Water PR24 References

The CMA Provisional Determinations – UUW consultation response

November 2025

This document contains UUW’s comments in response to the CMA’s Provisional Determinations in relation to the Water PR24 References made by Ofwat on behalf of disputing companies.

Executive Summary

This document sets out United Utilities Water (UUW)'s representations in relation to the CMA's Provisional Determinations (PDs) for PR24 Water References. The CMA redetermination is an important process that supports the accountability and effectiveness of the economic regulatory framework.

UUW is committed to ensuring that the regulatory regime works well for customers, investors and the environment. To this end, we are providing representations to the CMA's PDs to ensure that any decision that might influence future regulatory periods supports this objective. We would like to thank the CMA for the opportunity to respond to its PDs and for its transparency in providing additional coding detail used for its econometric modelling.

Although UUW has not asked Ofwat to refer its final determination to the CMA, the approach that the CMA takes to setting its determinations, particularly to assessing efficient costs, can have a wider long-term consequence for the whole industry, including UUW. In terms of the provisional determinations, **UUW supports** the CMA's changes to:

(1) The **underlying parameters of the allowed return** that allow to reflect a more appropriate average cost of equity of the sector, notwithstanding additional improvements that should be made to the asset beta to set the allowed return;

(2) The **changes to the frontier shift** as part of the wider cost efficiency assessment;

(3) The rationale of why additional allowances are required in light of company specific challenges in relation to **energy resilience**; and

(4) The direction to Ofwat to **restate** the performance of the **disputing companies under the Outturn Adjustment Mechanism** (OAM).

However, we have significant concerns about the use of machine learning techniques for deriving base allowances. This is a novel and untested approach in the context of setting cost allowances for utility sectors. Whilst we are not opposed in principle to the development of new and improved estimation techniques, upon detailed review of the CMA's base models, we note the proposals represent a very significant **U-turn against previous regulatory cost assessment methodologies**, which have centred around appropriate economic and engineering principles rather than purely statistical driven approaches. **The change of approach also runs counter to the general principle of regulatory consistency and predictability, and if it were to be adopted at future price controls, we consider it would likely lead to suboptimal outcomes for customers and the environment by misallocating the resources required by companies to deliver their functions in delivering a vital public service.**

Our review of the models has focused on cross referencing the CMA's methodology against Ofwat's cost assessment methodology and UUW's principles of regulatory cost assessment, as set out in previous published papers to develop the approaches used at PR24. The approach adopted is therefore a long standing consistent and principled approach.

In particular, the new base models present the following fundamental issues:

(1) The reduction **of base allowances across the water industry relative to Ofwat's PR24 Final Determinations by around £4.3bn, at a time when the Independent Water Commission (IWC) has called for a greater focus on asset health and resilience**;

(2) The **resulting lack of predictability of the new modelling approach to select cost drivers increases the uncertainty of future base allowances**. This runs contrary to the expectation that there should be an underlying stable set of factors that drive water companies' costs. This limits companies' ability to plan and deliver sustainable capital maintenance over the long term. Even in the limited time available to compile this response, we have performed substantial analysis and present a wide range of sensitivities confirming the models' instability in Appendix A, which we encourage the CMA to consider carefully;

(3) The l**ack of robustness and consistency with engineering and economic rationale**, **often exhibiting counterintuitive features and lacking interpretability.** We note very limited explanation around why the model's explanatory factors have counterintuitive features that do not appear to be related to the actual underlying factors driving costs in the sector. This leads to a less robust assessment of companies' individual efficient costs and low confidence in the quality and suitability of model results; and

(4) **An over-reliance on the results of a reduced suite of models** (three models) rather than triangulating results across a larger range of diverse models (32 models used by Ofwat). The approach fails to sufficiently capture the varied operational characteristics faced by companies, incorrectly attributing additional expenditure incurred as 'inefficiency'. It means that attempting to use one single 'best' model for cost assessment is unlikely to lead to a robust and fair allocation of allowances across companies, to the detriment of customers.

From a process standpoint, we fully recognise the challenge that the CMA is facing in reaching a determination in such complex areas, like cost assessment, within very tight timescales. By the same token, given the **limited time available to understand, investigate and respond to such a novel statistical approach for the sector, it is possible that the CMA will receive limited responses from the wider industry stakeholder groups on such a complex topic.** We would like to note that the water industry is unlikely to have the in-house expertise to be able to fully and timely assess such a highly technical area, especially given that the extent of the CMA's reappraisal of the base model approach was largely unanticipated. To this end, we have supplemented our own assessments with external expertise on machine learning to be able to better comprehend and review the models.

In relation to the base models, we therefore ask that the CMA:

- **Recognises the limitations of a purely data driven approach** to developing base models. This would likely involve considering whether **machine learning models, such as LASSO, should be used more as a diagnostic and investigative tool with appropriate caution**, assisted by expert judgment and economic intuition. LASSO and similar tools should be used alongside (rather than as an alternative to) the established cost modelling approaches to identify new cost drivers that might have not been detected through existing models;
- **Conducts appropriate ex-post validation tests** to ensure that any suite of models developed as an alternative to Ofwat's existing base models are coherent, intuitive and interpretable and accord with reasonable expectations based on engineering priors; and
- **Considers utilising a more diverse suite of models** to better reflect the differing operational circumstances faced by companies, which cannot be fairly captured within one (or at most two) single model(s).

We would also recommend that the CMA undertakes an external peer review of these models to test for accuracy and consistency of the models given the untested and novel approach adopted in the provisional determinations.

While we welcome the development of new improved estimation techniques, following our detailed review of the new base models developed by the CMA for its PDs, **we believe there are fundamental issues with the new models that mean they would be unsuitable for use at future price reviews for the purpose of setting base costs allowances.** As a result, we consider that the CMA should proceed with considerable caution if it is minded to apply them in the redeterminations.

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1. Introduction

1.1 Background and context

United Utilities Water (UUW) is the appointed water and wastewater provider for the North West of England. Our purpose is to provide great water for a stronger, greener and healthier North West. We serve more than three million homes and 200,000 business across a region that stretches from Carlisle in north Cumbria to Crewe in south Cheshire, whilst safeguarding 1,300 km of coastline and 7,000 km of rivers.

The North West is a diverse area with more than seven million people living across both major metropolitan areas such as Greater Manchester and Merseyside as well as small rural villages in the heart of Cumbria. To deliver our services to customers we manage hundreds of reservoirs, treatment works and pumping stations, more than 120,000 kilometres of water pipes and sewers.

Like the appellant companies in this case, UUW is regulated by Ofwat – amongst other regulators – and is subject to Ofwat's price review determinations.

1.2 Why we are responding to the CMA's preliminary decision

The CMA determination is an important process supporting the transparency, accountability and effectiveness of the regulatory framework. We are committed to ensuring that the regulatory regime works well for customers, investors and the environment and, to this end, we are providing representations to the CMA's PDs to ensure that any decision that might influence future regulatory periods supports this objective.

Although UUW has not asked Ofwat to refer its final determination to the CMA, the approach that the CMA takes to setting its determinations, particularly to assessing efficient costs, can have wider long-term consequences for the whole industry, including UUW. To this end, UUW's representations are aimed at ensuring that any potential change to future cost assessments improves the accuracy and fairness of the allocation of funding allowing each individual company to meet their obligations to the benefit of customers and local communities.

We do not seek to opine on the merits or otherwise of the specific circumstances that individual companies may represent to the CMA or have represented previously to Ofwat. For the most part, our observations in this submission focus on the potential impact that these decisions may have on future price control and reflect long-held policy positions and evidence promoted by UUW through Ofwat's engagement with the industry in the development of the PR24 methodology.

We set out our key representations in Section (2).

2. Representations

2.1 Risk and return

We recognise the importance of ensuring that the regulatory settlement is underpinned by an allowed cost of equity that can attract the financing required especially at a time when the water industry, as many other utility sectors, is facing significant investment needs.

To this end, we **welcome the CMA's methodological changes to estimating the asset beta**, in particular the **inclusion of Pennon** given that the dataset used by Ofwat only included United Utilities Group PLC and Severn Trent Plc. This addition will improve the accuracy of the asset beta and reflect a more appropriate average cost of equity.

We note however, that inclusion of **the asset beta for Pennon**, is **limited to the upper bound** and we further note the observations in relation to both **COVID-19** and the **impact of increasing capital intensity**[1]. In both cases, there is recognition that **greater weight should be applied to shorter-term beta evidence,** however as in the case of the asset beta for Pennon, these only feed into the **upper bound** assessment of beta.

We also note that the listed water companies are regarded by the equity market as the better performers in the sector – this can be observed for instance in companies relative credit spreads - and as such would be expected to have a lower cost of equity than the privately owned companies. **This approach means that the overall sector-wide cost of equity is being underestimated due to its overreliance on observations from the companies regarded as better performing than average.** This is a further consideration CMA should have in determining a final cost of equity.

We believe that it may be appropriate to place more weight on other utility sectors in light of the comparison that investors will make for example to Ofgem's beta for energy network businesses, as companies that have broadly the same underlying characteristics and risk profiles.

Finally, **we welcome the CMA's direction** for Ofwat to **restate the performance of the disputing companies under the Outturn Adjustment Mechanism (OAM)** to ensure that decisions taken by the CMA on Performance Commitment Levels and/or Outcome Delivery Incentives do not have unintended consequences for the returns of companies that have not appealed, such as UUW. This is an essential point to ensure overall fairness of the process to all companies potentially impacted by the redeterminations, including those that are not directly subject to the redeterminations themselves.

2.2 Cost assessment

We **support the CMA's adjustment of the 'Frontier Shift' from 1% to 0.7% per annum** and believe that this new level is a better reflection of the evidence around productivity and technological trends related to the UK wider economy. This level of frontier shift is more consistent with evidence submitted by the industry during PR24 – for example, we embedded a frontier shift assumption of 0.55% in our business plan submission[2].

We also acknowledge the CMA's determination on funding for improved **power resilience** and welcome its recognition that the **exposure to extreme weather and associated risks can vary significantly between companies and should therefore be appropriately recognised in setting investment allowances for power resilience**. We consider this to be an important step in recognising that targeted funding is appropriate in areas where company-specific conditions, such as exposure to extreme weather, impact investment needs to provide and retain appropriate service and asset resilience.

From a process standpoint, we are surprised to see such a fundamental change in approach to setting base expenditure adopting new complex and untested machine learning based models without separate engagement prior to the PDs. Although we recognise that the CMA is responsible for conducting a determination

[1] Competition and Markets Authority (October 2025). PR25 PD Volume 4, pg. 97: para. 7.430.

[2] United Utilities (October 2023). UUW46 Cost Assesment Proposal, pg. 55-62: section 6.

of the price controls for the disputing companies, its decisions **can create influence the approach adopted at future price controls**. Indeed, Ofwat's approach to cost assessment was developed in response to the CMA's recommendations that the PR14 models should not be solely concerned with the statistical performance[3] of the models and should ensure interpretability and consistency with the industry's engineering and economic rationales.

In response to this, Ofwat's PR24 models, whilst admittedly not perfect, have been developed collaboratively with the industry over the last ten years. Importantly, at the outset of the cost assessment process, two important guiding principles were established, namely 1) consistency *"with engineering, operational and economic rationale*" and 2) "*sensibly simple and transparent*[4] models". These principles, however, have not been considered in these Provisions Determinations in developing a new cost assessment for base expenditure.

