Assessment of cost drivers for RIIO-ED2 benchmarking

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Overview

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1. Background and findings

Background

Glossary of terms (I)

Term	Definition
DPCR5	Distribution Price Control Review 5 (DPCR5) is the regulatory period preceding the current period (2011–15).
ED1	RIIO-ED1 or ED1 is the current price control (2016–23).
ED2	RIIO-ED2, or ED2 is the upcoming price control (2024–28).
TOTEX	Total expenditure
Cost function	The cost function is the mathematical formula that describes how expenditure is related to structural factors (e.g. scale) and other drivers of costs (e.g. operating environment).
OLS	Ordinary Least Squares (OLS) is an econometric method used to estimate the relationship between one dependent variable (e.g. TOTEX), and one or more independent variables (e.g. cost drivers). This was the method used by Ofgem to estimate cost functions in ED1.
P-value	The P-value is the probability of seeing the observed relationship in the data, on the assumption that the null hypothesis is true and other modelling assumptions are met. The typical thresholds at which something is considered 'statistically significant' are 0.01, 0.05 and 0.1, and these are often represented with ***, ** and * respectively.
SFA	Stochastic Frontier Analysis (SFA) is a well-established econometric method specifically designed to estimate cost/production functions and efficiency scores.
DEA	Data Envelopment Analysis (DEA) is a well-established linear optimisation method for estimating efficiency scores.
PCA	Principal Component Analysis (PCA) is a statistical approach for combining several correlated variables into one or more measures.
MEAV	Modern Equivalent Asset Value (MEAV) is defined as the weighted sum of DNOs' assets, where the weights are derived from engineering assessments. MEAV was used a cost driver for the ED1 determination.
Monte Carlo Analysis	The Monte Carlo Analysis is a simulation-based method that is used in this project to estimate the impact of data or modelling uncertainty on the analysis. It works by adding an error component to all data points and running the analysis many times to derive a distribution of estimates. The level of uncertainty (i.e. the magnitude of the error) is a user input, and can be informed by empirical evidence and/or an expert view.

Background

Glossary of terms (II)

Term	Definition
COLS	Corrected OLS (COLS) is an econometric method that Ofgem used to assess efficiency in ED1 and previous price controls. It involves estimating the cost function (regression line) using OLS, which represents the relationship between costs and cost drivers for the average company. The regression line is then shifted such that it represents the relationship between costs and cost drivers for an efficient company. At ED1, Ofgem shifted the regression line to the upper-quartile most efficient company.
Efficiency	In this context, the efficiency of a company represents the ability of a company to transform inputs into outputs relative to current best practice. The efficiency of a company is an unknown that must be inferred from modelling. In Ofgem’s approach, *estimated* efficiency refers to the difference between a company’s observed expenditure and that predicted by a model.
Uncertainty	As parameters like efficiency are unknown and have to be estimated from data and models, the estimates will be measured with some level of uncertainty. The uncertainty could relate to data errors (e.g. misreporting), data inconsistencies (e.g. differences in reporting between DNOs), and modelling uncertainty (e.g. omitted factors from a model).
Gini Index	A Gini Index is a statistical measure of dispersion. While it is often used as a proxy for income or wealth inequality, it can also be used to measure variations in population density within a given area.
CSV	Composite Scale Variables (CSVs) are cost drivers that are constructed as a combination of different measures of scale (e.g. customer numbers, MEAV). These can be constructed using simple averages, weighted averages or more sophisticated aggregation techniques.
DSO functionality	Distribution System Operator (DSO) functionality refers to activities such as active network management and the increased use of data and technology to intervene in the network. The level of DSO activity is expected to increase in ED2.
R-Squared	R-squared is a measure of how much the variation in cost drivers explains variation in expenditure. The adjusted R-squared is equivalent to R-squared, but imposes a penalty for adding extra cost drivers in the model to avoid overfitting.

Background

Study objectives: cost driver recommendations for ED2

Identify cost drivers for ED2

- multiple interviews with project participants to identify longlist and changes in the operating environment
- regulatory precedent is also used to inform relevant drivers

Composite scale variables

- comment on, and develop, the approach to constructing CSVs
- the scope for CSV construction includes regression- and activity-based modelling

Evaluate cost drivers for ED2

- use econometric analysis to evaluate the statistical properties of the models
- this allows one to narrow down the longlist of operationally relevant drivers into a shortlist

List of cost drivers

- propose a shortlist of cost drivers that are suitable for ED2 and that work from a modelling point of view

Background

Areas to be further examined at ED2

1. Data collection

- the data we have received is ‘noisy’ for most variables. The conclusions of the statistical analysis could be sensitive to whether, and how, this data is corrected and cleaned
- as we do not have ED2 business plan data, we cannot test for the stability of the cost/cost driver relationship in the forecast period. This test will be **essential** if the historical cost models are to be used to assess ED2 expenditure

2. Estimation approaches

- we focus on using OLS to estimate the cost function and define efficiency as the ratio of predicted to observed expenditure. Alternative methods, such as SFA and DEA, could also be explored
- our CSV analysis focuses on regression- and activity-based modelling, in line with precedent from ED1. Alternative approaches, such as PCA and DEA can be used to construct CSVs and assess cost drivers

3. Disaggregated modelling

- the analysis presented here is used to develop cost drivers for TOTEX. Additional disaggregated levels of modelling can be used (i) to cross-check the results from TOTEX modelling, or (ii) to directly inform cost allowances alongside TOTEX models. These should be explored

Background

Process followed

Deriving a longlist

- review of relevant regulator precedent from ED1 and previous price controls
  - ED1 provides a useful starting point, where the relevant drivers and their respective weight in the analysis are discussed in detail
  - the changes between fast- and slow-track determinations provide additional insight
- engagement with the participating DNOs to develop and refine the list from regulatory precedent
  - engaging with DNOs and industry experts aids the identification of new cost drivers for ED2 that were less relevant at previous controls
  - the engagement can also be used to validate the outcomes from modelling, including the weight attached to specific drivers

Refining the longlist

- econometric modelling to validate quantify the relationship between costs and cost drivers in the sample
  - are the relationships between cost and cost drivers consistent with operational and economic expectations?
- the statistical properties of the model are also assessed through a battery of statistical tests to explore the robustness of the model
  - are the chosen cost drivers good at explaining differences in costs between DNOs and over time (i.e. model fit)?
  - is the relationship between costs and cost drivers statistically significant?
  - is the relationship stable over time?
  - are the modelling assumptions met?

Findings and recommendations
Data collection and assurance

- the historical data for most variables is ‘noisy’ for at least some DNOs
  - before Ofgem starts the analysis, it should ensure, through discussions with the DNOs, that all cost and cost driver data is recorded and reported accurately
  - if there have been changes to reporting methodologies, this should be backdated to the greatest extent possible
  - pre-modelling adjustments may also be useful for addressing potential issues with the data, such as structural breaks

- data for certain periods could be more or less relevant for assessing ED2 expenditure
  - operational insight should inform the appropriate time period of analysis (e.g. does the data come from a period that is sufficiently similar to ED2?)
  - this can be supported by statistical tests for structural breaks

- it may be useful to model the impact of data uncertainty on the cost models and DNOs’ performance (e.g. through sensitivity analysis, Monte Carlo simulations and alternative estimation approaches like SFA, DEA)
  - this analysis could also be used to inform other parts of the cost assessment (e.g. the stringency of the benchmark, uncertainty mechanisms)

Findings and recommendations

Regional adjustments—wage and density

- it appears difficult to account for regional wages directly within the model in a way that yields statistically significant and operationally intuitive coefficients
  - there could potentially be grounds for Ofgem to investigate alternative approaches to accounting for regional wage adjustments directly in the modelling process
  - if alternative methods do not yield robust and intuitive results, pre- or post-modelling adjustments may be needed (provided that these adjustments are robustly evidenced)

- density can be accounted for in the model directly, but not in isolation
  - for the coefficient on density to be consistently both positive and statistically significant, intra-regional variations have to be captured through the Gini index
  - it might be inappropriate to dedicate two cost drivers to capture one characteristic if other important characteristics (e.g. outcomes) are unaccounted for

- the magnitude and significance of wages and density depend on the other cost drivers included in the model
  - in this context, further consideration of uniform pre-modelling adjustments may be necessary
  - multiple methods of pre-modelling, within modelling and post-modelling adjustments should be fully explored to ensure that the results are not skewed towards particular companies

Findings and recommendations
MEAV

- cost models are not particularly sensitive to potential uncertainties that we have detected in the MEAV measure, but DNO efficiency rankings can be sensitive
  - the coefficients on the cost driver does not change materially under adjustments to the MEAV data, nor do the statistical diagnostics considered

- the impact of any MEAV uncertainty may be reduced when it is included in a CSV
  - moderating weight on MEAV might mitigate the impact of data uncertainty for this variable, although this may introduce other sources of uncertainty if the other variables are measured with noise
  - sensitivity analysis is needed to ensure that the results are robust to small changes

