

4.19 Figure 4.2 below illustrates the evolution of average efficiency scores from 2011/12 to 2023/24. Both models track closely until the early 2020s, a period of relative stability in input prices. From 2021 onwards, however, Ofwat's average efficiency score rises sharply above 1.10, while our model remains nearer 1.00.

Figure 4.2: Average modelled efficiency scores over time (financial years ending in March) - wastewater



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

4.20 As explained in section 3 (paragraphs 3.19 to 3.24) above, our current view is that this difference is largely explained by the inclusion of energy and input prices in our econometric modelling. Accordingly, we currently view the UQ challenge produced by our model as not necessarily over stringent and broadly aligned with previous price controls.

Cost allowances

4.21 Table 4.3 below shows the resulting cost allowances under our updated approach for wastewater. For all Disputing Companies, our updated model produces lower allowances compared to Ofwat's PR24 FD. Compared to our PR24 PD all receive lower allowances except for Wessex.

Table 4.3: Wastewater cost allowances comparison – after UQ catch-up challenge applied, wastewater (£m, 2022-23 prices)

Company	Ofwat PR24 FD (including RPEs (£m)	CMA PR24 PD (£m)	CMA Updated (£m)	CMA Updated vs Ofwat PR24 FD	CMA Updated vs CMA PR24 PD
Anglian	1,970	1,933	1,870	-5.1%	-3.3%
Northumbrian	867	828	790	-8.9%	-4.6%
Southern	1,921	1,926	1,849	-3.7%	-4.0%
Wessex	973	886	898	-7.7%	1.4%
All Disputing Companies	5,731	5,572	5,407	-5.6%	-3.0%
Industry	18,636	17,913	17,333	-7.0%	-3.2%

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

4.22 Although resulting allowances are lower than Ofwat's PR24 FD, as in wholesale water (discussed in paragraph 3.19 above), this is largely due to the increased UQ catch-up challenge applied in our updated model.

4.23 Table 4.4 below compares Ofwat and CMA wastewater cost allowances before and after the efficiency challenge, including RPEs. Before applying efficiency adjustments, CMA allowances for the Disputing Companies are broadly similar to Ofwat's PR24 FD; differences range from +1.8% for Southern to -3.7% for Northumbrian. At the industry level, CMA allowances are 1.7% lower than Ofwat's before catch-up challenges are applied. This suggests that there are only modest divergences in baseline cost allowances.

4.24 There is a more significant impact after catch-up challenges: our updated model applies a more stretching catch-up challenge, reducing Disputing Companies' cost allowances by around 6% compared to Ofwat's PR24 FD. This pattern is consistent with the analysis presented in the discussion of efficiency scores (paragraph 3.21 above), highlighting that efficiency scores—and by extension the inclusion of industrial energy prices—are likely to be the primary drivers of cost differentials rather than the underlying cost models themselves.

Table 4.4: Wastewater cost allowances comparison – before and after UQ is applied (£m, 2022-2023 prices)

Company	Pre-efficiency challenge incl. RPEs Ofwat PR24 FD	CMA Updated	Difference: CMA Updated – Ofwat PR24 FD (%)	Post-efficiency challenge incl. RPEs Ofwat PR24 FD	CMA Updated	Difference: CMA Updated – Ofwat PR24 FD (%)
Anglian	1,981	1,988	0.3%	1,970	1,870	-5.1%
Northumbrian	872	840	-3.7%	867	790	-8.9%
Southern	1,932	1,966	1.8%	1,921	1,849	-3.7%
Wessex	979	955	-2.4%	973	898	-7.7%
All Disputing Companies	5,764	5,748	-0.3%	5,731	5,407	-5.6%
Industry	18,743	18,428	-1.7%	18,636	17,333	-7.0%

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

Sensitivity analysis

Sensitivity tests

4.25 Table 4.5 below shows the results of Ofwat's suite of statistical tests when applied to our wholesale water model. As noted above and by Ofwat, it is not necessary for a model to pass every individual test to be considered sufficiently robust and fit for the purpose cost benchmarking.[39]

Table 4.5: Statistical test results of the CMA's wastewater model

Statistical test	P-value (rounded to 2 dp)	Interpretation
RESET	0.11	No evidence of model misspecification
Max VIF	5.07	No serious multicollinearity (VIF > 10 would suggest severe multicollinearity).
Shapiro-Wilks	0.05	We cannot reject the hypothesis that residuals are normally distributed
Breusch-Pagan	0.01	Heteroskedasticity present
R-Squared	0.95	Model explains ~95% of variance
Adjusted R-Squared	0.95	Adjusted R^2 confirms strong explanatory power after accounting for the number of predictors.

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

4.26 The test results indicate that the model passes model specification and multicollinearity checks, supporting the robustness of the modelling framework. As discussed above, we do not consider the inability to reject heteroskedasticity sufficient to invalidate the predictions of the model.

4.27 The VIF score is less than 10, but slightly above 5. This suggests the existence of some multicollinearity in the selected cost drivers. While do not view this as invalidating predictions of the model for benchmarking, we consider that caution should be used when interpreting model coefficients.

[39] Ofwat (2024) PR24 final determinations: Expenditure allowances - base cost modelling decision appendix, p16.