While we welcome the development of new improved estimation techniques, following our detailed review of the new base models developed by the CMA for its PDs, we believe there are fundamental issues with the new models that mean they would be unsuitable for use at future price reviews for the purpose of setting base costs allowances. As a result, we consider that the CMA should proceed with considerable caution if it is minded to apply them in the redeterminations. We have summarised the key issues in the following section.

2.3 Base cost models

There are four key issues associated with the new base cost models developed by the CMA.

2.3.1 A material reduction in base allowances for the industry

The revised base models developed by the CMA result in significant reductions in the industry wide allowances for operational and maintenance expenditure. In particular, the CMA revised base allowances imply a £4.3[5] billion reduction relative to the allowances set by Ofwat in its Final Determinations for PR24. We find this incongruent with the findings of both the Independent Water Commission (IWC)'s report[6] - which has recommended a greater focus on asset health and resilience – as well as Ofwat's own work in implementing a new Asset Health cost change item to allow companies to deliver greater investment in capital maintenance.

While we appreciate that the CMA should not be constrained by the IWC's findings for the purpose of the CMA's PR24 price determinations, its approach to developing these base models and its full reliance on them to set appropriate allowances **is in stark contrast with the recommendations by the IWC** and the broader recognition within and beyond the sector that the types of activities dealt with through base expenditure should better funded as a priority going forward.

2.3.2 Increased uncertainty

The entirely data-driven approach to model development reduces regulatory certainty of future base allowances. This is evidenced by the lack of stability in the explanatory variables selected, in the coefficient signs and in companies' specific allowances when performing sensitivity tests.

Reduced predictability runs counter to the principles of stability set out in the government's Better Regulation Framework[7] and, ultimately, limits companies' ability to plan and deliver sustainable asset maintenance so critical for a long-term sector like the water industry. The predictability of the regulatory regime is also a key consideration for credit rating agencies, increasing the cost of capital and, ultimately, customer bills. This means

[3] The CMA has been primarily focused on the Root Mean Square Error (RMSE) using the LASSO technique.

[4] Ofwat (April 2023). Econometric Base Cost Models PR24, pg.15.

[5] Competition and Markets Authority (October 2025). PR24 PD Volume 5: Appendices and Glossary, pg. 28.

[6] Independent Water Commission (July 2025). Independent Water Commission Final Report, pg. 380: recommendation 67: "*Improving the amount of available data will allow companies and regulators to make informed, accurate and cost-effective decisions on improving system resilience and reaching a sustainable level of maintenance and replacement"*; pg. 377: para. 877: *"it is not possible to form a clear view on the condition of water industry assets, the adequacy of past renewal and maintenance".*

[7] As set out in Department for Business and Trade (September 2023). Better Regulation Framework.

that, if the CMA chooses to use the LASSO approach mechanistically to select the explanatory variables for base models in its final determinations, it would likely be ill suited for the purpose of setting price controls at future periodic reviews.

The Least Absolute Shrinkage and Selection Operator (LASSO) machine learning technique adopted by the CMA results, **by design, in a different selection and combination of cost drivers, coefficient signs and allowances over time, depending upon which variables improve the statistical fit of historic data**. This effect is further exacerbated by the industry's inherent small dataset and limited variance in explanatory variables over time. Consequently, adopting LASSO for the purpose of developing base models therefore yields a greater level of instability relative to Ofwat's PR24 base models as shown in Appendix A.

2.3.3 Lack of robustness

Considering the empirical investigations presented in Appendix A, we believe that the current base models lack the necessary robustness undermining confidence in their predictive capabilities to be able to set appropriate base allowances for each company at the next price review. This is evidenced by some of the counterintuitive signs in the models, inconsistencies with the economic and engineering rationale and lack of interpretability of the coefficients in the models which suggest that the variables selected may not be fully reflected of the actual underlying factors driving costs in the sector.

It is important to recognise that the ultimate objective of any robust cost assessment should not be model optimisation and statistical fit, but rather a fair and accurate allocation of funding to ensure each individual company is able to meet their obligations. These new base models however are primarily derived through a statistical approach which seeks to maximise the statistical fit of the model on a **purely data driven basis, with no robust coherent testing against the industry's established and well documented economic and engineering relationships.**

Absent such testing, while the **new models might perform better from a purely average statistical predictive basis, they may reflect spurious relationships that are not grounded in the underlying cost structure of the water industry**. **A good data fit does not guarantee alignment with efficient sector costs, especially given factors like inefficiency, varying costs across periods, and maintenance cycles. This leads to an inappropriate selection of cost drivers and suboptimal outcomes for companies and customers**.

Indeed, we have performed extensive sensitivity analysis of the models and have observed material changes in the signs and magnitude of coefficients when dropping specific years or individual companies from the model, relative to Ofwat's comparable models. We consider that this is driven by the high levels of multicollinearity among the independent variable set. Under these conditions, LASSO is known to fail[8].

The CMA's model suite also appears in stark contrast with previous determinations by the CMA where Ofwat's models were criticised for their shortfalls and their incapability "*to interpret the relationships that they imply between costs and explanatory variables in economic and engineering terms*[9]" with the "*counter-intuitive and unstable coefficients*"[10].

2.3.4 Over relying on small set of oversimplistic models

We suggest that the CMA reconsiders what we believe to be an over-reliance on a single set of models (one for wholesale wastewater and two for wholesale water) rather than using multiple models with different variables as developed by Ofwat at PR24, in light of the limits of any econometric modelling technique used in small samples with limited variability in the explanatory factors.

While LASSO statistical models have been widely used to develop forecasts of the average dependent variable (for example the average forecast of stock prices or house prices), this is undertaken with large datasets and

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[8] Zhao, P. and Yu, B. (2006). On Model Selection Consistency of Lasso. *Journal of Machine Learning Research,* 7: pgs. 2541-2563.

[9] Competition and Markets Authority (October 2015). Bristol Water plc: A reference under section 12(3)(a) of the WIA91 - Report, pg. 72: para. 4.50.

[10] Competition and Markets Authority (October 2015). Bristol Water plc: A reference under section 12(3)(a) of the WIA91 - Report, pg. 107, para. 4.177.

pools of explanatory variables for selection. Recognising the issues caused by small datasets, the CMA has previously stated that "*any model must be seen as an approximation*"[11] and *"… all econometric models are imperfect, and it is not possible to establish with certainty that they incorporate every single determinant of costs.*"[12] Although the fitness of the single set of models developed by the CMA may improve the predictive ability of the models relative to the historic data, it does so only for an average company. It therefore does not address or improve the ability to address the issue of companies' heterogeneity and operational characteristics such as topography and geology. Using multiple models with different variables on the other hand allows for a better reflection of individual companies' specific operational characteristics, as shown in Appendix A.

We therefore believe that the CMA should not be dismissing proposals to consider the inclusion of different variables and rejecting the need for companies' specific cost adjustment claims solely on the basis that a relevant cost variable is already included in the model.

We recommend that, in line with the PR24 approach adopted by Ofwat, **future determinations adopt a suite of models that use different types of variables to capture a cost driver and then triangulate the results across the different models**. This is a fairer approach to companies given it allows to reflect better the operational characteristics of individual companies leading to a more robust setting of efficient allowances. Triangulating also accommodates differences in companies in a more transparent and contestable way. Meanwhile, if the CMA proceeds with its LASSO based approach, it should do so with caution, particularly given the issues identified so far in its modelling.

We provide a detailed discussion of each of these issues and supporting evidence in Appendix A.

2.4 Key recommendations to the CMA

The CMA has adopted LASSO at the PD stage. However, this is a strikingly novel approach to cost assessment in the context of the water industry and, as far as we know, untested in the UK regulated utility sectors. We have reviewed the CMA's base models against the principles and frameworks developed by Ofwat and water companies over the last two regulatory periods.

These frameworks are not used to identify the 'best model' in a purely statistical sense, but to support the prediction of efficient costs for each company. This is an important distinction, because the ultimate goal of cost assessment is not necessarily model optimisation, but a fair and accurate allocation of allowances that ensures each individual company is able to meet their obligations. We set this assessment out in full in Appendix A.

In light of the issues raised above, we recommend that the CMA:

1. Proceeds with caution if it wishes to continue with a LASSO based approach and recognises **the limitations of a purely data driven approach and considers off-model ex-post adjustments to manage cost drivers,** such as energy or wage, that do not exhibit intuitive signs or specifications in the model or contribute to the instability of the model. **It may be more appropriate to use machine learning models such as LASSO as complementary and investigative tools alongside (rather than in alternative to) the more established engineering and economic cost modelling approach** to identify new appropriate cost drivers that might have not been detected through the existing approaches. Certainly, we consider that the inherent instability of the models and the lack of consistency with engineering priors would suggest that such a singular approach would be unsuitable for use at future periodic price reviews.
2. Considers **reviewing company-specific claims through engineering *deep dives* rather than automatically including all variables** to control for specific company characteristics. This is particularly the case when the model that results from the inclusion of new variables is inconsistent with the economic and engineering rationale.

[11] Competition and Markets Authority (October 2015). Bristol Water plc: A reference under section 12(3)(a) of the WIA91 - Report, pg. 59: para. 4.9 and pg.73: para. 4.50.

[12] Competition and Markets Authority (2025). Water PR24 Redetermination References, pg. 13: para. 46.

3. **Undertakes appropriate *ex-post* validation to ensure that any model developed in alternative to Ofwat's existing base models is coherent, interpretable and consistent with economic and engineering rationale, regardless of whether it has been developed through machine learning or other more traditional statistical approaches**. If the results are counterintuitive, there may be benefit in developing a different approach, considering other machine learning tools, implement rules around the variables to be selected. Any revised model should withstand these tests.
4. **Undertakes an external peer review of these models to test technical accuracy and consistency. This is required given the untested and novel approach to adopting LASSO to develop new base models to set companies' individual cost allowances.**

In conclusion, we recognise that the CMA has developed its approach to cost assessment to address the specific issue raised by disputing companies, as recognised in the following excerpt "*We have sought to apply LASSO in a way (...) targeted at resolving the issues raised in these redeterminations.*"[13]. Were the CMA to confirm its use of the LASSO approach, we believe that these revised base models do not represent a suitable alternative for setting wholesale allowances and should therefore not set a regulatory precedent for the wider industry at future Price Reviews

Our points made are generally a summarised version of the public positions previously set out by UUW in our various thought-pieces and consultation responses on this area. We would be pleased to provide any additional supplementary information or explanation that would assist the CMA with its deliberations.

[13] Competition and Markets Authority (2025). PR24 PD Volume 1: Background Chapters and Base Costs, pg. 50: para. 4.47.

Appendix A

A.1 Introduction

The CMA's approach to assessing base costs is entirely novel within regulatory cost assessment in the English and Welsh water sector. It uses a machine learning technique called LASSO to identify an appropriate set of cost drivers for use within the botex model suite. In doing so, it overrides Ofwat's model suite which, while not perfect, is the product of almost a decade of cross-industry collaboration and development. In particular, the focus on backward-looking statistical model fit undermines a focus on engineering, economic and operational rationale within the model suite.

Crucially, this prioritises the overall model fit over the ability of the model to make appropriate predictions for each company. As such, the CMA's approach seems to confuse the purpose of regulatory cost assessment. Cost assessment should not seek the best performing statistical model. Instead, it should provide an allocation of cost that is broadly appropriate for each company's individual circumstances in a future regulatory period (or AMP). **It is entirely possible that the model(s) that achieves this does (do) not 'fit' historic data better than an alternative – we are ultimately interested in the ability of the model to make predictions of future costs. As such, we are sceptical of an approach which uses LASSO in isolation from industry knowledge and experience.**

We have also identified some issues with the CMA's methodology that stem from implementing LASSO within a small dataset characterised by time-invariant variables and high levels of multicollinearity. For example, we find that the model results are unstable when the dataset is systematically varied. We have also identified a potential error within the CMA's code.