- the current analysis takes the assets and their respective weights as given
  - Ofgem should work to update the asset weights to reflect the costs associated with each asset class
  - additional or different asset classes could be included in the measure (if appropriate from operational and data-quality perspectives)
  - if other assets are included in the MEAV measure (as was defined at ED1), then care must be taken to maintain the correspondence between costs and cost drivers

Findings and recommendations
Individual cost driver analysis

- MEAV is the single best cost driver when modelling historical data in terms of model fit, but this does not necessarily mean that it is the only cost driver of importance
  - MEAV is defined in terms of costs and assets, so the relationship may be tautological
  - models with or without MEAV may help to validate, corroborate or triangulate outcomes
  - consideration of multiple models may lead to more robust results

- it is difficult to estimate ‘sensible’ models with multiple cost drivers, likely due to collinearity issues
  - this indicates that alternatives to top-down benchmarking with multiple drivers may be required, for example, through CSV construction or activity-level analysis
  - using multiple models to assess DNOs’ expenditure and triangulating outcomes could also mitigate this problem

- high-level cost drivers considered in previous price reviews remain relevant from statistical and operational perspectives on ED1 outturn data (i.e. over 2016–20)
  - these drivers include MEAV, customer numbers, network length and units distributed
  - other cost drivers (such as outcome measures and drivers of ‘Net Zero’) are discussed elsewhere
  - all analysis needs to be updated with new data (e.g. 2020/21 outturn and ED2 business plan data) for further validation

Findings and recommendations

CSV construction

- CSVs do not need to account for the MEAV in order to produce ‘sensible’ results with good model fit
  - models such as these can be used in combination with (or as a cross-check on) models that control for the MEAV

- there is no material difference in the statistical quality of models using a unweighted average of cost drivers and those where the weights are informed by regression analysis
  - unweighted averages should not be excluded ex ante if this remains the case

- Ofgem does not necessarily need to be limited by ED1 and GD2 precedent when developing CSVs
  - extending Ofgem’s current methods and undertaking sensitivity analysis can offer additional insights and should be considered
  - different methods, such as PCA and DEA, could also potentially be explored

Findings and recommendations
Controlling for outcomes

- it may be possible to account for outcomes in the cost assessment by simply including them in the econometric model
  - coefficients on some outcome variables are of the correct (incentive-compatible) sign and are statistically significant
  - care must be taken to avoid over- or under-compensating for any one outcome measure, and to avoid having too many regressors—a 'Composite Outcome Variable' could be constructed to account for this

- accounting for outcomes can have an impact on the rankings of some DNOs
  - DNOs may be mis-identified as inefficient if they provide a higher quality of service

- if inclusion does not work, simple transformations (e.g. taking a long-run average) to the data may improve the quality of the model
  - alternative estimation approaches (e.g. SFA, DEA, PCA) should also be tested
  - it may be useful to also explore additional transformations (e.g. constructing monetised measures of service quality and adjusting expenditure or outputs)

Findings and recommendations
Other potential drivers at ED2

- as there are several anticipated changes in the regulatory and operational environments that DNOs face in ED2, a simple extrapolation of historical cost models is likely to be inappropriate
  - these include ‘Net Zero’ policy objectives (including distributed generation); a renewed focus on cyber security; the introduction/expansion of ‘DSO functionality’; and other investments to comply with legislation (e.g. health and safety)

- it is difficult to estimate robust models with LCT connections using historical data
  - the incorporation of ED2 business plan data should be explored to address some of the issues associated with LCT drivers (and other future drivers of costs)
  - other drivers, such as excess capacity, can be important to consider

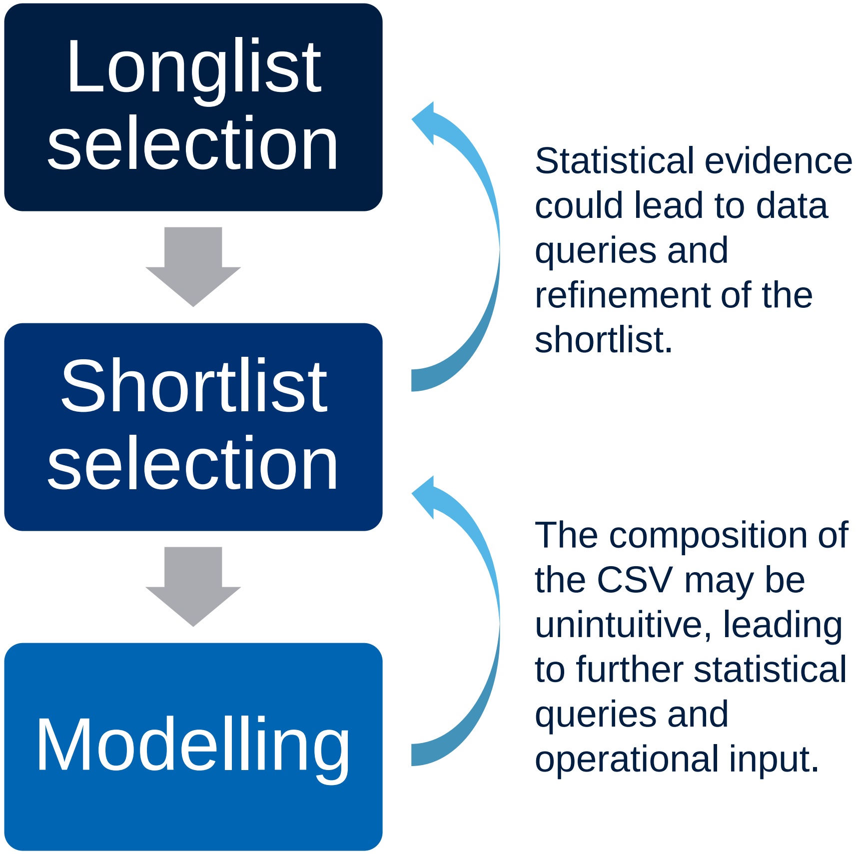
- we were unable to identify drivers of DSO functionality as part of our industry engagement
  - if no drivers can be identified and DSO functionality (and other future costs) is material, this may need to be assessed outside of the TOTEX models
  - careful treatment of the modelling and benchmark periods and potential structural changes might accommodate some new expenditure—some approaches might only pick up such expenditure if as all DNOs face similar and proportionate cost pressures

2. Methodology

Methodology
Overview

1. **fundamental cost driver selection**	• understanding the fundamental cost drivers in order to develop a longlist of potential cost drivers to use in the cost regressions
2. **selection criteria**	• developing criteria to qualitatively and quantitatively assess the longlist of cost drivers, and narrowing it down to a shortlist
3. **econometric modelling**	• running regression models to assess and contrast the quantitative performance of different cost drivers • this would include the construction and evaluation of specific cost drivers, e.g. weights in a CSV

Methodology
Iterative procedure



- cost driver analysis is an iterative process and industry engagement is required at every step
  - we have had 4–8 engagements with each DNO throughout this project
- the process is iterative—the key results are shared and discussed with participating DNOs as the work progresses
- regular email exchanges, with several workshops throughout the project

Methodology

1. Fundamental cost driver selection
2. Cost driver selection criteria
3. Econometric modelling

Methodology: fundamental cost driver selection
Overview

Regulatory precedent

- in cost benchmarking, the starting place is a review of the relevant regulatory precedent
- RIIO-ED1 provides a useful starting point, where the relevant drivers and their respective weight in the analysis are discussed in detail
- the changes between fast- and slow-track determinations provide additional insight
- regulatory precedent is only the starting point in developing a list of cost drivers
- regulatory precedent cannot, in itself, identify new drivers of expenditure for ED2

Industry engagement

- qualitative input from the participating DNOs to develop, populate and refine the longlist from regulatory precedent
- this engagement aids one to:
  - validate the cost drivers identified through regulatory precedent
  - identify new cost drivers that were rejected or not tested in previous price controls
  - map cost drivers to specific cost categories to derive an appropriate weight
  - understand whether cost drivers can be collected on a consistent basis, with minimal errors across DNOs and through time

When summarising DNOs' views on the relevance of certain cost drivers, the border of the slides will be in light blue. Oxera's comments on the DNOs' views will be clearly demarcated.

Methodology

1. Fundamental cost driver analysis
2. Cost driver selection criteria
3. Econometric modelling

Methodology: cost driver selection criteria

Longlist selection criteria: why not test everything?

Rationale	• collecting data is time- and resource-intensive • focus on (additional) cost drivers with highest potential

Criteria	• engineering, scientific and operational relevance • model balance (i.e. completeness) • stability of relationship with costs (conceptual) • measurability • exogeneity

Methodology: cost driver selection criteria

Longlist selection criteria: detail

Engineering, scientific and operational relevance

Consider only those cost drivers that have a clear conceptual relationship with costs. This list is usually derived using industry experts, technical literature and regulatory precedent.

Model balance (completeness)

The set of cost drivers should capture all distinct drivers of costs, such as scale, sparsity/ density, asset health measures, decentralised generation and quality of service.

Stable relationships with costs

Structural changes in the relationship between costs and cost drivers (e.g. through new regulatory requirements) limit the ability of historical cost models to predict future expenditure.