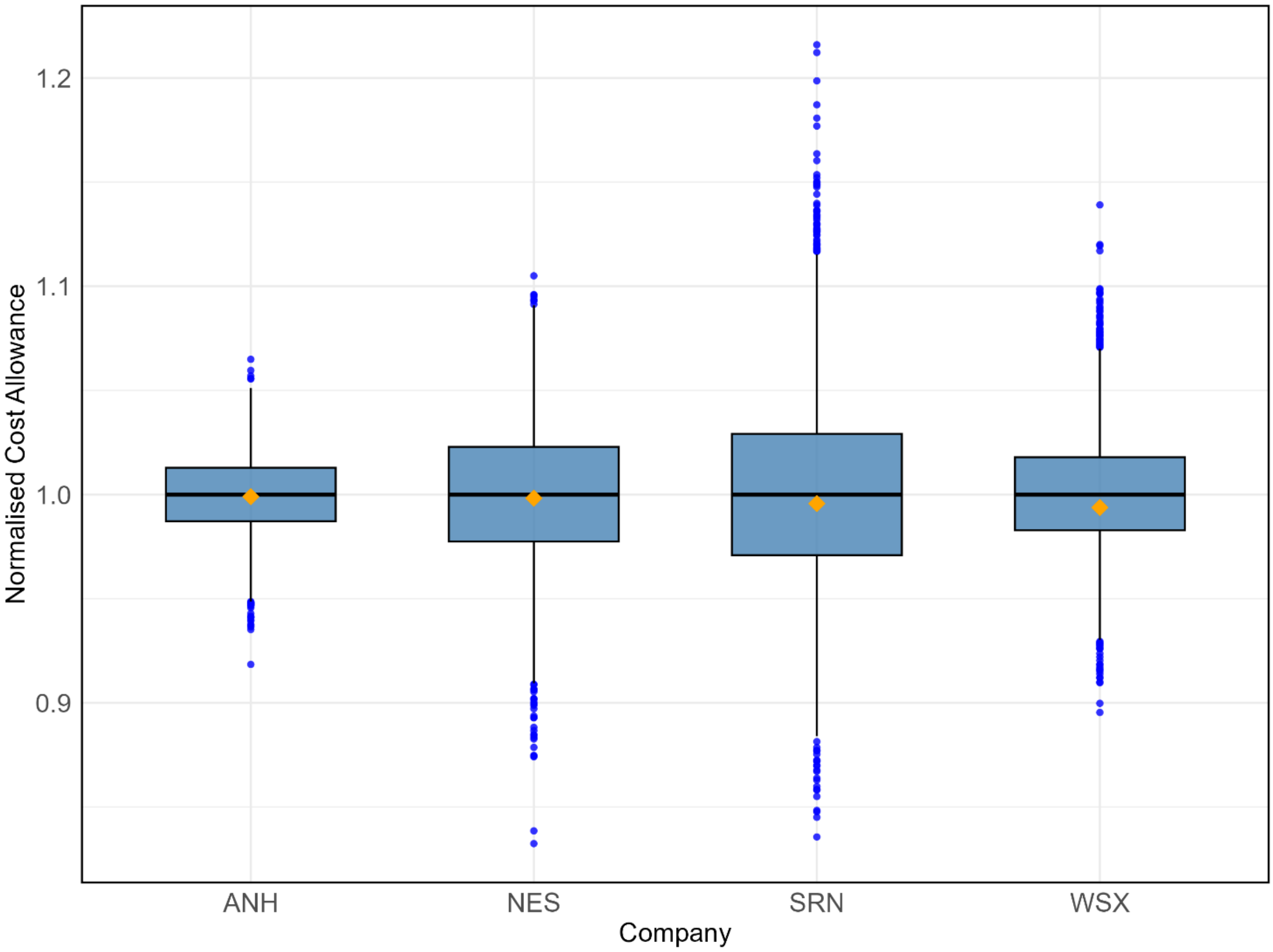
Bootstrap LASSO

4.28 To evaluate stability of the LASSO procedure, we implement a ‘bootstrap’ technique on our modelled results. See Appendix A for details.

4.29 Figure 4.3 plots post-efficiency cost allowances for the Disputing Companies, normalised by the median cost allowance of that company. The lighter blue boxes represent the interquartile range of results across the repeated runs of the model, the black line in the box represents the median, the dark blue crosses represent outliers in the data, and the orange diamond represents the modelled cost allowance in our baseline results.

4.30 The results show that the baseline (orange diamond) is in the middle, near the median of the distribution. The results also show the IQR is narrow. This indicates robust results for cost allowances of all the Disputing Companies, reinforcing the finding that the model is stable under small perturbations in the data.