This appendix gives an overview of the analysis we have carried out in response to the CMA's proposed approach to assessing base expenditure allowances.

A.1.1 Overview of our approach

We requested the code that the CMA used to implement its approach, which allowed us to examine its methodology in detail. We would like to thank the CMA for demonstrating a commitment to regulatory transparency.

Our approach has focused on cross referencing the CMA's methodology against Ofwat's cost assessment methodology and UUW's principles of regulatory cost assessment, as set out in a UUW in Methodology paper to inform and develop the approaches used at PR24[14]. The approach adopted here is a long standing and principled approach. In particular, this has involved:

- Testing the robustness of the CMA's models and examining how this compares to Ofwat's models' robustness.
- Considering how intuitive and interpretable the CMA's methodology and model suite is.
- Assessing the engineering, operational and economic rationale that underpins the CMA's approach.
- Analysing the statistical validity of the CMA's approach and testing how this compares to Ofwat's.
- Considering how coherent the CMA's framework is.

The following sections outline our assessment of the CMA models against a set of principles developed over the last two regulatory periods by both Ofwat and water companies. These principles have not been developed to prescribe a single best technical solution to cost assessment, but to provide an objective framework grounded in sound economic and engineering rationale to assess methodological choices transparently, recognising that no one-size fits all approach can appropriately reflect the complexity of the sector.

We consider it appropriate to apply these principles given the CMA's adoption of LASSO – a novel approach to cost assessment in the context of the water industry and, as far as we know, untested in the UK regulated utility sectors for the purpose of assessing efficient costs and setting appropriate allowances. Its use by the CMA marks

[14] United Utilities (July 2021). The Principles of Regulatory Cost Assessment.

a significant departure from previous methodologies and introduces a fundamentally different way of modelling base expenditure allowances.

This assessment allows us to evaluate whether the CMA's methodology aligns with an objective cost assessment framework, which was designed to cope with changes in technical approaches to cost assessment. Importantly, **the principles are not intended to identify the 'best model' in a purely statistical sense, but to support the prediction of future efficient costs for each company**.

While LASSO is objective in that it is determined by algorithms, it focuses solely on maximising statistical fit in the historic dataset. We consider that it is better to define an objective framework that can best achieve a suitable base cost allowance for each company in future periods. A purely backwards-looking approach (such as LASSO) does not, in our view, achieve this.

A.1.2 Ofwat's cost assessment framework

Firstly, we have reviewed the base models developed by the CMA and have applied the following tests consistently with the framework developed by Ofwat and that underpin a robust cost assessment modelling approach:

- **Stability and robustness.** Are the estimated model results stable / robust to changes in the underlying assumptions and data (e.g. different sample period; alternative model specification)?
- **Intuitive and interpretable.** Are the estimated coefficients of the right sign and of plausible magnitude?
- **Predictive power.** Can the models accurately predict the efficient expenditure of companies?
- **Statistical validity.** How do the models perform across a range of statistical diagnostic tests?

Table 1 below outlines our assessment across the wholesale Water Resource Plus (WRP), Treated Water Distribution (TWD) and Wastewater (WWN). The following sections investigate each dimension in more detail.

Table 1: Assessment of CMA models against Ofwat's principles

Model	Stability and robustness	Intuitive and interpretable	Predictive power	Statistical validity	Pass/fail
WRP					**Fail**
TWD					**Fail**
WWN					**Fail**

This is based on a points-based system: red is zero points, amber is one point and green is two points. The threshold for a pass is five points.

Source: UUW analysis of CMA publication

A.1.3 UUW's Principles of Regulatory Cost Assessment

We have also assessed the models against the principles developed by UUW in a Methodology paper to inform and develop the approaches used at PR24[15]. We note that these principles were substantially debated and ultimately largely adopted by Ofwat in its PR24 Final Methodology[16] and by companies in their subsequent submissions.

[15] United Utilities (July 2021). The Principles of Regulatory Cost Assessment.

[16] See Figure 2.1 in Ofwat (2022). *PR24 Final Methodoly: Setting Expenditure Allowances*, pg. 8.

Table 2: Assessment of the PD approach opposite UUW's principles

Principle	Summary of principle	Assessment
Define the services provided	Identify and define the services provided, including interdependencies and local cost variations, to ensure fair industry comparisons.	**Disregarded.** The CMA does not refer to a definition of the services its models are seeking to explain. It relies on LASSO to identify cost drivers that best fit the historic looking data. However, this approach ignores the risk that the nature of service delivery may change in future due to external factors e.g. climate change.
Prioritise engineering economic rationale	Use clear engineering and economic logic to link cost drivers to observed costs consistently and transparently.	**Disregarded**. The models rely on predictive power and statistical fit with no robust consideration for economic and engineering relationships, complex and often lack interpretability.
Protect the benchmark's independence	Use exogenous cost drivers outside of company control to preserve benchmark credibility and avoid manipulation	**Disregarded**. The CMA includes variables that are objectively under short-term management control such as wages and average pumping head.
Expenditure outside of the modelled historical period	Integrate external validity to ensure models support future decisions with reliable forward-looking rationale.	**Disregarded**. The CMA's model prioritises the statistical fit of historic data i.e. the internal statistical fit within the data sample. No consideration is given to whether this relationship may change in future i.e. the statistical fit external to the data sample. The CMA's models are internally valid but cannot be said to be externally valid.
A coherent approach to benchmarking and the wider framework	Explain the modelling strategy, and its balance between complexity and out of model adjustments.	**Disregarded**. No balance between the level of parsimony (less variables and less models) and the recognition of the need of individual cost adjustments. Instead, the CMA seeks to deal with all cost assessment issues through one main avenue.
Challenge efficiency with a transparent, objective and stable framework	Set efficiency targets using a stable, objective framework that balances ambition with realism, and considers efficiency across an appropriate level of aggregation.	**Requires further investigation** **Frontier shift**: The approach is stretching but consistent with a more realistic Frontier Shift. **Catch up efficiency**: The efficiency scores move from 0.99 and 1.0 for respectively water and wastewater to 0.94 and 0.95 as the UQ is more efficient. UQ should not be selected a priori and ensure a stretched achievable efficiency. **Real price effects**: Wages and energy now included as variables within base models but no clarity on how ex-post reconciliation would apply.

Source: UUW analysis of CMA publication

A.1.4 How we have dealt with a potential error in the CMA's code in our analysis

Our examination has found a potential error in the R code used for the LASSO estimation of the base models. Our understanding of LASSO suggests that the code should use a threshold of one standard error around the mean square error and then select the largest corresponding lambda value. However, the code appears to erroneously add the standard error to the lambda value directly, and not to the MSE threshold[17]. While we believe this was unintended, we have not seen any correction made by the CMA since its publications of its PDs.

We have therefore focused our analysis on the original models. However, our analysis suggests that most of the points that we raise are valid for both versions (i.e. the original published models by the CMA and the ones that would result from a corrected R code).

The following section sets out the impact of this error. Note the remainder of the appendix focuses upon the CMA's published models.

A.1.5 Assessing the impact of the R code correction

We have observed a potential error in the CMA's modelling code, specifically relating to its selection of the penalty parameter, Lambda. The following three tables compare the allowances and coefficients produced by the CMA's model, with those derived from a corrected version of the code.

When we have corrected the code, we obtain a different Lambda value which causes significant volatility in the models, both in terms of coefficient selection and magnitude. As the CMA itself acknowledges, "*If Lambda is set too high, important variables are excluded, and the error rises sharply*"18. This issue is evident in the revised wastewater model which excludes all density-related drivers. This can be observed in Table 5 below, where we see the following drivers are dropped relative to the CMA's model.

- Properties per sewer length - weighted average density (log)
- LAD from MSOA - weighted average density (log)
- MSOA - weighted average density (log)
- Load treated in size bands 1 to 3 (%)

Because of the subjectivity of the CMA's decision to use the Lambda 1se rule, we would expect that the model should be relatively insensitive to minor adjustments in Lambda. This is clearly not the case. The model is not only volatile, but, by construction, is sensitive to the level of targeted parsimony. This significant shift in selected variables, despite relatively minor amendments in the modelling procedure, illustrates the potential instability associated with the use of LASSO. It raises concerns about the robustness of the original model specification and the sensitivity of the results to the modelling choices.

Table 3 below shows the difference in coefficients between the CMA's model, and the corrected model.

Table 3: WWNP: Correct 1se Rule

	CMA's model	Corrected model
Load (log)	0.675***	0.668***
Pumping capacity per sewer length (log)	0.115	0.272***
Load treated with ammonia consent ≤3mg/l	0.004**	0.006***
Weighted average treatment size (log)	(0.122)**	(0.078)***
Urban rainfall per sewer length (log)	0.088**	0.085*
Energy index interacted with pumping capacity	0.016***	0.016***
Wages interacted with load		(0.003)
Properties per sewer length - weighted average density (log)	0.599*	

[17] The error relates to adding the standard error of the smallest MSE to the lambda (associated with the smallest) rather than finding the largest lambda that results in a MSE below the smallest MSE plus one standard error, as most of the scientific literature would suggest.

[18] Competition and Markets Authority (2025). PR24 PD Volume 5: Appendices and Glossary, pg. 20: para. D7.

	CMA's model	Corrected model
LAD from MSOA - weighted average density (log)	0.193*	
MSOA - weighted average density (log)	(0.281)	
Load treated in size bands 1 to 3 (%)	0.011	
Sewer length (log)		
(Intercept)	(3.894)**	(2.789)***
Number of observations	130	130

This amendment to the code results in a £578m reduction in industry-wide allowances across water and wastewater. Table 4 and Table 5 below illustrate the significant cost allowance movements across companies. The magnitude of these fluctuations across both water and wastewater are compelling evidence of the instability of model outputs in response to relatively minor changes in the selection of lambda.

Table 4: Allowance Changes for Water

	CMA DD allowances (£m)	Corrected model (£m)	Difference (£m)	%
Anglian Water	1,722.5	1,712.9	-9.5	-0.6%
Northumbrian Water	1,403.0	1,437.0	34.1	2.4%
United Utilities	2,410.4	2,448.5	38.2	1.6%
Southern Water	888.3	893.4	5.2	0.6%
South West Water	865.6	906.2	40.6	4.7%
Thames Water	4,327.9	4,038.5	-289.4	-6.7%
Welsh Water	1,260.4	1,282.8	22.4	1.8%
Wessex Water	633.6	694.9	61.3	9.7%
Yorkshire Water	1,870.6	1,761.6	-109.0	-5.8%
Affinity Water	1,137.7	1,104.3	-33.4	-2.9%
Bristol Water	462.5	455.5	-7.0	-1.5%
Portsmouth Water	163.1	161.2	-1.9	-1.1%
SES Water	192.6	203.8	11.2	5.8%
South East Water	867.3	817.6	-49.7	-5.7%
South Staffs Water	450.8	441.6	-9.2	-2.0%
Severn Trent Water	2,822.7	3,194.0	371.3	13.2%
Hafren Dyfdwy	137.5	135.4	-2.1	-1.5%
	21,616.4	**21,689.2**	**72.8**	

Table 5: Allowance Changes for Wastewater

	CMA DD allowances (£m)	Corrected model (£m)	Variance (£m)	%
Anglian Water	1,932.6	1,887.2	-45.4	-2.3%
Northumbrian Water	827.6	785.3	-42.4	-5.1%
United Utilities	2,384.0	2,314.1	-69.9	-2.9%
Southern Water	1,926.3	1,850.2	-76.1	-3.9%
South West Water	766.3	685.7	-80.6	-10.5%
Thames Water	3,751.4	3,580.2	-171.2	-4.6%
Welsh Water	1,160.4	1,123.2	-37.2	-3.2%
Wessex Water	885.7	900.4	14.7	1.7%
Yorkshire Water	1,720.7	1,782.2	61.6	3.6%
Severn Trent Water	2,531.3	2,329.2	-202.1	-8.0%
Hafren Dyfdwy	26.5	24.4	-2.1	-8.0%
	17,912.9	**17,262.2**	**-650.7**	

Please note that all further analysis has been undertaken on a consistent basis with the CMA's modelling code to ensure consistency.