Measurability

The cost drivers cannot remain conceptual (e.g. 'weather'), but have to be clearly defined and measured if they are to be included in the cost models. Data also needs to be captured consistently across networks and time.

Exogeneity

Ideally, cost drivers should be outside of management control and should not create perverse incentives. Completely exogenous variables are relatively limited, so good cost drivers could still be influenceable (to some extent) by networks.

Methodology: cost driver selection criteria

Exogeneity—a misunderstood concept?

- exogeneity is not a binary concept in practice
  - DNOs can have varying degrees of control over cost drivers
- Ofgem has generally given considerable weight to measures of assets
  - there is a view that this could favour those DNOs that construct large quantities of assets, regardless of need

Increasing management control?

Increasing correlation with costs?

Exogenous drivers?

- peak load
- population density
- customer demographics

Asset-based measures

- MEAV
- length of network
- network capacity

Endogenous drivers?

- workload and activity
- service quality
- ambition

Methodology

1. Fundamental cost driver analysis
2. Cost driver selection criteria
3. **Econometric modelling**

Methodology: econometric modelling

Accounting for multiple cost drivers

Approach	Pros	Cons
Using cost drivers separately	• data determines the relevance and magnitude of the cost effects • results can be checked against engineering, scientific and operational evidence	• with a small dataset, the number of cost drivers is limited • relevant cost drivers can be overlooked due to multi-collinearity
Constructing a single CSV	• can use a larger number of cost drivers • complex relationships and unwieldy data types can be combined	• interpretation of results is difficult • weights for creating CSVs can be arbitrary and the results sensitive

Extensive data analysis: different sets of possible cost drivers, as well as different methods to construct CSV weights (e.g. cost proportions, econometric analysis).

Methodology: econometric modelling
Shortlist selection criteria

Rationale	• given the small size of the sample, the choice of cost drivers is limited (even if CSVs are used) • *underfitting* relates to the concern that relevant differences between networks are not adequately addressed
Criteria	• check all results against engineering, scientific and operational evidence • overall explanatory power and statistical properties • quantitative performance or statistical stability

The overall goal is to identify a set of cost drivers that can 'best' describe the cost differences across networks and over time.

Methodology: econometric analysis

Statistical tests considered (I)

Statistical issue	Description	Test	Potential solution	Caution to be exercised
Model fit	Models that fit the data poorly are likely to exclude relevant cost drivers. Under Ofgem's COLS approach, this could risk conflating the impact of omitted factors with inefficiency.	Examination of adjusted R-squared and information criteria such as the Akaike information criterion (AIC) and the Schwartz–Bayesian information criterion (BIC)	Include more or different explanatory variables in the cost model.	“Overfitting” the model can result in counterintuitive and incorrect parameter estimates.
Statistical significance of coefficients	If a coefficient is statistically insignificant, it could be a sign that its effect is already captured by other variables or is irrelevant. In this case, it could be adding more noise to the model and should be removed.	T-tests and F-tests	Remove cost drivers that have a statistically insignificant relationship with costs.	The statistical significance of a coefficient can be sensitive to the data used and the assumptions made.
Multi-collinearity	If the explanatory variables are highly correlated with each other, there will be a large degree of uncertainty in the estimated coefficients, resulting in wide confidence intervals.	Examination of the variance inflation factor (VIF). A VIF greater than 10 typically indicates multi-collinearity concerns	Reduce the number of explanatory variables in the cost models, or combine multiple explanatory variables into a single composite variable.	Including colinear cost drivers does not *bias* the analysis, but simply increases uncertainty. If models are ‘full’ with unnecessary drivers, it can prevent inclusion of relevant ones that can cause bias.
Functional form	The relationship of the explanatory variables to the dependent variable may be assumed to be linear, but may not be so. For example, there may be non-linearities, and variables may have interaction terms with each other.	RESET, link test	Test alternative functional forms.	The tests for functional form do not tell *which* higher order terms or additional factors are omitted, so these need to be explored from an operational perspective.

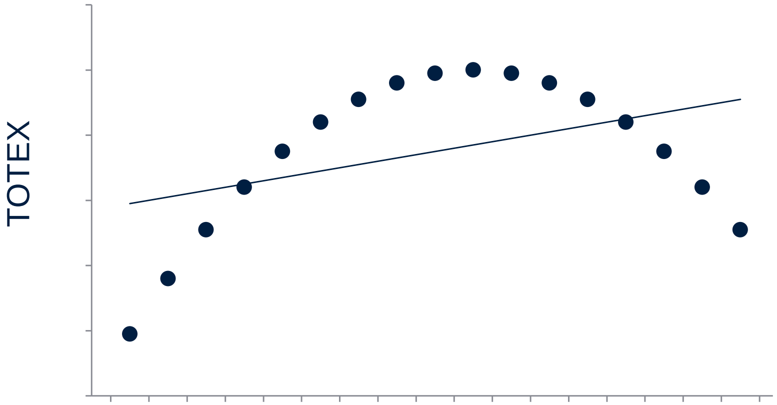
Methodology: econometric analysis
Statistical tests considered (II)

Statistical issue	Description	Test	Potential solution	Caution to be exercised
Structural breaks	The relationships between costs and cost drivers could change over time (e.g. due to changes in technology, in regulatory requirements, or in data definitions).	Chow test applied to DPCR5 data and to forecast ED1 data	Remove time periods that represent structural breaks or model the structural change directly	Tests for structural breaks may capture the usual expenditure profiles, in which case the data should not be necessarily dropped
Heteroscedasticity	The error term is heteroscedastic if its variance is correlated with any of the cost drivers. If heteroscedasticity is present, the standard errors on the coefficients will be biased and statistical tests will be uninformative.	White test	Use robust standard errors; use alternative estimators that model heteroscedasticity (e.g. random effects); transform the data	Certain types of robust errors (e.g. cluster robust errors) are only asymptotically valid (i.e. rely on large samples).
Normality	The error term must be normally distributed for most of the above tests to provide valid inference. However, if there is inefficiency in the data, the error term would be expected to be non-normally distributed.	SK-test, Shapiro–Wilk test	Model alternative estimators that can account for non-normal errors, such as stochastic frontier analysis (SFA)	If errors are non-normal, the coefficient will be unbiased even if the statistical inference is invalid.

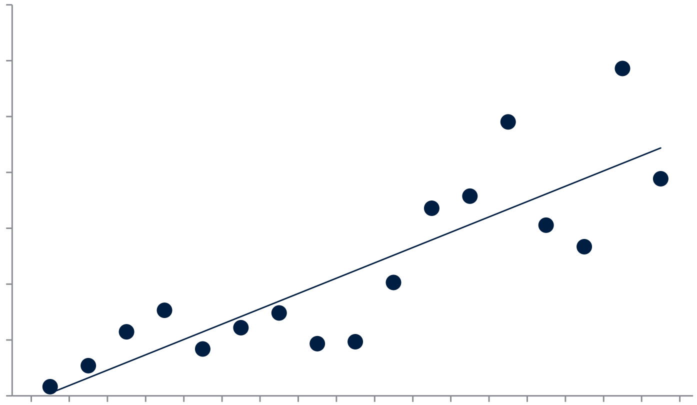
All of these tests rely on assumptions that may not be met. The operational intuitiveness of a model should be given more weight than its statistical properties when undertaking cost driver analysis especially in small datasets.

Methodology: econometric analysis
Functional form

- in many instances, there are operational reasons to hypothesise that there could be a non-linear relationship between costs and cost drivers—for example:
  - if operating in extremely dense and extremely sparse regions leads to higher costs, we would expect a non-linear relationship between costs and population density
  - if scale economies vary by size, we would expect a non-linear relationship between costs and scale (e.g. MEAV, customers)
- variables that can explain costs well in a non-linear setting may not be selected if there is no strong linear relationship. Similarly, less appropriate drivers of expenditure may be selected if the relationship with expenditure is roughly linear