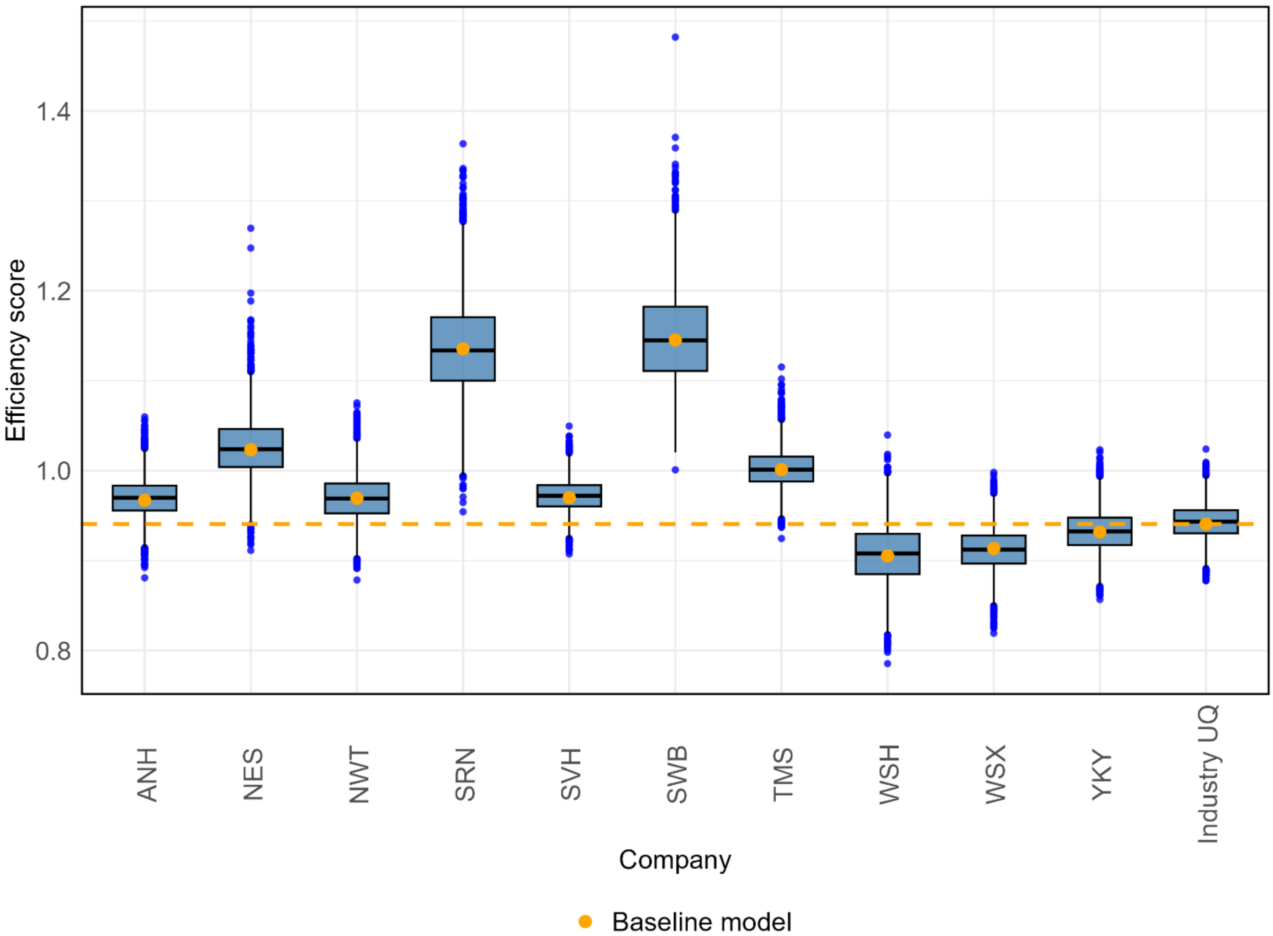
Figure 4.3: Resulting cost allowances after UQ applied under the bootstrap LASSO – wastewater, normalised using median across bootstrap samples



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

4.31 We see similarly stable results for the distribution of efficiency scores across the industry in Figure 4.4 below. The additional dotted orange line represents the Industry UQ challenge (at 0.94). The results highlight stability in the model, with narrow distribution boxes, and the baseline (orange dot) in the middle near the median for all companies.

Figure 4.4: Stability of Industry-wide efficiency scores from bootstrap LASSO – wholesale water



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

4.32 Table 4.6 shows the percentage of bootstrap runs in which each cost driver is selected. The figure shows that the model selection is stable with our chosen cost drivers selected in more than 50% of runs. Even where the selected probabilities are closer to 50%, we do not see this reflected in increased instability in the bootstrap results for cost allowances and efficiency scores as can be seen from Figures 4.3 and 4.4 above. In large part, we believe that this can be explained by the correlations between the cost drivers as can be seen in Figure C1 in Appendix C.[40] Where cost drivers are correlated it is well known that there can be instability

[40] For example, the correlation between Weighted average treatment size (log) and Load treated in size bands 1 to 3 (%) cost drivers are -0.76.

in model selection under LASSO.[41] This has a limited impact on predicted allowances as the instability is between cost drivers all capturing similar variation in the data. Given we primary consider the predictability of our model we consider this is not a concern.

Table 4.6: Percentage of bootstrap runs in which costs drivers are selected – wastewater

Cost Driver	% of runs selected
Scale combined (log)	100%
Pumping capacity per sewer length (log)	100%
Weighted average treatment size (log)	71%
Load treated in size bands 1 to 3 (%)	57%
Load treated with ammonia consent <3mg/l	100%
Urban rainfall per sewer length (log)	100%
Energy index (log)	100%
Construction wages (log)	59%

Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

[41] Hastie, T., Tibshirani, R., and Wainwright, M. (2019), Statistical Learning with Sparsity: The Lasso and Generalizations.

5. Approach to true-ups and certain claims

5.1 In this section we provide further information on our current thinking on two areas:

(a) true-ups; and

(b) four company claims which interact with the base cost modelling:

(i) South East economies of scale at water treatment works (**WTW**);

(ii) Southern coastal population;

(iii) Southern energy costs; and

(iv) Southern regional wages.

Approach to true-ups

5.2 We did not set out a detailed approach to true-ups for energy and wages in our PR24 PD.

5.3 As a means of assessing this, we are considering taking the proportion of total costs attributable to wages or energy across the industry, determining the implied value of this component within the modelled allowance, and then adjusting for changes in the relevant index (such as the ONS ASHE construction wage index or DESNZ energy price index net of CPIH) over time.