A.2 Stability and robustness

We do not consider that a data-led approach supports regulatory certainty. It also risks the stability of future allowances and companies' ability to plan activity across regulatory periods.

As recommended by the IWC's recent report *"The regulator needs to make the (economic) framework simpler, less aggressive, more predictable, more realistic and easier for investors to understand and forecast"*[19]*.* **The predictability of the regulatory regime is a key consideration for credit rating agencies and will, ultimately, impact the cost of capital. It is also important to recognise that the water sector is a long-term industry, and companies require certainty and stability around their base expenditure allowances to be able to plan and manage the maintenance of their assets.**

We therefore believe that if the LASSO approach were to be adopted beyond this determination at future price controls in the absence of further testing against the economic and engineering rationale, there would be a material decrease in certainty and predictability of companies' base allowances. This could increase the cost of capital and, ultimately, increase bills to consumers. Reduced certainty in allowances will also limit companies' ability to deliver sustainable and cost-effective maintenance programmes, reducing benefits to customers and the environment.

A.2.1 We have concerns over a strictly data-led approach such as LASSO

LASSO is a technique used to select variables from a defined pool of variables and define the appropriate specification for each variable (e.g. linear, quadratic, interactive), based on the impact on the Root Mean Square Error (RMSE). Using mechanistically LASSO for determining base models could result in a different selection and combination of cost drivers and parameters over time, depending on which variables best explain the variance in the data.

Typically, LASSO can be effective in high-dimensional environments where there are many regressors and fewer observations. Applying this technique to small samples with few regressors, however, leads to issues of

[19] Independent Water Commission (July 2025). Independent Water Commission Final Report, pg. 326: para. 755.

consistency and interpretability. A pure data-led approach introduces instability to model predictions, as changing data results in different model specifications, which in turn leads to uncertainty over long-term allowances. This problem is likely to be further exacerbated by the small dataset, where minor changes to inputs can lead to large variations in results. Machine learning models such as LASSO could be used instead as diagnostic and investigative tools alongside more traditional cost modelling approaches to identify new appropriate cost drivers that might have not been detected through established approaches.

In light of this, we have undertaken extensive sensitivity testing of the CMA models and have concluded that there is significant instability in the model specifications and in the final cost-efficient allowances when dropping specific years, changing the penalty function used and excluding specific companies. We have also compared the stability of the CMA models relative to Ofwat's PR24 base models and have also tested more granular model variations (disaggregating costs across the value chain) with LASSO and have concluded that this approach is inherently unstable and unsuited for the purpose of setting companies' efficient base allowances.

The use of LASSO in regulatory cost assessment would mechanistically result in frequent model changes due to sensitivity to new years of data. This will make it difficult for companies to plan and invest with confidence given the material changes in base allowances that could result from one AMP to another just as the result of the inevitable changes to the model. Crucially, we do not consider the CMA has robustly explained why the significant reduction in industry base allowances is appropriate and how this aligns with the wider cost pressures the industry is under.

A.2.2 LASSO fails under extensive multicollinearity

LASSO is known to fail when multicollinearity is too high[20]. We present evidence later in this appendix that the CMA's models fail conventional multicollinearity tests (see Table 12 in section A.2.5). There are several symptoms within the CMA's results which indicate the unsuitability of LASSO for determining the 'true' relevant variables within this industry:

- The inclusion of three correlated density variables in each of the base models.
- Instability in the selection of relevant variables, particularly within subsets of highly correlated variable types, across alternative model periods and company groups (see Table 8: Description of Modelling Results).
- The inclusion of variables which run contrary to economic rationale (see Table 8: Description of Modelling Results).

We consider that this demonstrates LASSO's unsuitability for use in regulatory cost assessment.

A.2.3 Model Stability

This section presents how the coefficients vary across the different modelled scenarios, showing how small changes in the modelling period, lambda penalty parameter and scale drivers, lead to dramatic differences in variable selection and coefficient magnitudes, significance and signage. This volatility raises questions about the stability of the underling model relationships, and the extent to which these outputs can be relied upon for setting cost efficient allowances. Our scenarios only test minor model modifications yet result in materially different outcomes.

The scenarios tested, for WRP, TWD and WWNP respectively, are as follows:

[20] Zhao, P. and Yu, B. (2006). On Model Selection Consistency of Lasso. *Journal of Machine Learning Research,* 7: pgs. 2541-2563.

Table 6: Modelled scenarios

Scenario 1 – Drop scale interaction term from wages (length of mains)
Scenario 2 – Drop scale interaction term from energy (length of mains)
Scenario 3 – Drop scale interaction term for both wages and energy (length of mains)
Scenario 4 – Remove energy and wages as variable for selection
Scenario 5 – Drop 2023-24 data
Scenario 6 – Drop 2022-23 and 2023-24 data
Scenario 7 – Drop 22-23data
Scenario 8 – Drop 21-22 data
Scenario 9 – Drop 20-21 data
Scenario 10 – Drop 19-20 data
Scenario 11 – Drop Thames from dataset
Scenario 12 – Drop Portsmouth from dataset [WRP and TWD only]
Scenario 13 – Drop South Staffs from dataset [WRP and TWD only]
Scenario 14 – Replace Lambda_1se with Lambda_min
Scenario 15 – Use Alpha_0
Scenario 16 – Use Alpha_0.5

The 16 sensitivity scenarios can be grouped into three broad categories:

- the removal of interaction terms on power and/or wages (scenarios 1-4);
- changes to the sample size (scenarios 5-13); and
- changes to Lambda (scenario 14-16).

We have then assessed the impact of each scenario against three general broad criteria:

- the size of the coefficients generated in the resulting regression;
- the consistency of signage with the base case; and
- the volatility in the variable selection within LASSO.

We have summarised our review of how the resulting models perform in the table below. A full table of coefficients for each model is presented the following sections.

Table 7: Assessment of stability of CMA models

		Interaction terms	Sample size	Lambda
Size of coefficients	Water Resources plus	!	!	✖
	Treated Water Distribution	✔	✔	✖
	Wastewater Network plus	✖	✖	✖
Consistency of signage within selected variables	Water Resources plus	✖	!	✖
	Treated Water Distribution	✔	!	✖
	Wastewater Network plus	✖	✖	✖
Variable selection within LASSO	Water Resources plus	✔	!	✖
	Treated Water Distribution	✔	!	!
	Wastewater Network plus	✖	✖	!

Red: serious concerns with resulting models

Amber: material conflicts with CMA base case and/or engineering and economic assumptions
Green: no material issues

Table 8: Description of Modelling Results

Concern	Description	Relevant Scenarios
Counter-intuitive Signs	Properties per sewer length: changes sign when the modelling period does not include the most recent year(s) of data.	*Table 11:* WWNP Modelling Results Properties per sewer length: Scenarios 5 and 6
	Pumping capacity per sewer length: becomes negative when Thames is dropped. This is entirely counter to economic rationale.	*Table 11:* WWNP Modelling Results Pumping capacity per sewer length: Scenario 11
	Load treated in size bands 1 to 3: becomes negative when the modelling period does not include the most recent year(s) of data or Thames. This contradicts the CMA's statement that "all included variables are of the sign we would expect, suggesting the model has a strong economic and engineering rationale"[21]	*Table 11:* WWNP Modelling Results Load treated in size bands 1 to 3: Scenarios 5, 6 and 11
	Wage: in certain scenarios, such as when 19-20 data is excluded, scaled wage presents with a negative coefficient.	*Table 10:* TWD Modelling Results Wages interacted with length of mains: Scenarios 2 and 10
Coefficient Magnitude	Property: High volatility in the size of coefficient across scenarios. As a key driver of modelled costs, this leads to significant variance across company-level allowances. Changing the modelled period by a year should not substantially increase the influence of scale.	*Table 10:* TWD Modelling Results Connected Properties: All scenarios
	Load: The influence of the load variable varies markedly across modelling periods, with its coefficient nearly doubling when the 2023/24 data is excluded. This shift is difficult to rationalise, as there is no apparent change within that year of data that should significantly increase the influence of load on cost allowances.	*Table 11:* WWNP Modelling Results Load: All scenarios
	Properties per sewer length: High volatility in size of coefficient across most scenarios.	*Table 11:* WWNP Modelling Results Properties per sewer length – WAD Base case, Scenarios 5 to 10.
Shape of Relationships	Properties per Length: the base model reflects Ofwat's assumption that properties per length has a U-shaped effect on costs. However, the squared term drops out when the modelling period changes, or when energy and wages are excluded. The shape of the relationship should not alter from quadratic to linear across time periods.	*Table 9: WRP Modelling* Results Properties per length – WAD Properties per length – Squared WAD Base case, Scenarios 4 to 10

[21] Competition and Markets Authority (2025). PR24 Volume 5: Appendices and Glossary, pg.25: para. D.18.

Concern	Description	Relevant Scenarios
Chosen Variables	Wage: The removal of the lengths of mains interaction leads to the inclusion of wage within the model.	*Table 10:* TWD Modelling Results Wage: Scenario 1 *Table 11:* WWNP Modelling Results Wage: Scenario 3
	Weighted average treatment complexity: This enters into the model when each of the outlier companies are dropped in turn.	Weighted average treatment complexity: Scenarios 11 to 13
	Sewer length: This plays a role in most of the scenarios outside of the base case, with a prominent role when other time periods are considered.	*Table 11:* WWNP Modelling Results Sewer length: Scenarios 3 to 11
	Wages interacted with load: This enters into the model in most scenarios outside of the base case, including consideration of other modelling periods.	*Table 11:* WWNP Modelling Results Wage interacted with length of mains: Scenarios 5 to 11

Source: UUW analysis of CMA publication

Table 9, Table 10 and Table 11 below present the coefficients for WRP, TWD and WwNP across the same 16 scenarios run previously (outlined in Table 6 above). Each scenario can be compared against the base case outlined by the CMA in its provisional determinations.