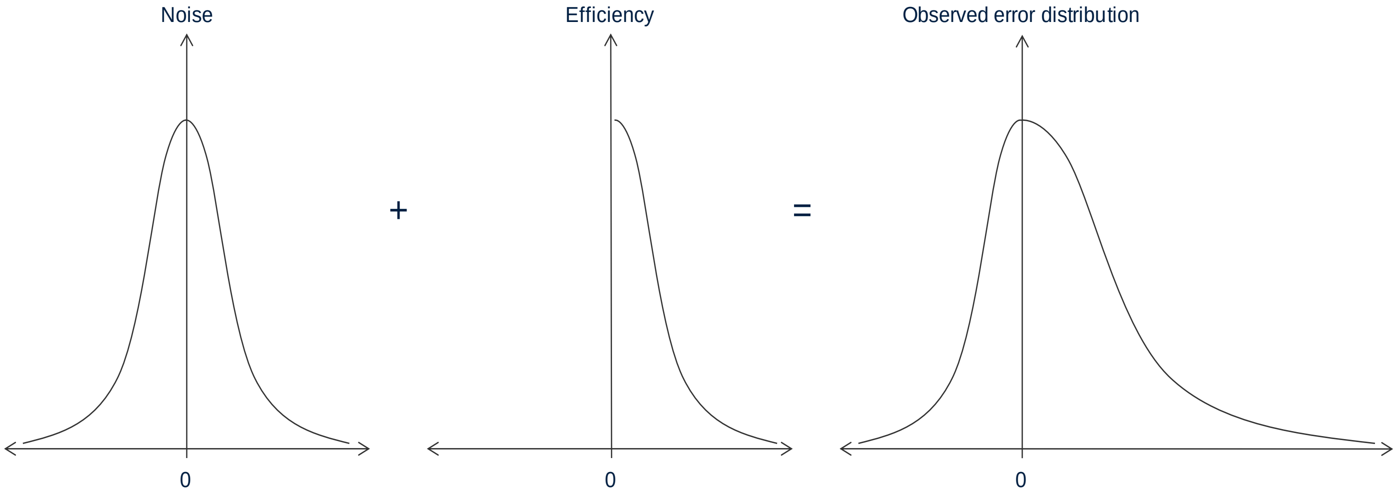
Non-linear output—correlation 0.42



Linear output—correlation 0.85

Methodology: econometric analysis
The issue of normality

- hypothesis testing using OLS relies on the assumption of **homoscedasticity** and **normally distributed error terms**
- as the diagram below shows, the **presence of inefficiency** means that, by definition, the error terms **cannot be normally distributed**. This is because efficiency is not a symmetric or random concept, but is rather an ‘unexplained positive impact’ on TOTEX, where the degree of estimated inefficiency can vary
- as such, there may be an inconsistency in cost driver analysis—on the one hand, assuming efficiency differences between companies, and on the other, relying on the assumption of normally distributed errors
- since the assumptions of homoscedasticity or normally distributed error terms are both violated, standard significance tests in OLS and its variants are generally invalid. Therefore, the statistical significance of cost drivers in OLS cannot be used as conclusive evidence in model development



Methodology: econometric analysis

Illustration: impact of changes to modelling assumptions

Variables	Top-down		Bottom-up	
	OLS	SFA	OLS	SFA
Macro CSV	0.780***	0.774***		
BU CSV (log)			0.835***	0.817***
Density (log)	-0.00528	-0.00627	0.0200	0.0184***
Density (log) p-values	(0.633)	(0.236)	(0.114)	(0.000710)
Time trend	-0.0109**	-0.0113***	-0.00828*	-0.00990***
Constant	15.28	16.02***	17.51*	20.77***

Note: A half-normal distribution is assumed for the error term, alternative functional forms and distributional assumptions should be explored.
Period in regression: 2011–20. 140 observations.

The coefficients on the CSVs change marginally.

The coefficient on density becomes **statistically significant** when using the SFA estimator.

The coefficient on the time trend becomes statistically more significant when using the SFA estimator.

- these results suggest that statistical analysis may be able to benefit from a more holistic approach
  - whether a coefficient passes a particular significance threshold or not may depend on the modelling assumptions made
- SFA could be used as a cross-check or alternative to the OLS modelling

3. ED1 replication

ED1 replication

1 **Exploring the data**

2 **Estimating the models**

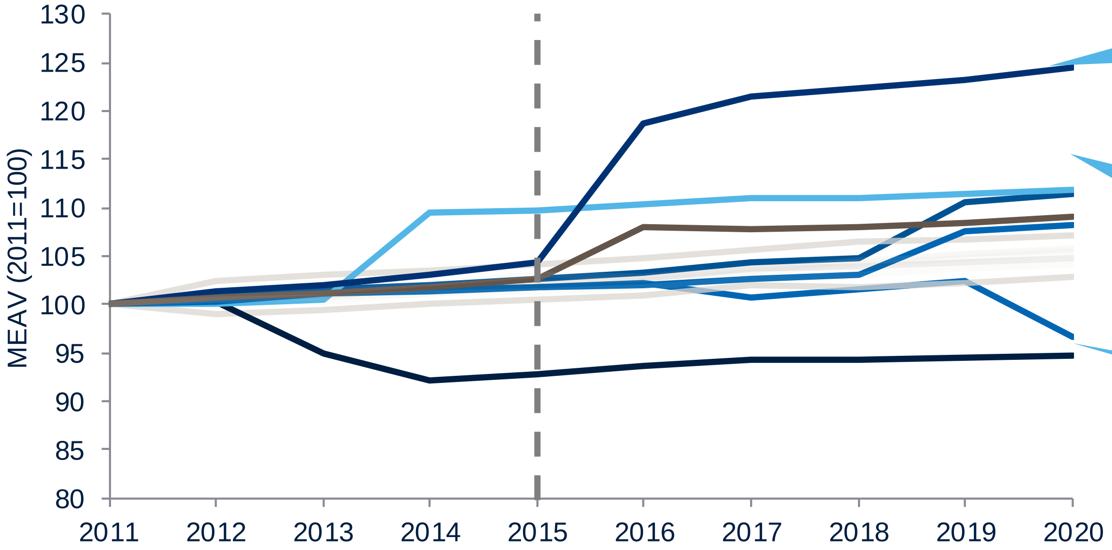
ED1 replication: exploring the data

Overview

- we requested data from the Cost and Volumes Reporting Packs for the year 2019/20 from all DNOs
  - while some of the data was redacted for some DNOs, we gathered sufficient data to replicate Ofgem's analysis and explore alternative model specifications
- all expenditure is expressed in 2012/13 prices
  - expressing expenditure in 2019/20 prices have no effect on results
- we also used data from the RIIO-ED1 annual returns and the Environment and Innovation Reporting Packs, both of which are publicly available
- for most of the variables, we have historical data for DCPR5 (2011–15) and ED1 (2016–20)
  - we do not have access to forecast data for ED2, which will be needed to:
    1. refine the modelling and estimate efficient cost allowances
    2. test whether it is appropriate to extrapolate historical models into ED2
    3. explore the use of cost drivers that *only* have an impact in ED2
  - the cost driver forecasts should be based on robust operational evidence and supported by third-party forecasts where possible to avoid companies being rewarded (or penalised) through inaccurate forecasting—e.g. extrapolating linear trends and historical averages may not be sufficient forecasting approaches for ED2 (see, for example, the CMA's discussion in the PR19 redeterminations on mechanism for effective ex-post reporting comparing actuals with forecasts and reputational incentive for important investments)
- further cost driver analysis should be undertaken once new outturn data and business plan data (i.e. forecast data) are published in the summer

ED1 replication: exploring the data

MEAV



At least seven DNOs experience material structural breaks in their reported MEAV.

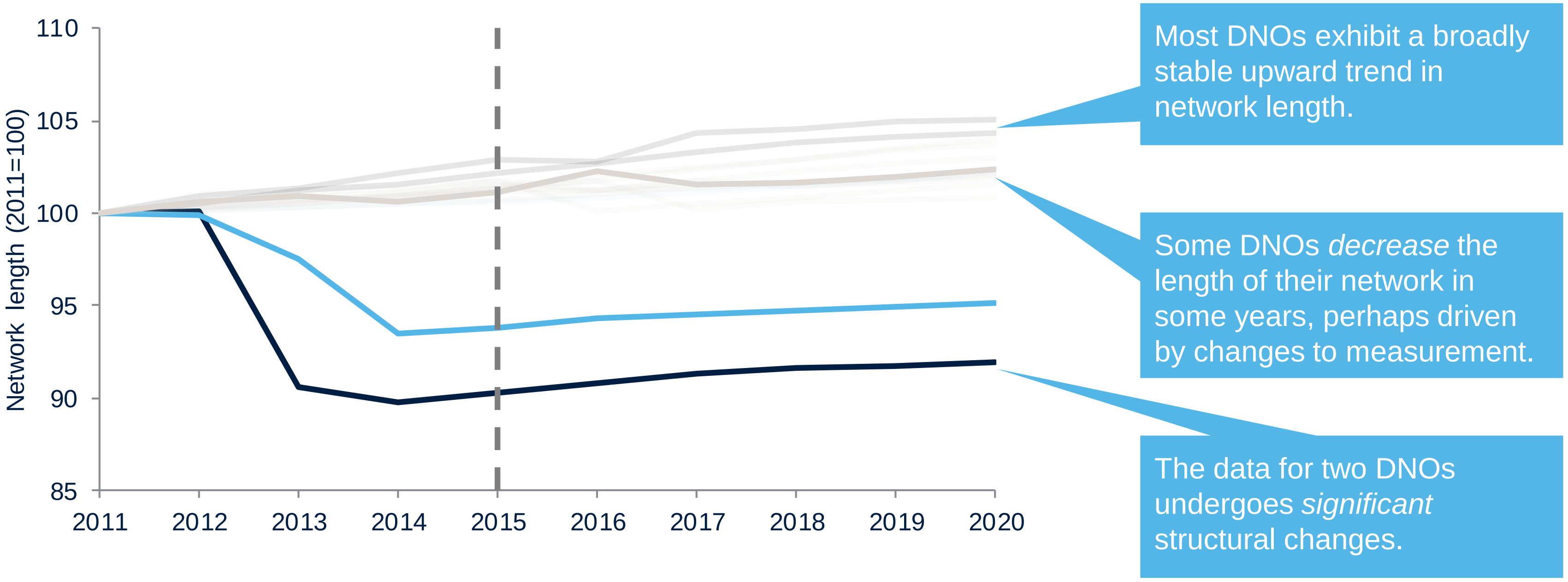
Most breaks occur before or at the start of ED1, but three DNOs report material breaks during ED1.