5.4 The resulting true-up would therefore be calculated as follows:

True-up = %contribution × modelled allowance × change in index

5.5 This proposed approach would ensure that end of period reconciliation adjustments made by Ofwat for input price movements would be transparent, proportionate, and not dependent on the precise model coefficients.[42]

South East: economies of scale at WTW

5.6 In our PR24 PD, we provisionally decided that the requirement underpinning this CAC was met by the inclusion of a variable for the average size of WTWs in the WRP model.[43]

5.7 We recognise that the coefficient on the average size of WTWs variable was not of the expected sign when included in our PR24 PD modelling. We also note that

[42] Ofwat (2025) PR24 Final Determinations – Expenditure Allowances, p55.
[43] PR24 PD Volume 1, paragraphs 4.485–4.499.

Ofwat assessed South East's claim for economies of scale at WTW by incorporating a weighted average treatment size variable within its WRP models. Ofwat then compared the resulting allowances with its unadjusted PR24 FD allowances which did not incorporate the weighted average treatment size variable. This approach led to an allowed cost adjustment of £14 million for South East.[44]

5.8 In light of responses to our PR24 PD and to inform our assessment of this CAC, we are considering the merits of adopting a similar approach to Ofwat:

(a) first, we would add the weighted average treatment size variable and the average size of WTW to the list of candidate variables for a separate version of the bottom up WRP model. This is because the impact of economies of scale is most important to the WRP model;

(b) second, we would allow LASSO to decide whether to select these variables; and

(c) third, if LASSO selects either or both of these variables and the results pass robustness and sensitivity checks, we would then calculate the value of the CAC based on the differences between this CAC-specific WRP model, and the updated WRP model based on the standard set of candidate variables.

5.9 We invite views on this approach and, in particular, the following topics:

(a) the variables which could be used to assess this CAC;

(b) whether the results should be applied symmetrically, so that if some companies are awarded an allowance, other companies should have their allowances reduced if the evidence shows they benefit from economies of scale; and

(c) whether there are reasons why these variables should only be used for assessing this CAC or whether they be added to the standard set of candidate variables.

Southern: coastal population

5.10 In our PR24 PD we provisionally decided that this CAC failed the need requirement as Southern had not provided compelling evidence of:

[44] Ofwat (2025) PR24 redeterminations: Expenditure allowance – cost adjustment claims, paragraphs 12.1–12.8. Southern and Wessex also received funding from this CAC.

(a) a material relationship between coastal operation and costs; and

(b) Southern's unique circumstances.[45]

5.11 In response to our PR24 PD, Southern said that we had not assessed this coastal population CAC within our modelling framework, and that Southern had provided econometric results using a coastal population variable.[46] We also note that Ofwat investigated Southern's modelling in its PR24 FD as part of its need assessment.[47]

5.12 In light of responses to our PR24 PD and to inform our assessment of this CAC, we are considering the merits of adopting a similar approach to that proposed by Southern and assessed by Ofwat:

(a) first, we would add the coastal population variable to the list of candidate variables for the STW model. This is because the impact of coastal effects is most important to the STW model;[48]

(b) second, we would allow LASSO to decide whether to select this variable; and

(c) third, if LASSO selects this variable and the results pass robustness and sensitivity checks, we would then calculate the value of the CAC based on the differences between this CAC-specific STW model, and the updated STW model based on the standard set of candidate variables.

5.13 We invite views on this approach and, in particular, the following topics:

(a) the variables which could be used to assess this CAC, including whether it is possible to construct a robust coastal load time series;

(b) whether the results should be applied symmetrically, so that if some companies are awarded an allowance, other companies should have their allowances reduced if the evidence shows they benefit from a lack of coastal population; and

(c) whether there are reasons why these variables should only be used for assessing this CAC or whether should they be added to the standard set of candidate variables.

[45] PR24 PD Volume 1, paragraphs 4.622–4.652.
[46] Southern (2025) Response to PD, paragraphs 3.91–3.92.
[47] Ofwat, Base cost adjustment claim feeder model – Southern Water, Sheet SRN_CAC6. Cell D23.
[48] As discussed in our PR24 PD, coastal load is likely to be more informative than coastal population, but our understanding is that there is no robust timeseries dataset for coastal load. PR24 PD Volume 1, paragraphs 4.649–4.650.

Southern: regional wages and Southern energy costs

5.14 In our PR24 PD we provisionally decided that the requirement underpinning Southern's regional wages claim was met by the inclusion of regional wages in the candidate set of variables for the base modelling. Therefore, we provisionally decided not to allow this CAC.[49]

5.15 Similarly, in our PR24 PD we provisionally decided that the requirement underpinning Southern's energy costs claim was met by the inclusion of energy costs in the candidate set of variables for the base modelling. Therefore, we provisionally decided not to allow this claim.[50]

5.16 As we continue to include regional wages and energy costs in the candidate set of variables, our current view remains as set out in our PR24 PD.

[49] PR24 PD Volume 1, paragraphs 4.500–4.522.
[50] PR24 PD Volume 1, paragraphs 4.758–4.777.

6. Next steps

6.1 We are inviting comments on our working paper.

6.2 All parties are requested to make any submissions in response to this working by **5:30pm (UK time) on Wednesday 7 January 2026,** by email to: waterpr24references@cma.gov.uk.

6.3 The CMA may publish non-sensitive submissions on the CMA's website. Where parties believe that information contained within a submission is sensitive information which should not be disclosed, the following should be provided to the CMA:

(a) a version with sensitive information clearly highlighted;

(b) a non-sensitive version with any sensitive information redacted; and

(c) a table setting out the reasons for treating each item or category of information as sensitive information.