Table 9: WRP Modelling Results

	CMA's model	Scenario 1 - Drop scale interaction term from wages	Scenario 2 – Drop scale interaction term from energy	Scenario 3 – Drop scale interaction term for wages and energy	Scenario 4 - Remove energy and wages as variables	Scenario 5 – Drop 2023-24 data	Scenario 6 – Drop 2022-23 and 2023-24 data	Scenario 7 - Drop 22-23 data	Scenario 8 – Drop 21-22 data	Scenario 9 – Drop 20-21 data	Scenario 10 – Drop 19-20 data	Scenario 11 - Drop Thames from dataset	Scenario 12 - Drop Portsmouth from dataset [WRP and TWD only]	Scenario 13 - Drop South Staffs from dataset [WRP and TWD only]
Connected properties (log)	0.897***	0.877***	1.021***	0.958***	0.973***	0.906***	0.941***	0.923***	0.907***	0.915***	0.988***	0.894***	0.808***	0.900***
Water treated at complexity levels 3 to 6 (%)	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.010***	0.016***	0.015***	0.013***
LAD from MSOA - Weighted average density (log)	(0.500)***	(0.511)***	(0.516)***	(0.503)***	(0.457)***	(0.463)***	(0.473)***	(0.454)***	(0.436)***	(0.437)***	(0.467)***	(0.474)***	(0.525)***	(0.410)***
MSOA - Squared weighted average density (log)	0.088***	0.090***	0.090***	0.088***	0.076***	0.075***	0.075***	0.074***	0.073***	0.073***	0.077***	0.083***	0.101***	0.070***
Properties per length - Weighted average density (log)	3.309	3.203	3.034	3.270	(1.375)***	(1.259)***	(1.291)***	(1.305)***	(1.336)***	(1.300)***	(1.309)***		2.130	(1.164)***
Properties per length - Squared weighted average density (log)	(0.563)*	(0.543)*	(0.539).	(0.565)*								(0.162)***	(0.416)	
Wages interacted with the length of mains			(0.024)								(0.037)			
Average volume per WTW (log)	(0.083)	(0.066)	(0.070)	(0.084).	(0.068)	(0.066)	(0.074)	(0.072)	(0.087).	(0.068)	(0.050)	(0.038)	(0.092).	(0.045)
Energy index interacted with the length of mains	0.013	0.016.				0.013	0.005	0.010	0.012	0.012	0.017.	0.016.	0.021**	0.016*
Energy			0.135	0.106										
Wage		(0.272)												
Weighted average treatment												(0.192)**	(0.281)***	(0.118)
MSOA - Weighted average density														
LAD from MSOA - Squared weighted average density (log)														
(Intercept)	(15.537)**	(14.630)**	(15.975)***	(16.099)***	(5.887)***	(5.915)***	(5.841)***	(5.856)***	(5.661)***	(5.882)***	(6.151)***	(8.355)***	(12.117)**	(6.154)***
Number of observations	221	221	221	221	221	204	187	204	204	204	204	208	208	208

*** significance at 0.1% level

** significance at 1% level

* significance at 5% level

. significant at 10% level

Red text = new variables selected (relative to CMA base case

Blue text = change in coefficient sign

Grey block = variable dropped relative to CMA base case

Table 10: TWD Modelling Results

	CMA's model	Scenario 1 - Drop scale interaction term from wages	Scenario 2 – Drop scale interaction term from energy	Scenario 3 – Drop scale interaction term for wages and energy	Scenario 4 - Remove energy and wages as variables	Scenario 5 – Drop 2023-24 data	Scenario 6 – Drop 2022-23 and 2023-24 data	Scenario 7 - Drop 22-23 data	Scenario 8 – Drop 21-22 data	Scenario 9 – Drop 20-21 data	Scenario 10 – Drop 19-20 data	Scenario 11 - Drop Thames from dataset	Scenario 12 - Drop Portsmouth from dataset [WRP and TWD only]	Scenario 13 - Drop South Staffs from dataset [WRP and TWD only]
LAD from MSOA - Weighted average density (log)	(2.280)***	(2.310)***	(2.279)***	(2.309)***	(2.301)***	(2.340)***	(2.357)***	(2.288)***	(2.279)***	(2.293)***	(2.206)***		(2.170)***	(2.303)***
LAD from MSOA - Squared weighted average density (log)	0.158***	0.160***	0.158***	0.160***	0.155***	0.161***	0.162***	0.158***	0.159***	0.161***	0.154***		0.151***	0.161***
MSOA - Squared weighted average density (log)	0.031***	0.031***	0.031***	0.031***	0.039***	0.032***	0.032**	0.031**	0.030**	0.028**	0.028**	0.179	0.030***	0.027**
Properties per length - Squared weighted average density (log)	0.040*	0.042*	0.042*	0.043*	0.043*	0.044*	0.048*	0.043*	0.038.	0.039.	0.043*	0.059**	0.039*	0.049*
Length of mains (log)	0.865***	0.970***	0.949***	1.052***	1.042***	0.883***	0.884***	0.873***	0.833***	0.847***	0.838***	0.807***	0.847***	0.864***
Booster pumping stations per length of mains (log)	0.306***	0.309***	0.304***	0.306***	0.265***	0.302***	0.293***	0.301***	0.333***	0.320***	0.330***	0.417***	0.319***	0.307***
Average pumping head TWD (log)	0.338***	0.341***	0.338***	0.340***	0.365***	0.374***	0.388***	0.347***	0.340***	0.338***	0.321***	0.276***	0.283***	0.360***
Wages interacted with the length of mains	0.037		0.036			0.034	0.026	0.031	0.050.	0.045.	0.053*	0.046*	0.041.	0.033
Energy index interacted with the length of mains	0.017**	0.017**				0.016.	0.021	0.019**	0.016**	0.016**	0.015*	0.017**	0.016**	0.020**
Wages		0.361.		0.349										
Energy			0.167**	0.167**										
MSOA - Weighted average density (log)												(2.595)		
Properties per length - Weighted average density (log)														
(Intercept)	(0.291)	(1.216)	(1.120)	(2.017)*	(0.775)	(0.371)	(0.463)	(0.355)	(0.131)	(0.101)	(0.374)	3.450	(0.259)	(0.282)
Number of observations	221	221	221	221	221	204	187	204	204	204	204	208	208	208

*** significance at 0.1% level

** significance at 1% level

* significance at 5% level

. significance at 10% level

Red text = new variables selected (relative to CMA base case

Blue text = change in coefficient sign

Grey block = variable dropped relative to CMA base case

Table 11: WWNP Modelling Results

	CMA's model	Scenario 1 - Drop scale interaction term from wages	Scenario 2 – Drop scale interaction term from energy	Scenario 3 – Drop scale interaction term for wages and energy	Scenario 4 - Remove energy and wages as variables	Scenario 5 – Drop 2023-24 data	Scenario 6 – Drop 2022-23 and 2023-24 data	Scenario 7 - Drop 22-23 data	Scenario 8 – Drop 21-22 data	Scenario 9 – Drop 20-21 data	Scenario 10 – Drop 19-20 data	Scenario 11 - Drop Thames from dataset
Load (log)	0.675***	0.675***	0.745***	1.164***	0.717*	1.146***	1.064**	1.215***	1.217***	1.248***	1.093**	0.942**
Sewer length (log)				(0.463)	(0.004)	(0.571).	(0.506)	(0.646).	(0.614).	(0.683).	(0.481)	(0.463)
Properties per sewer length - weighted average density (log)	0.599*	0.599*	0.534.	0.188	0.670.	(0.058)	(0.213)	0.009	0.071	0.061	0.311	0.316
Pumping capacity per sewer length (log)	0.115	0.115	0.191.	0.161	0.162	0.168	0.227.	0.079	0.073	0.076	0.048	(0.031)
Load treated with ammonia consent ≤3mg/l	0.004**	0.004**	0.004**	0.004**	0.005**	0.004**	0.005***	0.004**	0.003*	0.003*	0.004**	0.005*
LAD from MSOA - weighted average density (log)	0.193*	0.193*	0.204*	0.287**	0.158	0.292**	0.274*	0.289**	0.302**	0.356**	0.285*	0.530***
MSOA - weighted average density (log)	(0.281)	(0.281).	(0.299)*	(0.437)*	(0.258)	(0.532)*	(0.575)**	(0.479)*	(0.462)*	(0.545)*	(0.407).	(1.217)***
Weighted average treatment size (log)	(0.122)**	(0.122)**	(0.125)**	(0.147)**	(0.136)**	(0.112)*	(0.077).	(0.130)**	(0.143)**	(0.152)**	(0.161)***	(0.282)***
Load treated in size bands 1 to 3 (%)	0.011	0.011	0.011	0.005	0.012	(0.002)	(0.008)	0.001	0.004	0.004	0.008	(0.063)**
Urban rainfall per sewer length (log)	0.088**	0.088**	0.083**	0.056	0.093*	0.052	0.067	0.047	0.059	0.061	0.064	0.110*
Wages interacted with load						0.021	0.031	0.008	0.007	0.019	0.002	0.005
Energy index interacted with pumping capacity	0.016***	0.016***	0.183***			0.009	0.004	0.021***	0.018**	0.016**	0.017**	0.020***
Wages				0.097								
Energy				0.192**								
(Intercept)	(3.894)**	(3.894)**	(4.525)***	(3.178)*	(0.559)	(0.559)	0.454	(1.257)	(1.689)	(1.300)	(2.390)	5.243.
Number of observations	130	130	130	130	130	120	110	120	120	120	120	117

*** significance at 0.1% level

** significance at 1% level

* significance at 5% level

. significance at 10% level

Red text = new variables selected (relative to CMA base case

Blue text = change in coefficient sign

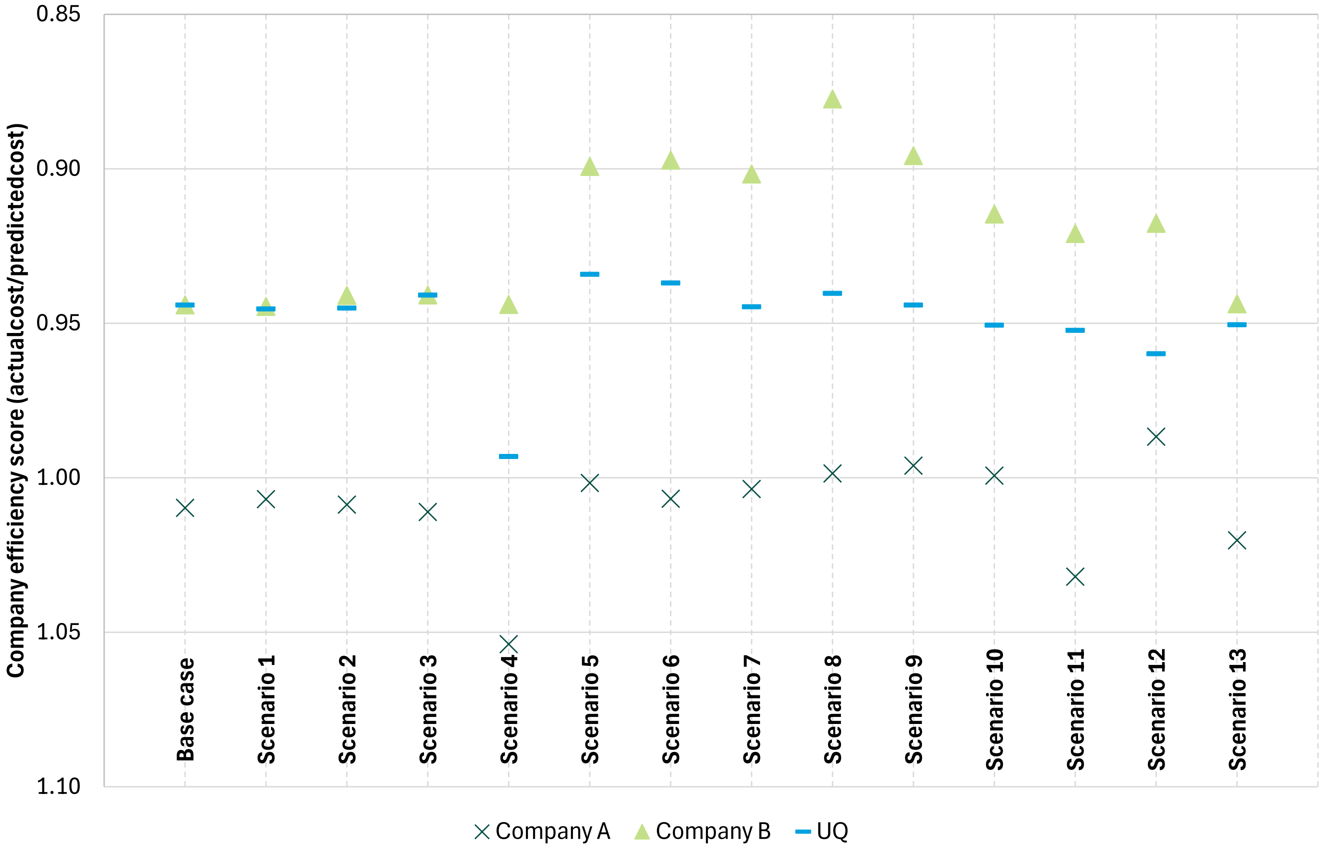
Grey block = variable dropped relative to CMA base case

The re-modelling exercise across the 16 scenarios above reveals notable shifts in variable selection and coefficient magnitudes and signs, particularly for density-related variables and scale interaction terms. These findings demonstrate that variable selection and coefficient sign and magnitude are highly sensitive to only minor structural changes in model specification and data inclusion.