The break led to a material decrease in reported MEAV for two DNOs.

- there are several significant structural changes in the MEAV measure that should be further investigated
- the apparent inconsistencies in the MEAV data has potential to bias results in models where MEAV is given a significant weight, so these should be validated against alternative models

ED1 replication: exploring the data

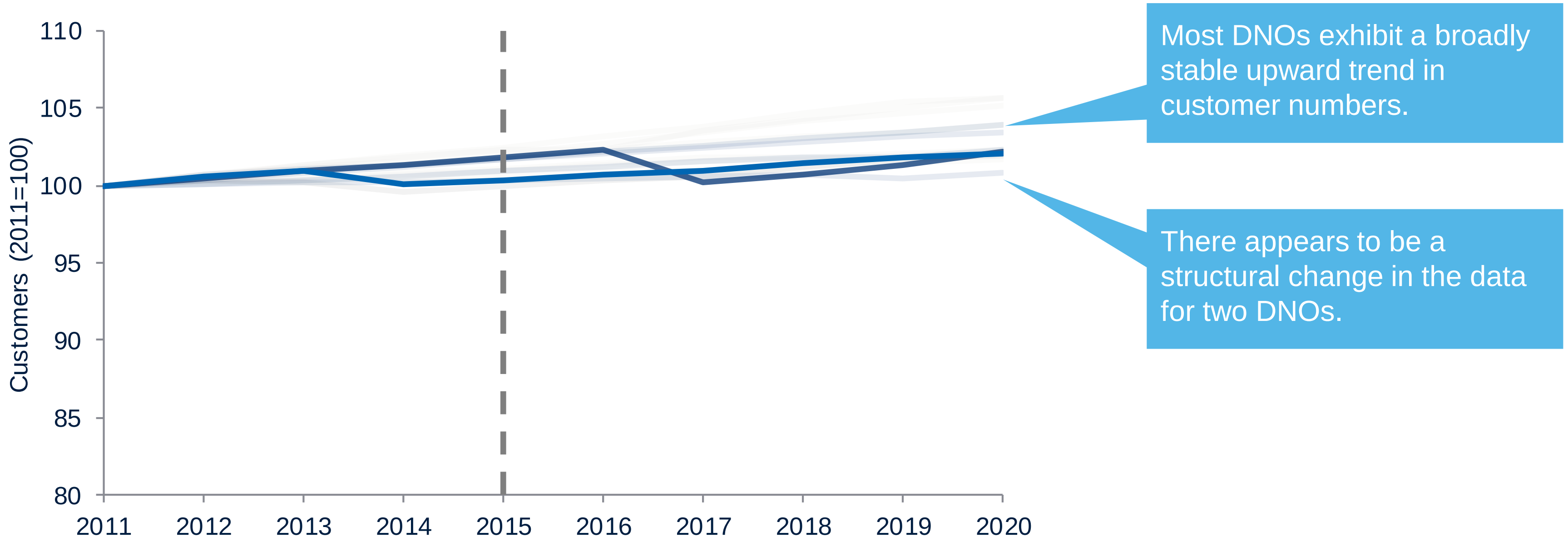
Network length



- network length is relatively more stable than MEAV
- the structural changes for the two DNOs should be explored further—if these are the result of data inconsistencies, then they should be corrected

ED1 replication: exploring the data

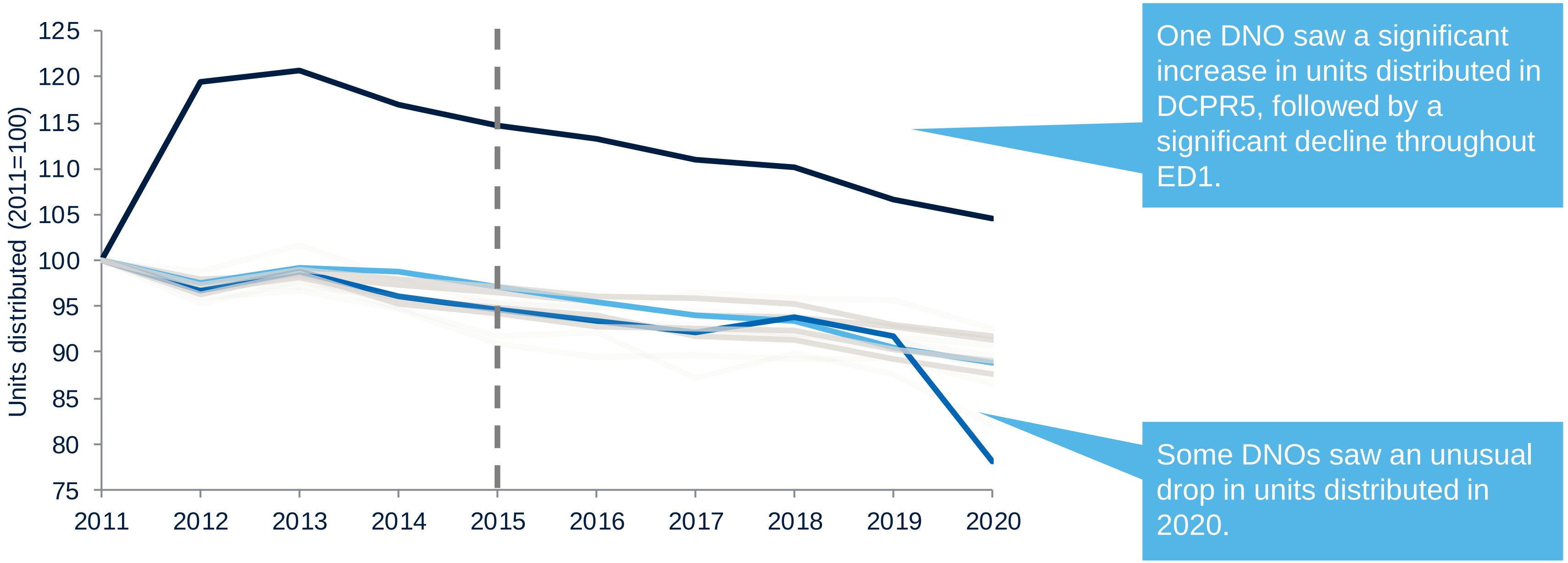
Customer numbers



- customer numbers are relatively stable for most DNOs
- while structural changes in the data do exist, these appear to be less material than for other scale variables

ED1 replication: exploring the data

Units distributed



- if the general downward trend in units distributed continues into ED2, an extrapolation of cost models controlling for this cost driver may underpredict allowances if other important drivers are ignored
- significant changes in units distributed should be investigated

ED1 replication

1 **Exploring the data**

2 **Estimating the models**

Estimating the models
Overview

Our estimation approach departs from Ofgem's ED1 approach in two ways:

1. we use all of the outturn data (2011–20) in the regression analysis, and do not incorporate any forecast data
   - we estimate efficiency scores over the ED1 outturn period (2016–20)
   - DPCR5 data is included in the regression to increase the size of the dataset and test for structural stability—this might not be necessary once new outturn data and ED2 forecasts are available
   - DPRCR5 data may be outdated and less relevant for assessing ED2 expenditure, and Ofgem should carefully consider which data it includes in the cost models
   - we estimate cost models using only ED1 outturn data as a sensitivity, and comment on this where insights differ to using the full outturn sample
2. we understand that Ofgem used an adjusted MEAV variable for one network in the ED1 Final Determinations, alongside an adjusted TOTEX variable. Since we do not have access to the TOTEX adjustment, we do not adjust the MEAV
   - note that this does not have a material impact on the cost models, although the DNO rankings may differ. The need for the adjustment may require re-examination

ED1 replication

ED1 TOTEX models, 2011–20

Variables	Top-down		Bottom-up	
	ED1	Updated	ED1	Updated
Macro CSV (log)	0.794***	0.773***		
BU CSV (log)			0.835***	0.860***
Time trend	-0.00864**	-0.0109**	-0.00711**	-0.00826*
Constant	10.36	15.32	15.26**	17.46*
Adj. R2	0.868	0.799	0.876	0.815
RESET	0.000254	0.00644	0.000213	0.0123
Link	-1.134	-1.097	-2.413	-3.154
Chow (DPCR5)	6.08e-05	0.000118	0.000283	0.000305

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices. Note that Ofgem used data 2011–23 so the coefficients differ to what is presented in the FD documents.