6.4 We will consider responses to our working paper before making our final determinations. The statutory deadline for our final determinations is 17 March 2026. Any changes to our administrative timetable will be indicated on our case page.

Appendix A: Technical implementation appendix

A1 Revised LASSO estimation approach

A.1 The Least Absolute Shrinkage and Selection Operator (**LASSO**) technique is widely used for variable selection and regularisation in regression models. Several technical refinements have been made to help address limitations identified after publication of our PR24 PD.

Least Angle Regression

A.2 In our PR24 PD, the implementation of LASSO used coordinate descent to solve the optimisation problem. Coordinate descent is computationally efficient and widely adopted in high-dimensional modelling contexts.[1] However, responses to our PR24 PD highlighted concerns about its stability when predictors exhibit high correlation – a common feature in regulatory cost models where scale, density, and network topology variables are inherently related.

A.3 With strong correlation between our cost drivers, small changes in data or penalty parameters may lead to different sets of selected variables using coordinate descent. This instability can undermine transparency and reproducibility, which are important in a regulatory setting to enable stakeholders to understand and replicate modelling decisions. In addition, when parameters are correlated coordinate descent can lead to the ordering of variables impacting the model selection.

A.4 To address these concerns, our updated methodology considered an alternative algorithm – Least Angle Regression (**LAR**) – as the basis for the LASSO implementation.[2] Unlike coordinate descent, which updates coefficients one variable at a time along coordinate axes, LAR works in a different way. LAR incrementally builds the model by selecting the variable most correlated with the current residuals and then adjusting all active coefficients simultaneously.

A.5 As such, we consider that LAR is well suited for our setting. In particular, its properties mean that it performs well for small samples and with correlated data.[3] LAR is not as commonly used as other methods typically due to its low computational efficiency which can make it slow for large problems however that is not a concern in our case.[4]

[1] Friedman, Jerome, Trevor Hastie, and Robert Tibshirani (2010), 'Regularization Paths for Generalized Linear Models via Coordinate Descent' *Journal of Statistical Software, Articles,* 33 (1): 1–22.
[2] Efron, B. et al (2004), 'Least angle regression', *The Annals of Statistics*, 32(2).
[3] Bach, F., Jenatton, R., Mairal, J., & Obozinski, G. (2012), Optimization with sparsity-inducing penalties. Foundations and Trends® in Machine Learning, 4(1), 1–106.
[4] Zhou, Y., & Li, X. (2023). A comprehensive survey on Lasso and its variants.

Leave-One-Out Cross-Validation for Regularisation Parameter Selection

A.6 In our previous version of LASSO used in the PR24 PD, the regularisation parameter (λ) was tuned using 10-fold cross-validation. While commonly used, this method is not deterministic and can be sensitive to the set of data points included in each fold.

A.7 In practice, the set of data points included in each fold is determined by a random component of the implementation. We considered repeating the cross-validation procedure 1,000 times and using the output of this process to choose a tuning parameter. However, this substantially increases computational cost and it is not clear how to use the output to transparently choose the tuning parameter.

A.8 In our revised approach, we instead have chosen to use Leave-One-Out Cross-Validation (**LOOCV**) to select λ. This method leaves out one observation at a time, fitting the model to the remaining data and evaluating predictive performance. The approach moderately increases computational cost, but we consider that it is justified by reducing the impact of randomness which can cause instability in cross validation when other fold choices are used.

A2 Principal Component Analysis

A.9 A principal component is a new variable that is constructed by taking a weighted combination of the original variables. It is designed to capture as much of the variation in the underlying data as possible. A principal component analysis (**PCA**) summarises the underlying data by producing as many principal components as there are original variables. They are ordered by the amount of variation they represent in the original data.

A.10 The first principal component is the single direction in the data that captures the maximum amount of variance. Each original variable contributes to this principal component with a specific weight (called a 'loading'). These weights measure how strongly each original variable influences that component. High positive weights mean the variable strongly pushes the component in one direction. High negative weights push it the opposite way.

A.11 If several of the original variables are highly correlated, they will tend to load heavily on the same principal component – often because they are all measuring aspects of the same underlying phenomenon. Variables that do not correlate with each other will load on different principal components.

A.12 Subsequent principal components capture the next largest amount of remaining variance, but with a crucial constraint: it must be completely uncorrelated (orthogonal) with the first component. The third principal component is orthogonal to both the first and second, and so on. This orthogonality means each component captures independent information – there is no redundancy between them, unlike the original variables.

A.13 Once calculated, a subset of the principal components can be included in a model in place of the original variables. For example, if the original variables are highly correlated, the first principal component may adequately capture the variation in the underlying data (eg 95% or more of the variation overall and in each of the underlying variables is explained by the first principal component). More generally, different combinations of principal components can explain the variation in each of the underlying variables. This may inform which principal components might be added to the model.

A.14 The advantage of this approach is the elimination of the effect of multicollinearity on the model from correlations between these variables.[5] This can aid model interpretability and stability. The main drawback of using principal components in a model can be the loss of a direct interpretation in terms of the original variables and statistical inference on them. However, the resulting model coefficients on the included principal components can be transformed back into the original variables using the PCA loadings.

A.15 For example, suppose there are three variables X_1, X_2, and X_3 that are different measurements of the same underlying feature of the model (ie the same cost driver in a cost model) that we would like to account for. However, given they all measure the same thing – albeit in slightly different ways – they are highly correlated. As such, one might be concerned about the multicollinearity created by including them all.