This volatility is concerning because it raises questions about the stability of the underling relationships being estimated in the model, and the extent these outputs can be relied upon for setting cost allowances. Our scenarios only test minor model modifications yet result in materially different outcomes.

This can be further evidenced by assessing the impact on company efficiency scores across the same scenarios outlined above[22]. It shows that the ability of the models to accurately predict company expenditure is highly sensitive to changes in sample data.

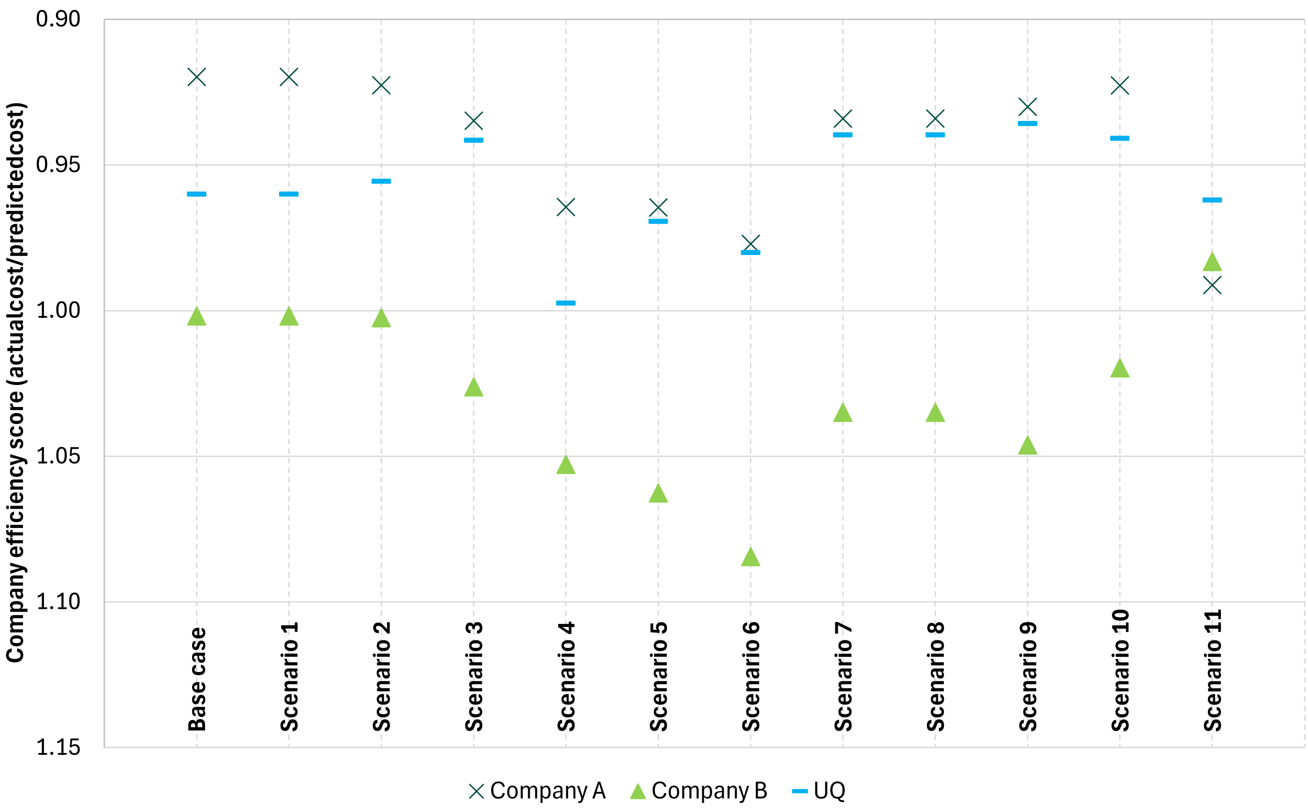
Figure 1: Impact on company efficiency scores of changes in sample data (Water)



Source: UUW analysis of CMA publication

[22] Note: we maintain the same 'catchupperiod' used in the base case for all scenarios.

Figure 2: Impact on company efficiency scores of changes in sample data (Wastewater)



Source: UUW analysis of CMA publication

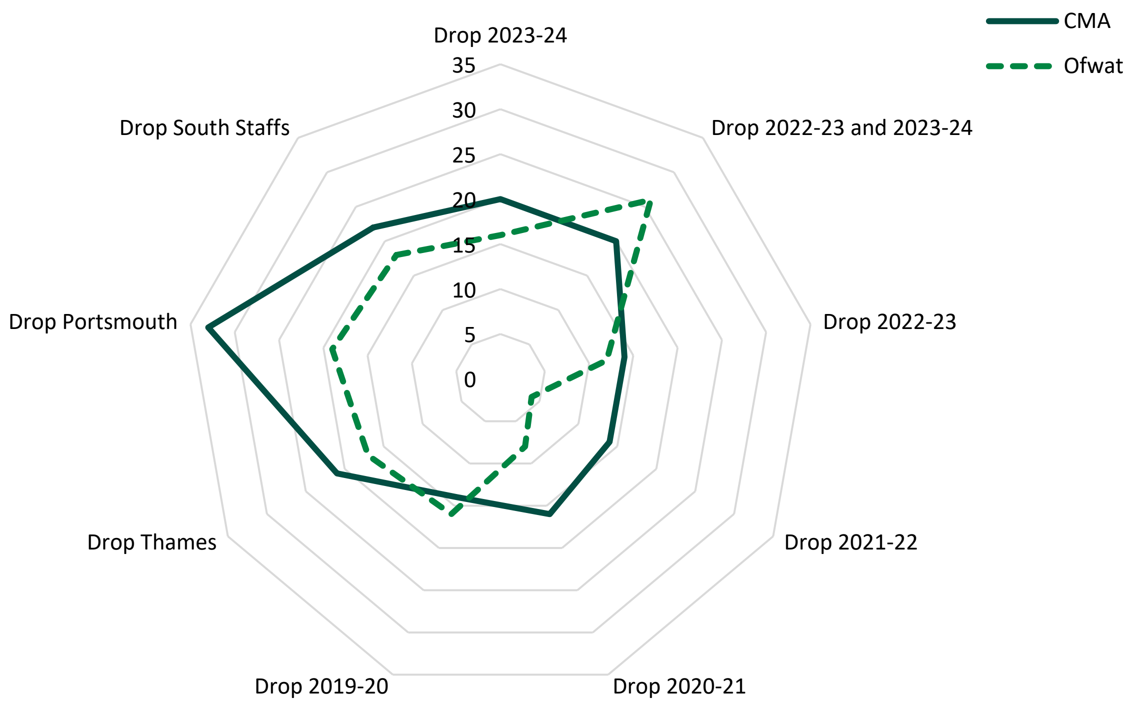
While these graphs are helpful in assessing the volatility within the CMA's model suite, we have assessed also how this volatility compares to that within Ofwat's model suite. To achieve this, we examined how relative efficiency rankings changed under each scenario for the CMA and Ofwat's model suite respectively. We would expect relative efficiency rankings to be stable as the underlying dataset is systematically varied – this aligns with the view that relative efficiency is driven by the underlying characteristics of each company, not the modelling methodology choice.

We calculated the total movements in efficiency rankings under each of the scenarios above for the CMA and Ofwat's model suite respectively. For example, if we altered the underlying dataset, reran the models and observed that Company A moved down two places and Company B moved up two places, the total movement in efficiency rankings would be five. We can compare the total movements for both Ofwat and the CMA. Fewer movements in efficiency rankings would indicate that the underlying model is more stable.

Figure 3 illustrates the outcome of this analysis using a spider diagram. This diagram measures the total movement in efficiency rankings, starting at zero in the centre. Under this framework, a smaller area shows that there are less movements in efficiency rankings under each scenario.

It's clear that Ofwat's model suite results in less movements in the overall efficiency ranking relative to the CMA. This demonstrates that Ofwat's models are more robust than the CMA's.

Figure 3: Sum of the movements in relative efficiency rankings relative to the base case by scenario



A.2.4 The CMA's model estimates are less robust than Ofwat's model to changes in the underlying dataset

The results above demonstrate that the CMA's models are sensitive to changes in the underlying dataset and model parameters. This section compares how the CMA's models respond to changes in the underlying dataset, relative to Ofwat's model.

To carry out this analysis, we iteratively dropped each company and year and examined how the model coefficients responded across the CMA's and Ofwat's corresponding models. A more stable model would be characterised by less variation in the coefficients following a change to the underlying dataset. Conversely, a less stable model would exhibit more variation in the coefficients. This is undesirable in the context of regulatory cost assessment because it undermines confidence in the robustness of the regulatory settlement.

Figure 4 shows the effect of iteratively varying the underlying dataset on the properties coefficient in the CMA's Water Resources Plus (WRP) model and Ofwat's WRP1 model using a histogram. A wider histogram shows that the coefficient varies more in response to changes in the underlying dataset, which suggests that the model is less stable. It is clear that the CMA's WRP model has more variation than Ofwat's. This demonstrates that Ofwat's model is more stable.

Figure 4, Figure 5 and Figure 6 each show the same analysis for 'percentage of water treated in complexity bands 3-6' and the squared 'weighted average density' variable respectively. Again, this analysis demonstrates that Ofwat's model is more robust than the CMA's.

For brevity, we have only presented a selection of results of our robustness testing. However, we note that the results presented below are indicative of our wider findings (for example, as set out in the previous section).