The coefficient on the CSVs is broadly similar between the ED1 and updated analyses

The model fit has worsened for both models, and the other diagnostics are largely unchanged

There is a structural break in DPCR5 (compared to ED1), and this continues throughout the deck. This may be due to the high level of activity in DPCR5 period. The DPCR5 data may be inappropriate for setting allowances in ED2

- the magnitude of the coefficients is largely unchanged between ED1 and the update with data since the ED1 Final Determinations
  - to the extent that the ED1 models were operationally intuitive, this remains the case with the updated data
- **however**: the model fit, measured by adjusted R2, has decreased ~8% with the updated data, indicating that alternative cost drivers or estimation approaches will be important for Ofgem to consider for ED2

ED1 replication

Efficiency rankings, 2011–2020

ED1 TD CSV	Updated TD CSV	ED1 BU CSV	Updated BU CSV
1	↓	1	↓
2	↓	2	↓
3	↓	3	↓
4	↓	4	↓
5	↓	5	↓
6	↑	6	↑
7	↑	7	↓
8	↓	8	↓
9	↓	9	↑
10	↑	10	↑
11	↑	11	↑
12	↑	12	↓
13	↓	13	↑
14	↑	14	–

Note: The period used to estimate the cost function is 2011–20 while the period used to estimate efficiency rankings is 2016–20. We have presented changes in rank with an arrow to preserve anonymity.

Updating the dataset on which Ofgem’s ED1 models are estimated has a **material** impact on the DNOs’ performance.

ED1 replication

Top-down CSV construction

Variables	ED1 TD	Updated TD
MEAV (log)	0.217***	0.191***
MEAV %	84.4%	74.9%
Customers (log)	0.0401	0.0639**
Customers %	15.6%	25.1%
Constant	5.444***	5.425***
Adj. R2	0.860	0.786

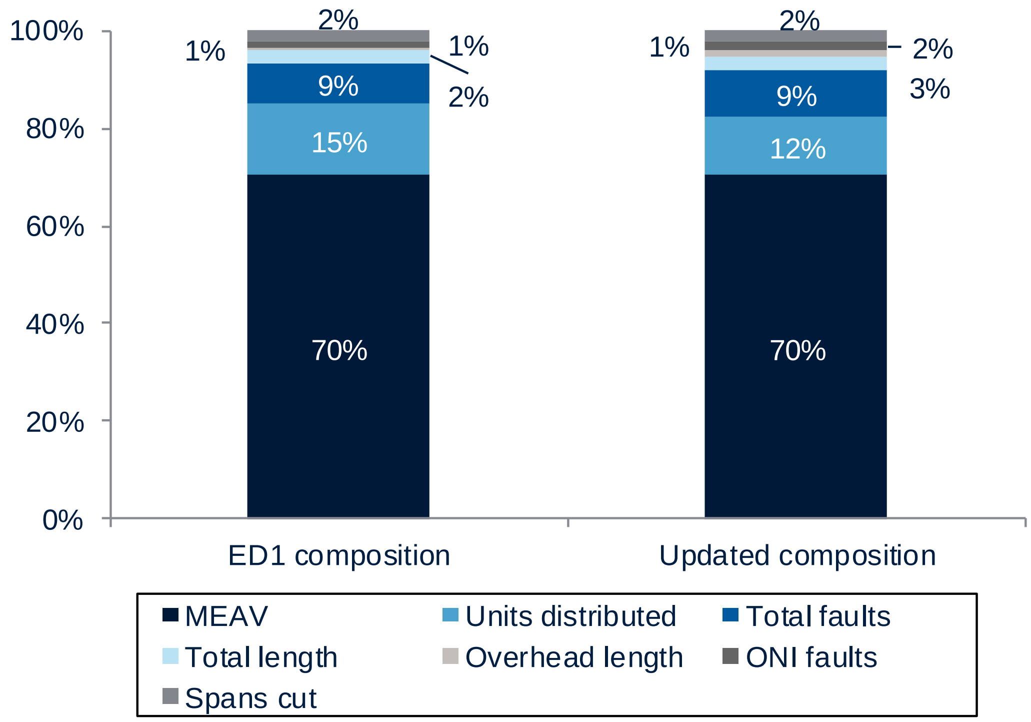
The weight on MEAV decreases, while the weight on customers increases materially, suggesting considerable volatility. Note the coefficient on customers is only significantly different from zero when using the updated dataset

The model fit deteriorates, indicating that the components of the CSV are less able to capture differences in expenditure between the DNOs and over time

The deterioration in the model fit and volatility in the weights are linked given the econometric approach to the CSV calculation

- the top-down CSV is less able to capture differences in expenditure with the updated data
- alternative (or additional) variables should be accounted for, and these are examined throughout this deck
- alternative approaches to CSV estimation could be more appropriate

ED1 replication
Bottom-up CSV construction

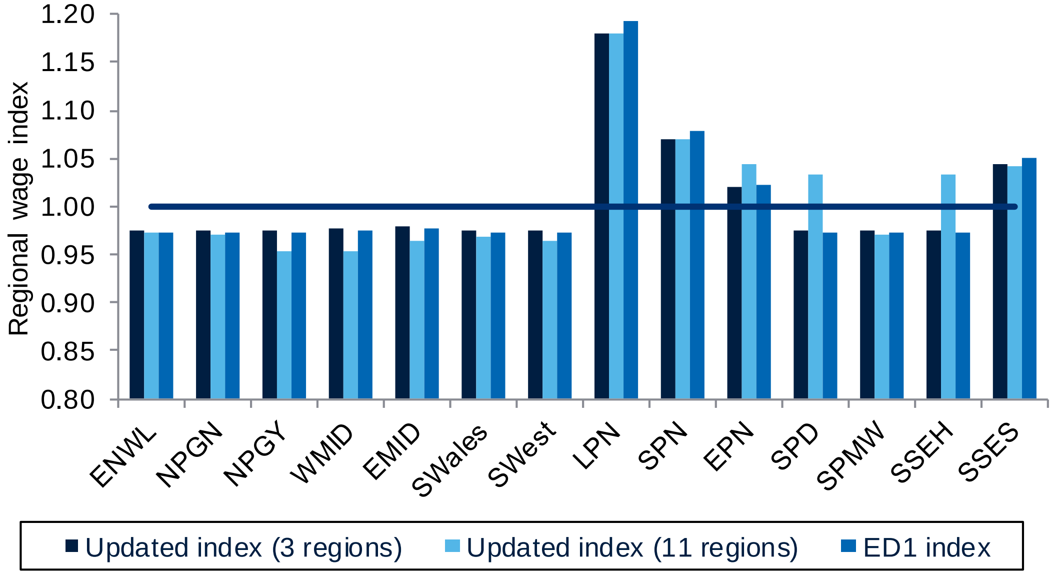


The cost driver composition within the BU CSV remains largely the same as in ED1

- the MEAV remains the dominant component within the BU CSV
- unlike the top-down CSV, the bottom-up approach gives no weight to customer numbers

ED1 replication

Updated regional wage adjustments



We have updated the regional wage index calculation using ASHE data up to 2020—the 2020 data is *provisional*.

- updating the index shows that regional wages have converged *slightly* since RIIO-ED1
- more granular regional wage indices can lead to materially different regional wage adjustments than Ofgem's 'three-region' approach

ED1 replication

ED1 TOTEX models, 2016–20

Variables	Top-down		Bottom-up	
	2011–20	2016–20	2011–20	2016–20
Macro CSV (log)	0.773***	0.717***		
BU CSV (log)			0.860***	0.795***
Time trend	-0.0109**	-0.00646	-0.00826*	-0.00514
Constant	15.32	7.122	17.46*	11.52
Adj. R2	0.799	0.794	0.815	0.838
RESET	0.00644	0.00294	0.0123	0.0567
Link	-1.097	-1.168	-3.154	-2.674
Chow (DPCR5)	0.000118	-	0.000305	-

Note: Modelling period is 2011–20 (140 observations) in the second and fourth columns and is 2016–20 (70 observations) in the third and fifth columns. Expenditure is expressed in 2012/13 prices.

The coefficients on the CSVs reduce when the modelling period is restricted to 2016–20

The coefficient on the time trend is no longer statistically significant.

The model fit remains broadly comparable for the different time periods, and the other diagnostics are largely unchanged

- the magnitude of the coefficients on the CSV is lower if the time period for regressions is restricted to 2016–20
  - in general, this will have an impact on the performance of large and small DNOs, and on the estimated cost-impact of growth if the models are extrapolated to set future allowances
- however, the coefficient for the time trend is materially lower and no longer statistically significant

ED1 replication

Efficiency rankings, 2016–2020

2011 TD CSV	2016 TD CSV	2011 BU CSV	2016 BU CSV
1	1	1	1
2	3	2	4
3	4	3	2
4	5	4	3
5	8	5	6
6	7	6	7
7	6	7	5
8	9	8	9
9	2	9	8
10	10	10	11
11	11	11	10
12	12	12	12
13	13	13	13
14	14	14	14

Note: The period used to estimate the cost function is 2011–20 for the first and third columns and is 2016–20 for the second and fourth columns. The period used to estimate efficiency rankings is 2016–20 in all columns.

Restricting the dataset to only the ED1 period has a **material** impact on some of the DNOs' performance.

In particular, one DNO improved from 9th to 2nd place in the rankings.