A.16 Rather than create a separate model for each variable and risking bias in the model estimates by virtue of omitting 2 of the 3 variables, a subset of their principal components can be included. To calculate the principal components, first the X variables are standardised and their scales: σ_i for $i = 1,2,3$ are calculated.

A.17 Given their high correlation and common purpose, further suppose that the first principal component captures almost all of the variance of each of the X variables (ie around 95%). The resulting first principal component provides a composite measure of the original variables by attaching PCA loadings α_1, α_2, and α_3 to the standardised variables, $\tilde{X}_i$ for $i = 1,2,3$.

$$PC_1 = \sum_{i=1}^{3} \alpha_i \tilde{X}_i$$

A.18 The first principal component may be included in the model to parsimoniously control for this feature of the model without inducing multicollinearity and $\hat{y}$ is the

[5] The principal components may still be correlated with other regressors not included in the PCA.

estimated coefficient on PC_1. Unfortunately, however, this coefficient has no direct interpretation. However, substituting the definition of PC_1 into the regression and adjusting for the rescaling, we can recover that the effective estimated coefficient on each original variable contributing to PC_1 is:

$$\widehat{\beta_i} = \hat{\gamma}\frac{\alpha_i}{\sigma_i} \ \ for\ i \in \{1,2,3\}$$

A.19 Thus, each original variable's contribution is proportional to its loading in PC_1 and the regression coefficient on PC_1. Once transformed back into the original variable's units the resulting coefficient contribution to the model can be interpreted, though inference is not as straightforward. A similar approach can be used to recover the coefficients on quadratic PCA terms.

A3 Implementation of bootstrap LASSO

A.20 As discussed in section 2, to model the stability of modelled results, we perform repeated random sampling analysis using a bootstrapping. We implement the bootstrap in a standard way. In particular:

(a) for each run resample the data with replacement to achieve a dataset of the same length of as the original;

(b) run the analysis and compute allowances and efficiency scores; and

(c) repeat the above sets 5,000 times saving results for each completed run.

A.21 Pooling results generates a distribution of efficiency scores and modelled allowances. We then compute the distribution of the inter-quartile range of results.

A4 Calculating Ofwat's implied RPE with and without catch-up efficiencies

A.22 We estimate Ofwat's real price effects (**RPE**s) using the same methodology applied in Ofwat's Base Cost Aggregator Model. The calculation is undertaken for the financial years 2025-26 to 2029-30 and applies only labour and energy RPE adjustments to the pre and post-catch-up efficiency cost allowance. The calculation methodology is set out here below.

A.23 We use the following Ofwat data:

(a) PR24 FD pre catch-up and post catch-up modelled cost allowances (pre-RPE and pre-frontier shift) by company and financial year;[6]

[6] We replicate the calculation of Ofwat's post catch-up modelled costs using the beta parameters estimated in Ofwat's wholesale water and wastewater models, forecast cost drivers, and using Ofwat's post modelling methodology.

(b) real input price inflation for 2024-25 to 2029-30 for wholesale water and wastewater; and [7]

(c) energy adjustment data by company and financial year between 2025-26 and 2029-30.[8]

A.24 We estimate Ofwat's PR24 FD post catch-up cost allowance that includes energy and labour RPEs as follows.

(a) We first calculate cumulative real input price inflation by compounding each year's real input price change with that of all previous years, using Ofwat's inflation series, separately for water and wastewater.[9]

(b) Second, for each company and year, this cumulative real input price inflation is then applied to Ofwat's post catch-up cost allowance and to Ofwat's energy adjustment. These two elements are added together to produce the total labour and energy RPE adjustment.[10]

(c) Finally, this adjustment is added to Ofwat's post–catch-up cost allowance to give the post catch-up cost including RPEs.[11]

A.25 A corresponding calculation is done for Ofwat's PR24 FD pre catch-up cost allowance, where the post catch-up cost allowance is changed to the pre catch-up cost allowance in the above steps.

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[7] Ofwat (2024) PR24 FD: Base cost aggregator model, Sheet 'Controls', cells C21:C26 for water and I21:I26 for wastewater.

[8] Ofwat's energy adjustment data from Ofwat (2024) PR24 FD: Base cost aggregator model, (i) Sheet 'Water-Calculations', sum of Column G (for water resource) and Column AC (for water network plus) and (ii) Sheet 'Wastewater-Calculations', Column G (for water network plus).

[9] We compute the cumulative real input price inflation used by Ofwat (2024) PR24 FD: Base cost aggregator model as follows:
$CumRPI_{i1} = 0$; $CumRPI_{it} = (1 + CumRPI_{it-1})(1 + R_{it}) - 1, t \geq 2$, where R_{it} is the real input price inflation which is different for water and wastewater. Water uses $CumRPI_{it}^{W}$ and wastewater uses $CumRPI_{it}^{WW}$.

[10] We consider E_{it}^{W} to be the energy adjustment for wholesale water, E_{it}^{WW} to be the energy adjustment for wastewater and M_{it} is Ofwat's post-catch-up modelled cost allowance. The labour and energy RPE adjustment for water is the following:

$$RPEAdj_{it}^{W} = M_{it} CumRPI_{it}^{W} + E_{it}^{W}(1 + CumRPI_{it}^{W})$$

For wastewater, the equivalent calculation is the following:

$$RPEAdj_{it}^{WW} = M_{it} CumRPI_{it}^{WW} + E_{it}^{WW}(1 + CumRPI_{it}^{WW})$$

[11] For both water and wastewater, the final allowance with RPEs is: $M_{it}^{RPE} = M_{it} + RPEAdj_{it}$, where $RPEAdj_{it}$ is the relevant expression above.