Figure 4: The properties coefficient is more stable in Ofwat's WRP model

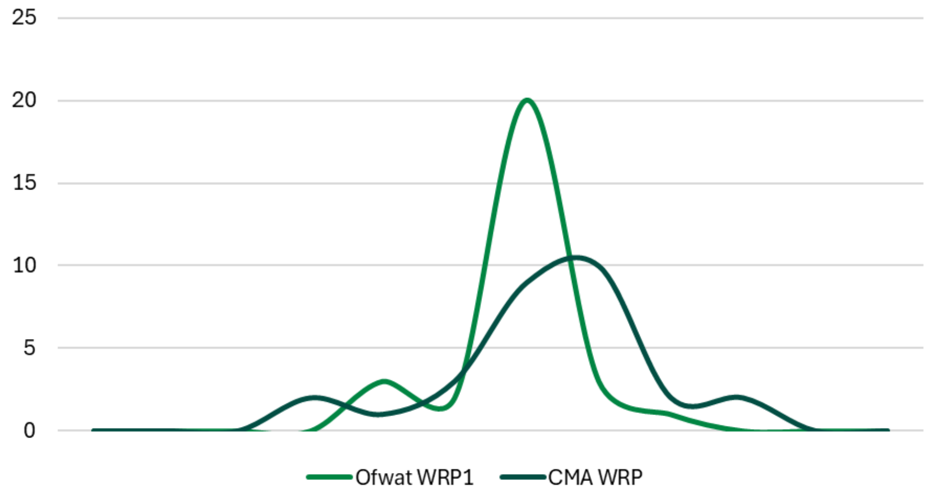


Figure 5: Percentage of water treated in complexity bands 3-6 is more stable in Ofwat's WRP model

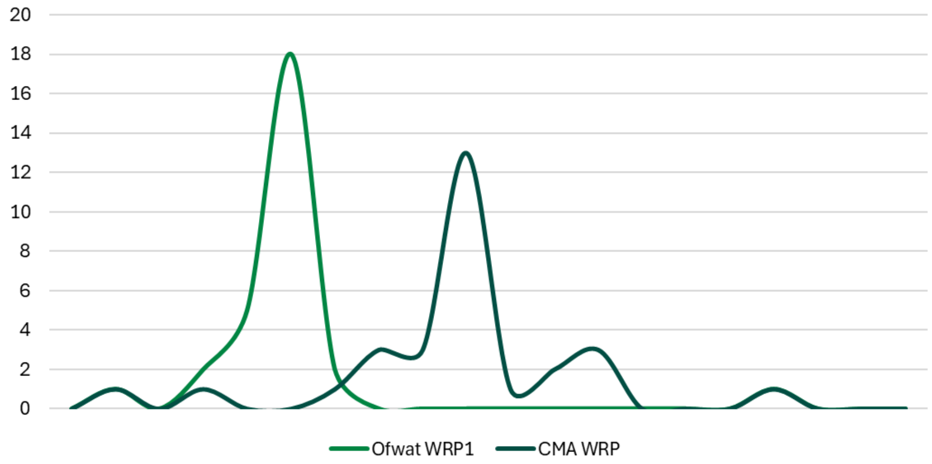
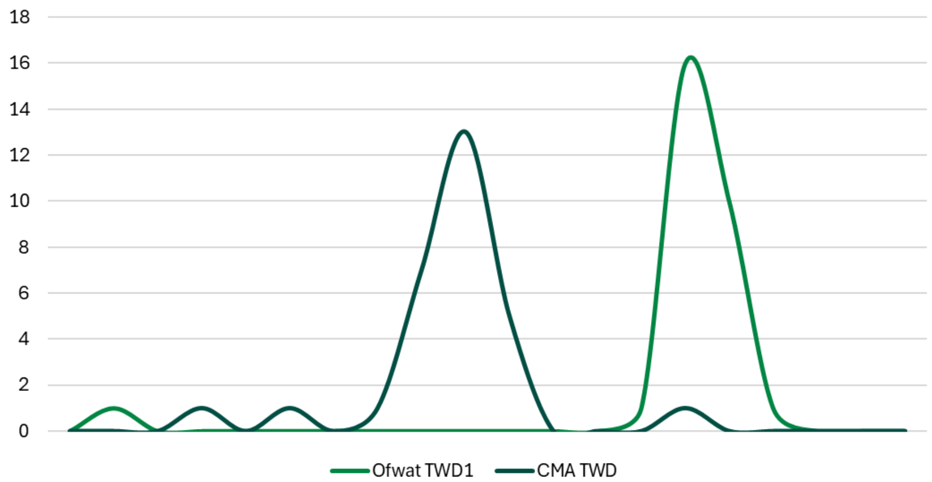


Figure 6 Weighted average density squared is more stable in Ofwat's model



Source: UUW analysis of CMA publication

A.2.5 Statistical validity

We have performed an established suite of tests to check for statistical validity consistently with the approach adopted at PR24 and have compared the CMA suite of models against the suite of PR24 models developed by Ofwat. We have performed these for all models separately and have compared this to those Ofwat published in tables 10 to 24 of the PR24 FD base cost modelling appendix[23].

The results are set out in Table 12. We have coded the outcome of each test according to the following criteria:

- **Green:** Objectively strong statistical tests across most/all models. We use the 10% significance level to judge statistical significance for the t, RESET, normality and heteroscedasticity tests. We use 10 as the benchmark in the Variance Inflation Factor test.
- **Amber:** Mixed statistical results across most/all models. We use the 10% significance level to judge statistical significance for the t, RESET, normality and heteroscedasticity tests. We use 10 as the benchmark in the Variance Inflation Factor test.
- **Red:** Objectively weak statistical results across most/all models. We use the 10% significance level to judge statistical significance for the t, RESET, normality and heteroscedasticity tests. We use 10 as the benchmark in the Variance Inflation Factor test.

Table 12: Statistical validity tests of CMA base models and Ofwat PR24 base cost models

	Ofwat			CMA		
	WRP	TWD	WwNP	WRP	TWD	WwNP
Statistical significance of individual tests (t test)	Green	Green	Green	Amber	Amber	Amber
RESET test	Green	Green	Red	Red	Red	Green
Variance Inflation Factor (VIF)	Green	Green	Green	Red	Red	Red
Normality test	Amber	Green	Red	Red	Green	Green
Heteroscedasticity test	Red	Amber	Amber	Red	Green	Red

Source: UUW analysis of CMA publication

This analysis shows clearly that Ofwat's models perform better than the CMA's across most statistical tests. This supports the finding presented above that Ofwat's models are more robust than the CMA's.

We also note that the CMA doesn't control for the presence of autocorrelation, heteroskedasticity or company-specific effects e.g. through the use of cluster robust standard errors or a fixed/random effect estimator. This appears contrary to best practice in cost assessment.

A.2.6 Reordering of Variables

In LASSO, the ordering of the variable list can impact the results of the selected variables causing greater instability.

The CMA's R code involves building a model matrix, which includes all the variables within the following section of code for the WRP model:

```
cols_to_keep<-c("lnrealbotexpluswrp", "lnproperties", "pctwatertreated36", "wac",
"lnWAD_MSOAtoLAD_population", "lnWAD_MSOA_population", "lnWAD_MSOAtoLAD_population2",
"lnWAD_MSOA_population2", "lnpropperlength", "lnpropperlength2", "wage_scale", "ratiowtw",
"energy_scale")
```

[23] Ofwat (December 2024). PR24 FD: Expenditure Allowances-Base Cost Modelling Decision Appendix, pgs. 64-78.

We have tested the impact that the ordering of the variables would have by amending the code:

cols_to_keep <- c("lnrealbotexpluswrp", "wage_scale", "wac", "ratiowtw", "pctwatertreated36", "lnWAD_MSOAtoLAD_population2", "lnWAD_MSOAtoLAD_population", "lnWAD_MSOA_population2", "lnWAD_MSOA_population", "lnpropperlength2","lnpropperlength", "lnproperties", "energy_scale")

This resulted in significant changes to the resultant model. For example, the squared term for properties per length disappears. This ultimately leads to a £53 million increase in industry allowances for water overall, including a stark £115 million uplift for Thames.

Table 13: Impact of changes in the ordering of variables within the LASSO operation

	Base Case	Reordered Variable List
Connected properties (log)	0.897***	0.916***
Water treated at complexity levels 3 to 6 (%)	0.009***	0.009***
LAD from MSOA - Weighted average density (log)	(0.500)***	(0.446)***
MSOA - Squared weighted average density (log)	0.088***	0.075***
Properties per length - Weighted average density (log)	3.309	(1.310)***
Properties per length - Squared weighted average density (log)	(0.563)*	
Wages interacted with the length of mains		
Average volume per WTW (log)	(0.083)	(0.065)
Energy index interacted with the length of mains	0.013	0.012
Energy		
Wage		
Weighted average treatment complexity		
MSOA - Weighted average density (log)		
LAD from MSOA - Squared weighted average density (log)		
(Intercept)	(15.537)**	(5.896)***
Number of observations	221	221

Source: UUW analysis of CMA publication

This implies that there is an important level of arbitrariness and subjectivity involved in the execution of the CMA's LASSO code. This contradicts the CMA's intention to 'apply LASSO in a way that is objective'.[24]

[24] Competition and Markets Authority (2025). PR24 PD Volume 1: Background Chapters and Base Costs Provisional Determinations, pg. 50: para. 4.47.

A.3 Intuitive and interpretable

The new base models exhibit counterintuitive features; the coefficients of several variables lack interpretability and are of unexpected magnitude and sign.

A.3.1 LASSO results in unusual model specifications, increasing complexity and reducing transparency and interpretability

Ofwat's base models included a range of different cost drivers within each model, typically using only one variable to proxy for the impact of each cost driver. It changed which variable it used as a cost driver proxy across the suite of models and triangulated the results. This approach helped maintain simplicity within individual models, enabling stakeholders to transparently assess whether the estimated coefficient were a reasonable sign and magnitude.

The LASSO approach used for model selection for base models has led to a model specification that includes several different proxies for each cost driver within the same model. Table 14 summarises how many variables proxying each cost driver category have been included in each of the three models developed by the CMA. It shows that three different 'density' variables have been included in each model. Additionally, the water resources plus model includes two separate 'topography' variables, while the wastewater model includes two distinct proxies for economies of scale. This appears to be counter to what would be expected under a LASSO approach, which prioritises parsimony.

Table 14: Count of variable by cost driver category in each CMA botex model

Cost driver category	Water resources plus	Treated water distribution	Wastewater
Scale	1	1	1
Complexity	0	1	1
Density[25]	3	3	3
Topography	2	0	1
Urban rainfall	0	0	1
Economies of scale	0	1	2
Cost adjustment	2	1	1

Source: UUW analysis of CMA publication

We note that the CMA does not attempt to justify the inclusion of three variables that proxy for the same cost driver in a single model. We consider that there are two issues with this approach.

- **Interpretability**. Firstly, the interpretation of each cost driver's impact on cost is unclear. For example, to estimate the impact of density on base costs, we would need to jointly consider the coefficients for all three variables holding everything else constant. While cost assessment is primarily concerned with prediction rather than interpretation, we consider that interpretation helps us to understand the robustness of the model prediction. As such, we would question the robustness of an approach that makes interpretation more difficult.
- **Model complexity.** Secondly, the inclusion of several variables that proxy for the same cost driver increases the complexity of the model. While their inclusion may be justified statistically on the basis that the variables collectively reduce the RMSE given the penalty function, this runs contrary to the CMA's stated justification that it was reducing complexity of Ofwat's approach as stated at PR14: "*While regulation is a complex activity,*

[25] The water cost models incorporate both a linear and a squared density term, enabling the model to capture a U-shaped relationship between costs and density. Although these are two separate coefficient terms, estimated separately, they work together to represent a single underlying effect of density on cost. As such, we treat them jointly as one variable when interpreting model results.

and to some extent necessarily so, we consider it important to guard against over-complexity"[26]. Rather than reducing the complexity, the CMA appears to have swapped a large model suite made up of simple models with a small number of more complicated models derived using advanced machine learning methods. As such, it is not clear to us that the overall complexity of the base cost modelling approach has reduced. We strongly consider Ofwat's approach to be more transparent to stakeholders in general. Transparency underpins an effective regulatory framework that supports long-term planning.

A.3.2 LASSO produces a model that has counter intuitive coefficients

As well as an over specified model, LASSO appears to have produced coefficient estimates that are contrary to conventional engineering and operational rationale. The coefficients for density variables also appear to be inconsistent. As Table 15 below shows, the 'properties per length – weighted average density' variables suggest that economies of scale exist. This can be seen through the positive coefficient of 3.31 on the linear variable and the negative coefficient of -0.56 on the squared variable. However, 'MSOA – squared weighted average density' has a positive sign which suggests the opposite effect.