ED1 replication

ED1 TOTEX adjusted-data models, 2011–20

Variables	Top-down		Bottom-up	
	Updated	Corrected	Updated	Corrected
Macro CSV (log)	0.773***	0.755***		
BU CSV (log)			0.860***	0.852***
Time trend	-0.0109**	-0.00950*	-0.00826*	-0.00700
Constant	15.32	12.89	17.46*	14.96
Adj. R2	0.799	0.789	0.815	0.799
RESET	0.00644	0.00618	0.0123	0.00320
Link	-1.097	-1.154	-3.154	-3.699
Chow (DPCR5)	0.000118	0.000350	0.000305	0.00134

The coefficients on the CSVs are broadly insensitive to the corrections made to the data

The coefficient on the time trend becomes less statistically significant

The model fit worsens for both models, and the other diagnostics are largely unchanged

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices. Note that Ofgem used data 2011–23 so the coefficients differ to what is presented in the FD documents.

- based on discussions with DNOs, we have ‘corrected’ historical data where there are clear anomalies
  - some ‘corrections’ require ad hoc assumptions regarding the impact of changes to reporting guidelines, so analysis of this data is a sensitivity. For example, we backdate MEAV data for three DNOs, and network drivers data for one DNO, to eliminate structural breaks.

ED1 replication

Efficiency rankings, 2011–20

Updated TD CSV	Corrected TD CSV	Updated BU CSV	Corrected BU CSV
1	5	1	7
2	2	2	6
3	3	3	1
4	9	4	4
5	11	5	3
6	1	6	12
7	4	7	5
8	8	8	11
9	6	9	2
10	7	10	13
11	12	11	8
12	10	12	9
13	14	13	10
14	13	14	14

Note: The period used to estimate the cost function is 2011–20 while the period used to estimate efficiency rankings is 2016–20.

Updating the dataset on which Ofgem's ED1 models are estimated has a **material** impact on the DNOs' performance.

Given the impact of potential data inconsistencies on the efficiency rankings, it is essential that the data is thoroughly examined and corrected to the extent possible.

4. Regional adjustments—wage and density

Regional adjustments—wage and density

1. Background and industry engagement
2. Empirical analysis
3. Observations and recommendations

Regional adjustments—wage and density
Background: Pre-modelling adjustments to the data

Focus of this study

1. Regional labour costs

- real wages (i.e. labour input prices) can differ across regions of GB and are largely exogenous to the DNO
- in ED1, Ofgem used the ASHE dataset to calculate a DNO-specific index, assuming that wages differed across three regions: London, South East England, and the rest of GB

2. Company-specific factors

- there may be DNO-specific factors that cause its costs to be higher that cannot be captured in the econometric modelling
- Ofgem made adjustments for three DNOs, which largely correlated with density and sparsity

3. Exclusions from TOTEX

- some costs are difficult to benchmark robustly because they are not well explained by TOTEX cost drivers or there are substantial changes to the nature of the cost between periods
- these types of cost can be assessed separately (e.g. through activity-level analysis)

4. Other adjustments

- costs outside of the price control should not be benchmarked, nor should costs that are completely outside of management control (e.g. taxes)

Regional adjustments—wage and density

Industry views: need to adjust for regional wages

Regional wages are not the only exogenous driver of labour costs. DNOs have to pay more for workers to visit remote locations (e.g. islands) and this would not be reflected in a regional wage adjustment

Pre-modelling adjustment for regional wages is best in order to avoid the wage effect being conflated with other factors

The pre-modelling adjustment may be excessive and should be modelled explicitly, rather than through pre-modelling adjustments

Too little?

Too much?

London and the South East are *not* the only regions that require adjustments

Adjustment *might be* required for London and the South East. Wage differentials are less material between other regions as workers are generally mobile

Prices for inputs essential for compliance are unlikely to differ in ED2 as all DNOs will be going to the same market for the same skillsets and materials at the same time

Regional adjustments—wage and density

Industry views: adjustment for regional wages

Is the current approach appropriate?

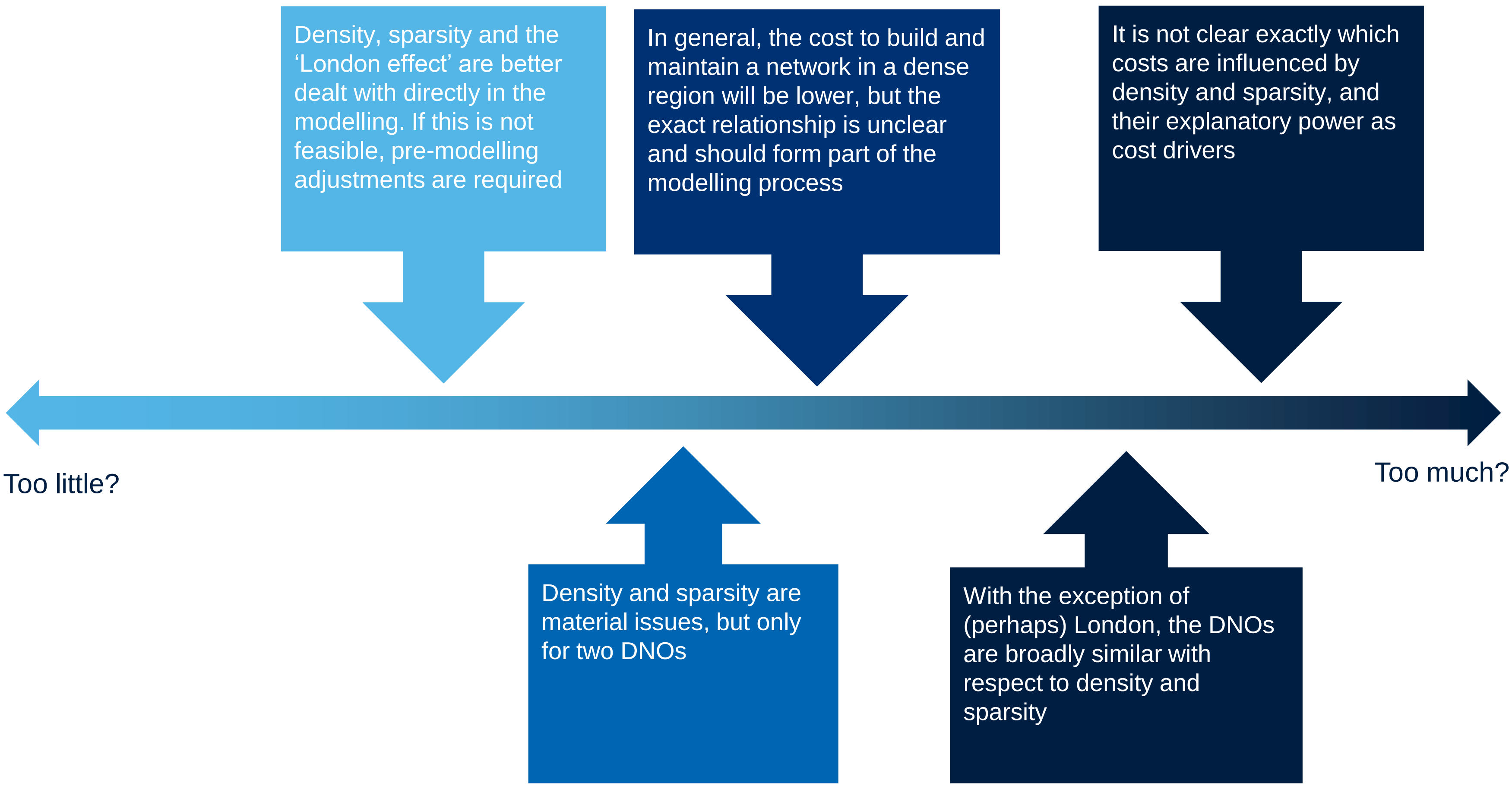
- at a granular level, the ASHE dataset is broadly sensible and well established. Regardless, labour costs must be accounted for somehow
- the current dataset is *inappropriate* because the ‘London effect’ is biased by the presence of more high-wage *roles* in London
- the focus on wages is inappropriate and is not reflective of all exogenous labour costs—either a different index or an additional adjustment is required to address these
- pre-modelling adjustments are not appropriate *in general* as they can ignore the overlapping impact of several factors if applied in isolation
- significant geographic mobility of the contractor workforce limits regional wage differentials

What are the alternatives?

- examine regional wage differences in other, similar sectors, such as the regional variation in wages paid to staff at Network Rail
  - Ofgem’s selected SIC codes may be better targeted
- include a wage index in the model directly:
  - if the index is found to be statistically insignificant, it can be removed from the model
  - the dataset is small, and including the variable results in a loss of valuable degrees of freedom—if inclusion in the model does not ‘work’ then a pre-modelling adjustment should be used
- potentially account for regional wages through asymmetric, post-modelling adjustments

Regional adjustments—wage and density

Industry views: need to adjust for density/sparsity



Regional adjustments—wage and density

Industry views: adjustment for density/sparsity

Is the current approach appropriate?