Appendix B: Wholesale water – cost drivers and additional results

B1 Cost drivers

B.1 The cost drivers included in Ofwat's PR24 FD suite of bottom-up and top-down models are listed in Table B.1 below.

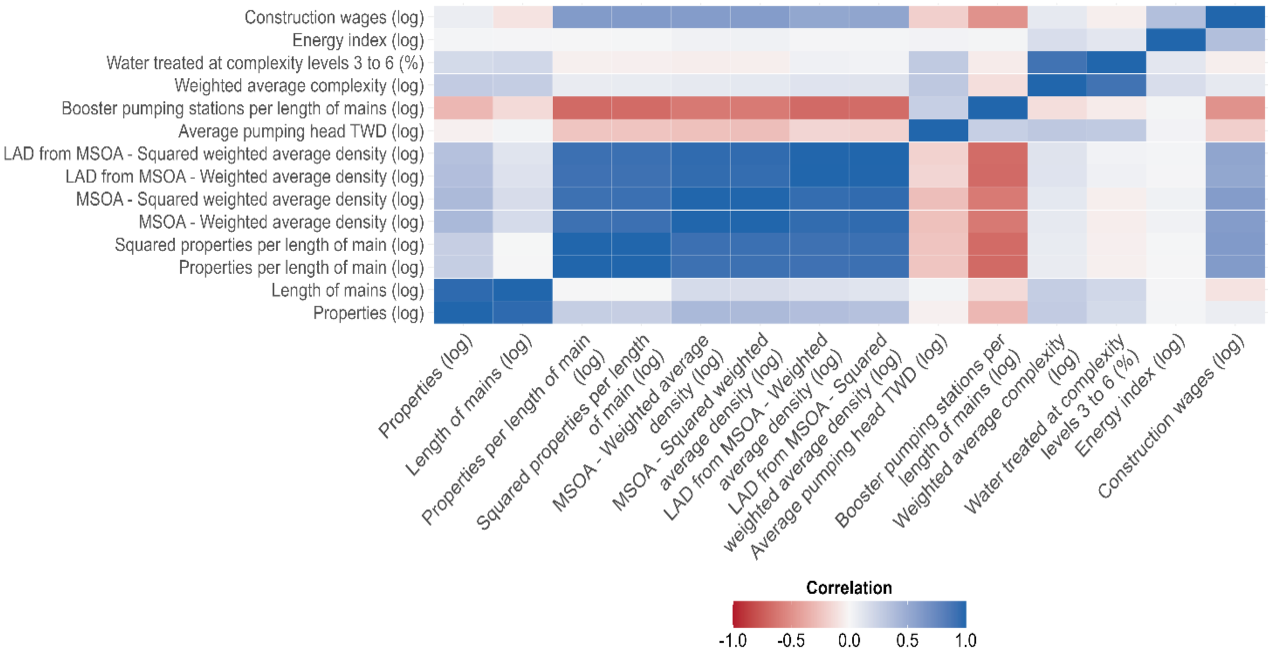
Table B.1: Cost drivers included in the Ofwat PR24 wholesale water models

	Bottom-up models		*Top-down models*
Variable	Water Resources Plus (**WRP**)	Treated Water Distribution (**TWD**)	Wholesale Water (**WW**)
Number of Properties (log)	✓		✓
Length of Mains (log)		✓	
Properties per length of mains (log)	✓	✓	✓
Properties per length of mains (log) squared	✓	✓	✓
MSOA - weighted average density (log)	✓	✓	✓
MSOA - weighted average density (log) squared	✓	✓	✓
LAD from MSOA - weighted average density (log)	✓	✓	✓
LAD from MSOA - weighted average density (log) squared	✓	✓	✓
Average Pumping Head TWD (log)		✓	✓
Booster Stations per length of mains (log)		✓	✓
Weighted Average Complexity (WAC) (log)	✓		✓
Water treated at complexity levels 3 to 6 (%)	✓		✓

Source: CMA analysis of Ofwat (2025) PR24 FD models data.

B.2 Figure B.1 below shows the correlation between the cost drivers as they enter Ofwat's PR24 FD wholesale water cost models and the energy and regional wages indices added to the set of cost drivers in our updated approach. Red shaded cells indicate the two corresponding cost drivers are negatively correlated and blue shaded cells that they are positively correlated. Darker colours show stronger correlation.

Figure B.1: Correlation between Ofwat wholesale water cost drivers and input prices



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

B2 Additional bottom-up base cost model results

B.3 This sub-section provides additional results for our wholesale water models. Table B.2 and Table B.3 show the coefficients of the bottom-up approach. The variables included are those described in section 3.

Table B.2: WRP Model

Cost Drivers	WRP Model		
	Coefficient	Standard Error	Significance
Intercept	-11.734	0.956	***
Properties (log)	1.049	0.025	***
(log) Density combined	-0.091	0.017	***
Squared (log) density combined	0.017	0.005	***
Weighted average complexity (log)	0.674	0.135	***
Energy index (log)	0.179	0.097	*
Construction wages (log)	-0.217	0.335	

*Note: *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level*
Source: CMA analysis and CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

Table B.3: TWD Model

Cost Drivers	TWD Model		
	Coefficient	Standard Error	Significance
Intercept	-7.666	0.588	***
Length of mains (log)	1.046	0.014	***
(log) Density combined	0.154	0.011	***
Squared (log) density combined	0.039	0.003	***
Average pumping head TWD (log)	0.296	0.044	***
Booster pumping stations per length of mains (log)	0.338	0.061	***
Energy index (log)	0.127	0.056	**
Construction wages (log)	0.556	0.200	***

*Note: *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level*
Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

Appendix C: Wastewater – cost drivers and results

C1 Cost drivers

C.1 The cost drivers included in Ofwat's PR24 FD suite of bottom-up and top-down wastewater models are listed in Table C.1 below.