Table 15: Analysis of the CMA's water resources plus model

Variable	Coefficient	Commentary
(Intercept)	-15.54**	
Connected properties (log)	0.90***	A coefficient less than one in log-log functional form implies economies of scale in water resources plus costs.
Water treated at complexity levels 3 to 6 (%)	0.01***	
LAD from MSOA - Weighted average density (log)	-0.50***	This suggests that costs decrease as scale increase, which implies economies of scale increase.
MSOA - Squared weighted average density (log)	0.09***	LASSO appears to have selected a squared term without a linear counterpart. However, the coefficient's sign appears to run counter to the result implied by the other squared density term i.e. more density increases costs exponentially.
Properties per length (log)	3.31	These variables jointly imply an inverted u-shape relationship. This suggests economies of scale exist, which aligns with engineering rationale. However, this is contradictory to the coefficient on 'MSOA – squared weighted average density'.
Properties per length squared (log)	-0.56*	
Average volume per WTW (log)	-0.08	This implies economies of scale exist. However, the value of including this variable alongside other variables that capture economies of scale in a more exogenous way (such as population density) is unclear.
Energy index interacted with the length of mains (log *log)	0.01	

Source: UUW analysis of CMA publication

While we acknowledge that these variables need to be jointly interpreted to understand whether the modelled marginal effect of density on cost is intuitive, this is a technically complex exercise. As such, the inclusion of two alternative quadratic density terms means that, rather than enhancing transparency as the CMA intended, transparency reduces. The CMA states in paragraph 4.57 of its PDs that *'the models that result from this approach*

[26] Competition and Markets Authority (October 2015). Bristol Water plc: A reference under section 12(3)(a) of the WIA91 - Report, pg.370: para. 12.24.

are considerably simpler'. Our view is this revised approach may instead make the models more difficult to interpret and less accessible to non-specialist audiences than Ofwat's existing suite of models.

The inherent complexity in the use of two separate quadratic density terms raises the question of how the CMA has satisfied itself that the modelled marginal effect aligns with engineering and operational rationale. Each alternative measure suggests an opposite impact on cost, with 'weighted average density' suggesting a parabola and 'properties per length' suggesting an inverted parabola.

We have also observed unintuitive coefficients in the wastewater model. Table 16 shows that the population density coefficients have contradictory signs. It isn't clear why this would be expected or appropriate – they are picking up similar information, albeit derived at different levels of granularity.

Table 16: Analysis of the CMA's wastewater model

Variable	Coefficient	Commentary
(Intercept)	-3.89**	
Load (log)	0.68***	
Properties per sewer length - weighted average density (log)	0.60*	This implies that higher property density leads to higher cost.
Pumping capacity per sewer length (log)	0.11	
Load treated with ammonia consent ≤ 3mg/l	0.00**	
LAD from MSOA - weighted average density (log)	0.19*	This implies that higher population density leads to higher cost.
MSOA - weighted average density (log)	-0.28	This implies that higher population density leads to lower cost. This is inconsistent with the coefficients of the two density measures.
Weighted average treatment size (log)	-0.12**	
Load treated in size bands 1 to 3 (%)	0.01	
Urban rainfall per sewer length (log)	0.09**	
Energy index interacted with pumping capacity (log * log)	0.02***	

Source: UUW analysis of CMA publication

We note that the CMA has acknowledged the contradictory signs of coefficients across density variables, stating in D.17, that this is '*consistent with the view that impact of density on costs is unclear'*. We disagree that the impact of density on cost is unclear – we consider the impact has been well established and documented over the last ten years of industry collaborative analysis[27].

It is true to say that the impact of density on cost is different across different elements of the value chain and within certain value chain areas, different levels of density. For example, high population density tends to reduce treatment costs because it facilitates economies of scale at a treatment site. Conversely, very rural and very dense areas may both tend to be associated with higher network costs through a u-shaped relationship. However, while the impact of density changes depending on the value chain element being modelled, it is not correct to say that density's impact overall is unclear.

The CMA's willingness to accept a potentially counterintuitive coefficient sign, contrasts with Ofwat's approach, which involved extended engagement over several years. This process gave stakeholders the opportunity to challenge, amend and improve the base cost modelling approach. This led to a model suite that was transparent

[27] Ofwat (2023). Econometric Base Cost Models for PR24, pg.24.

and had been subject to extended scrutiny. The engineering and operational rationale underpinning each cost driver was clear to all participants. While disagreement on the specific variable choice exists, this is a natural and expected part of a zero-sum benchmarking approach.

A.4 Engineering and economic rationale

Cost assessment should begin with a clear hypothesis about cost causation, grounded in operational realities, engineering principles and economic logic. Statistical models can then be used to test and refine that initial hypothesis. This approach ensures that models are best able to explain costs at a company level in a future regulatory period. However, the CMA's cost models prioritise statistical fit at the expense of established engineering and economic judgement.

While the LASSO technique can be a powerful tool for identifying statistical relationships, it prioritises statistical fit and a low RMSE over engineering logic and economic rationale. An over-reliance on correlation may result in models that inappropriately capture cost differences between companies, leading to an inappropriate benchmark. In contrast, a focus on engineering and operational principles minimises the risk that the model picks up on spurious correlations.

The approach adopted by the CMA is solely reliant on a statistical and data driven approach, with no rigorous *ex-post* testing of the model against the industry's underlying economic and engineering relationships. There is no evidence that the CMA has undertaken a proper assessment of the model developed through LASSO against the industry's well-established and documented engineering and economic rationales[28]. While the new models maximise measures of statistical fitness, they exhibit concerning counterintuitive features and coefficient signs. The interactive terms and the non-linear relationships and multiple use of similar variables often lack interpretability and fail several statistical tests.

While we have principled issues with the CMA's relative prioritisation of statistical fit and engineering rationale, the remainder of this section focuses on the rationale underpinning a key difference between the variables included in Ofwat's models and the CMA's models: the use of interaction terms.

A.4.1 The rationale for the interaction terms is unclear and unexplained

The interaction terms included in these models add complexity without interpretability. In particular, in its PDs, the CMA states that input price variables (wages and energy) are multiplied by relevant scale variables, as the effect of changes in wages or energy prices on companies' expenditure depends on the size of their businesses and their requirements for labour and energy. Accordingly, the CMA incorporates interaction terms for both regional wages and energy index with scale measures.

The specific adjustments made are:

- In the treated water distribution model, regional wages are interacted with mains length.
- In both water models, the energy index is interacted with mains length.
- In the wastewater model, the energy index is interacted with pumping capacity.
- In the wastewater model, regional wages are interacted with load.

As an example, the interaction term allows the marginal effect of wages on cost to vary depending on the length of a company's mains. The positive coefficient of 0.037 on 'wages interacted with the length of mains' in the treated water distribution model implies that companies with a larger network face a higher marginal wage. We cannot think of an operational rationale to support this relationship.

Similarly, the positive coefficient on the energy index interaction terms in the water models imply that companies with larger networks require a higher marginal cost of energy than companies with smaller networks. Again, it isn't clear why the marginal cost of power would vary with network size. While larger networks may consume

[28] ARUP Vivid Economics (June 2017). Understanding the Exogenous Drivers of Wholesale Wastewater Costs; Ofwat (April 2023). Econometric Base Cost Models for PR24; Ofwat (January 2023). UUW Econometric Model Submission: Supporting Document.

more energy, this effect should already be captured by the scale coefficient. It is unclear why the marginal cost of energy would vary with network size.

We acknowledge that employing a scale cost driver to capture different energy requirements imposes an implicit assumption that the marginal cost of energy is constant across different main lengths. However, we are not clear what operational rationale suggests this is an appropriate assumption. While the CMA may argue that it is better to make its model more flexible and let the data decide, this approach is exposed to the risk of spurious correlation – particularly in the context of a small dataset, where the model may suggest relationships that do not exist in practice. Given the potential for significant impacts on base cost allowances and relative efficiency rankings, we consider this risk unacceptable.

Grounding variable choice in engineering and operational rationale would have mitigated this risk. The use of *a priori* assumptions precludes the addition of variables that appear to fit historic data well but may be less well suited to explain differences in the real world e.g. because of changes in future cost trends or because of a spurious correlation.

A.5 LASSO prioritises the average prediction rather than a company-specific prediction

All models are imperfect representations of reality. A single imperfect model can be acceptable in certain circumstances (e.g. when attempting to identify the causal impact of a particular variable). In the context of setting base cost allowances for individual companies, the risk of an imperfect model must be taken seriously and appropriately mitigated. This has led us to promote the use of a diverse and triangulated model suite. Ofwat adopted a similar approach in its PR24 model suite. However, the CMA relies on three models to set botex allowances. This approach increases the risk that imperfections in one variable or model have undue impacts on each company's cost allowance. In no way do we consider that this risk is outweighed by the perceived benefit of a smaller model suite.

A key feature of regulatory cost assessment in the water sector is that companies' regions are not homogenous. In this context, we would not expect that a single model can accurately predict allowances for all companies. This heterogeneity led Ofwat to a diverse model suite that mitigates the risk that a single model unduly benefits or penalises certain companies and minimises the risk of substantial incidence effects.

It also led Ofwat to supplement its modelling with the ability to adjust its company allowances for unique circumstances e.g. through cost adjustment claims. By definition, a cost adjustment claim is required when a company faces cost pressures from a factor that cannot be captured by the model. It is therefore puzzling that the CMA has chosen an approach where it rejects company claims on the basis that the modelling has deemed that the driver is not relevant.

In contrast, LASSO has been widely used to develop predictive models (for example for stock or house prices) with large datasets and large pools of potential explanatory variables, where the focus is on the average prediction.

On this basis, while LASSO can be effective in identifying variables that improve the statistical fitness of the model and improve the prediction of the efficient costs of the average company, using it mechanistically to establish the industry-wide model will, by design, inherently capture the cost relationship that exists on average. **As such, it may not be suitable for reflecting the cost relationship that exists at a company level. However, this is the sole objective of regulatory cost assessment. We note that a focus on company-specific factors within cost assessment was explicitly recommended by the IWC.**

A.5.1 Cost adjustment claims

Cost adjustment claims are by their nature, company-specific, and arise precisely because standardised econometric models are unable to fully capture the unique cost pressures faced by individual companies in certain areas. Attempting to resolve these issues through the use of LASSO seems counter-intuitive, given that LASSO is designed to identify variables that best explain cost variation across the industry as a whole.

LASSO prioritises variables with broad explanatory power, potentially overlooking factors that are critical for one, or a subset of companies but not statistically significant at the aggregate level. We would therefore expect that some legitimate cost drivers may not be selected by LASSO, despite being materially relevant to individual companies. This reinforces the importance of retaining mechanisms such as cost adjustment claims, that ensure that engineering-led company-specific circumstances are appropriately recognised and allowed for.

The CMA rejects bespoke cost claims or avoids engaging fully with the underlying rationale for operational specific characteristics. **In our view, not all company specific adjustments can be captured within the scope of the benchmarking model alone.** Post modelling adjustments are used where the model is not thought to be capable of capturing legitimate company or time specific variation in costs. They can serve as a necessary backstop in regulatory cost assessment and provide companies with an avenue to ensure all efficient cost pressures are reflected appropriately.

While we do not comment on the legitimacy or otherwise of the claims presented to the CMA, we consider that it is important that the CMA recognises the potential shortcomings of an approach that assesses company-specific claims through the prism of model estimated according to an industry average.

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