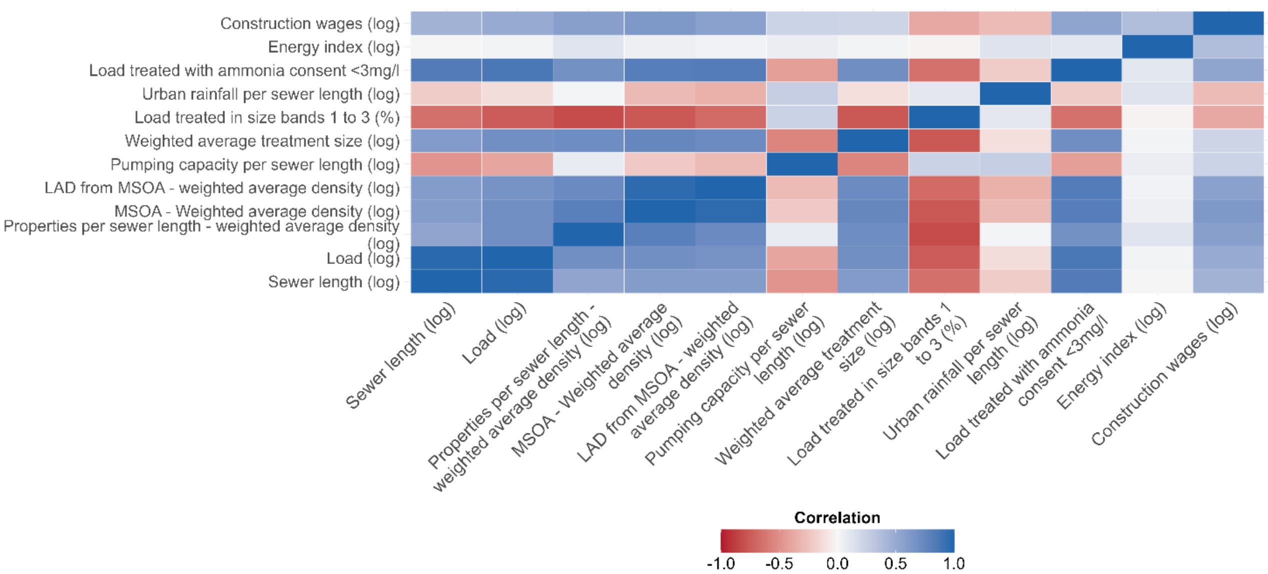
Table C.1: Cost drivers included in the Ofwat PR24 FD wastewater models

	Bottom-up models		*Top-down models*
Cost driver	Sewage Collection (**SWC**)	Sewage Treatment (**SWT**)	Wastewater (**WWW**)
Sewer length (log)	✓		
Load (log)		✓	✓
Properties per length of mains (log)	✓		
MSOA - weighted average density (log)	✓		
LAD from MSOA - weighted average density (log)	✓		
Pumping capacity per sewer length (log)	✓		✓
Weighted average treatment size (log)		✓	✓
Load treated in bands 1 to 3 (%)		✓	✓
Urban rainfall per sewer length (log)	✓		✓
Load treated with ammonia consent <3mg/l		✓	✓

Source: CMA analysis of Ofwat (2025) PR24 FD models data.

C.2 Figure C.1 below shows the correlation between the cost drivers as they enter Ofwat's PR24 FD wastewater cost models and the energy and regional wages indices added to the set of cost drivers in our updated approach. Red shaded cells indicate that the two corresponding cost drivers are negatively correlated and blue shaded cells that they are positively correlated. Darker colours show stronger correlation.

Figure C.1: Correlation between Ofwat wastewater cost drivers and input prices



Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

C2 Additional bottom-up base cost model results

C.3 This sub-section provides additional results for our wastewater models. Table C.2 and Table C.3 show the coefficients of the bottom-up approach. The variables included are those described in section 4.

Table C.2: Coefficients for the updated CMA SWC model

Cost Drivers	SWC Model		
	Coefficient	Standard Error	Significance
(Intercept)	-4.467	0.525	***
Sewer length (log)	0.825	0.038	***
Density combined (log)	0.099	0.011	***
Pumping capacity per sewer length (log)	0.431	0.056	***
Urban rainfall per sewer length (log)	0.118	0.036	***
Energy index (log)	0.137	0.055	**

*Note: *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level*
Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.

Table C.3**: Coefficients for the updated CMA SWT model**

Cost Drivers	SWC Model		
	Coefficient	Standard Error	Significance
(Intercept)	-5.387	0.825	***
Load (log)	0.842	0.051	***
Weighted average treatment size (log)	-0.215	0.026	***
Load treated with ammonia consent <3mg/l	0.004	0.001	***
Construction wages (log)	0.094	0.232	
Energy index (log)	0.292	0.067	***

*Note: *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level*
Source: CMA analysis of Ofwat (2025) PR24 FD models data and ONS ASHE data.