- density and sparsity apply only to extreme DNOs—it might be difficult to model this and it could be better dealt with through adjustments
- the impact of density and sparsity overlap with other aspects included in the model, and pre-modelling adjustments are difficult to separately (and accurately) quantify
- modelling is preferred, but density must be accounted for somehow
- DNOs are very similar when it comes to density and sparsity—with the exception of one DNO, all DNOs operate in a region containing at least one national park (sparse) and at least one large city (dense)

What are the alternatives?

- test different measures of density directly in the models
- simple measures of density/sparsity might be inappropriate as they cannot account for different levels of density within a DNO
    - GINI can capture this internal density variation

Regional adjustments—wage and density

1. Background and industry engagement
2. **Empirical analysis**
3. Observations and recommendations

Regional adjustments—wage and density

What we have tested

Regional wages

1. **ED1 approach**
   Pre-modelling adjustments, to reflect regional input prices for London and the South East
2. **No adjustment for regional wages**
   Reverse the adjustment for regional wages
3. **Wage included as a regressor**
   Accounting for regional wages by including an index that directly takes into account variations across *all regions* in the model
4. **ED1 approach with wage included as a regressor**
   Pre-modelling adjustments to reflect differences in regional wages, as well as accounting for regional wages in the model directly

Population density

1. **ED1 approach**
   Pre-modelling adjustments, to reflect operating differences for LPN and SSEH
2. **No density adjustment**
   Reverse the adjustment for density/sparsity
3. **Linear density**
   Accounting for density with a high-level, aggregated density variable
4. **Quadratic (non-linear) density**
   Modelling density squared to account for the higher costs associated with operating in extremely dense and extremely sparse regions
5. **Gini index**
   Using a Gini index to account for within-region variation in population density

Regional adjustments—wage and density

Regional wages—top-down model

Variables	ED1 approach	No regional wage adjustments	Wage included as a regressor	ED1 approach with wage as a regressor
Macro CSV	0.773***	0.768***	0.775***	0.785***
Time trend	-0.0109**	-0.0106**	-0.0106**	-0.0110**
Wage index (log)			-0.334	-0.654*
Constant	15.32	14.93	14.90	15.27
Adj. R2	0.799	0.813	0.816	0.816
RESET	0.00644	0.0758	0.119	0.0274
Link	-1.097	-0.669	-0.544	-0.987
Chow (DPCR5)	0.000118	0.000110	0.000266	0.000251
VIF	1.003	1.002	1.016	1.013

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

The wage index is **negative** and sometimes **statistically significant**

Model fit is **highest** when regional wages are **included as a regressor.** Model fit cannot be used to directly compare models with different dependent variables

- operationally, regional wages *could be* a material driver of expenditure for *at least some* DNOs
- the empirical analysis indicates that there may be grounds to explore *alternative methods* of accounting for regional wage differences
- note the general limitations with top-down modelling on a small dataset—the negative coefficient on the wage index could capture characteristics unrelated to wages (including efficiency) based on the sample used

Regional adjustments—wage and density

Regional wages—bottom-up model

Variables	ED1 approach	No regional wage adjustments	Wage included as a regressor	ED1 approach with wage as a regressor
BU CSV (log)	0.860***	0.873***	0.873***	0.864***
Time trend	-0.00826*	-0.00823*	-0.00824*	-0.00827*
Wage index (log)			-0.0352	-0.420
Constant	17.46*	17.32*	17.32*	17.45*
Adj. R2	0.815	0.819	0.818	0.821
RESET	0.0123	0.00349	0.00286	0.00285
Link	-3.154	-3.293	-3.279	-2.991
Chow (DPCR5)	0.000305	0.000296	0.000667	0.000673
VIF	1	1	1.003	1.003

The wage index is **negative** and **statistically insignificant**

Model fit is **highest** when regional wages are **included as a regressor**

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

- the high-level conclusions are *similar* between the bottom-up and top-down models—i.e. controlling for regional wages as a separate regressor does not yield sensible results
  - given the large weight attached to MEAV in both CSVs, the similarity may be unsurprising
- the analysis could indicate that the incremental impact of regional wages depends on what else is being accounted for in the model, although the confidence intervals around the coefficients on the wage index are large in all models

Regional adjustments—wage and density

Density—top-down model

Variables	ED1 approach	No density adjustment	Linear density	Quadratic density	Linear density with Gini	Quadratic density with Gini
Macro CSV	0.773***	0.756***	0.754***	0.732***	0.685***	0.593***
Time trend	-0.0109**	-0.0107**	-0.0106**	-0.0105**	-0.0106**	-0.0102**
Density (log)			0.00101	0.0528	0.0995***	0.300**
Density^2 (log)				-0.00449		-0.0152**
Gini index					0.854***	1.070***
Constant	15.32	15.17	15.18	15.17	15.14	15.11
Adj. R2	0.799	0.798	0.796	0.796	0.825	0.836
RESET	0.00644	0.0318	0.0305	0.0527	0.976	0.0419
Link	-1.097	-0.992	-0.946	-0.557	0.379	1.323
Chow (DPCR5)	0.000118	0.000125	3.63e-07	4.96e-07	2.28e-08	2.15e-07
VIF	1.003	1.002	1.266	36.40	6.225	59.58

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

The high-level density variable is sometimes **statistically significant**

A negative coefficient on density squared implies that very dense and very sparse DNOs are low cost, which **is unintuitive**

The positive coefficient on Gini implies that, for a given level of *average density*, a more unequal distribution of people leads to higher cost

- the high-level density variable does not work well in the model unless the Gini index is included
- accounting for density can improve model fit, but the negative coefficient on the quadratic term is unintuitive and suggests that the quadratic function is inappropriate

Regional adjustments—wage and density

Density—bottom-up model

Variables	ED1 approach	No density adjustment	Linear density	Quadratic density	Linear density with Gini	Quadratic density with Gini
BU CSV (log)	0.860***	0.851***	0.812***	0.780***	0.756***	0.657***
Time trend	-0.00826*	-0.00821*	-0.00824*	-0.00820*	-0.00832*	-0.00827*
Density (log)			0.0315***	0.106	0.0939***	0.292**
$Density^2$ (log)				-0.00661		-0.0150*
Gini index					0.551**	0.801**
Constant	17.46*	17.40*	17.50*	17.39*	17.35*	17.03*
Adj. R2	0.815	0.808	0.820	0.822	0.831	0.841
RESET	0.0123	0.00509	0.0603	0.182	0.726	0.321
Link	-3.154	-3.340	-1.992	-1.347	-0.936	0.323
Chow (DPCR5)	0.000305	0.000321	5.61e-07	7.80e-07	1.43e-07	7.95e-07
VIF	1	1	1.128	33.38	6.293	59.54

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

The high-level density variable is generally **positive** and **statistically significant**

The coefficient on density squared is always **negative** and **statistically significant**

Models typically ‘pass’ the functional form tests when density and Gini are included as regressors

- Gini and a linear density term together appears to work the best, in terms of model fit, passing diagnostics and consistently having intuitive and significant coefficients.
- the magnitude of the coefficients on the density variables differs between the models, requiring operationally validity of the cost impacts

Regional adjustments—wage and density

Density and wage—top-down model

Variables	No regional wage or density adjustments	Density and wage included as regressors	Density and Gini included as regressors	Density, wage and Gini included as regressors
Macro CSV	0.753***	0.724***	0.661***	0.636***
Time trend	-0.0104**	-0.0103**	-0.0103**	-0.0102**
Wage index (log)		-0.396		-0.594*
Density (log)		0.0239	0.121***	0.150***
Gini index			0.948***	1.031***
Constant	14.74	14.92	14.83	14.96
Adj. R2	0.807	0.810	0.841	0.850
RESET	0.228	0.00592	0.460	0.00237
Link	-0.541	0.958	0.955	2.003
Chow (DPCR5)	0.000120	8.01e-07	1.14e-08	3.66e-08
VIF	1.002	1.886	6.293	7.590

The wage index is **always negative,** even when accounting for population density

The density and Gini index terms remain **positive** and generally **statistically significant**

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

Regional adjustments—wage and density

Density and wage—bottom-up model

Variables	No regional wage or density adjustments	Density and wage included as regressors	Density and Gini included as regressors	Density, wage and Gini included as regressors
BU CSV (log)	0.864***	0.789***	0.741***	0.713***
Time trend	-0.00820*	-0.00826*	-0.00834*	-0.00838*
Wage index (log)		-0.480		-0.619**
Density (log)		0.0641***	0.118***	0.149***
Gini index			0.612***	0.709**
Constant	17.31*	17.51*	17.30*	17.33*
Adj. R2	0.806	0.842	0.849	0.859
RESET	0.00146	0.185	0.686	0.0631
Link	-3.409	-0.0542	-0.364	0.912
Chow (DPCR5)	0.000305	5.19e-07	1.12e-07	2.58e-07
VIF	1	1.629	6.296	7.559

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

The wage index is **always negative,** even when accounting for population density

The density and Gini index terms are always **positive** and **statistically significant**

- the high-level conclusions are *similar* between the bottom-up and top-down models

Regional adjustments—wage and density

Impact of adjustments on top-down CSV construction

Variables	Updated TD	No wage adjustments	No regional adjustments	No wage or regional adjustments
MEAV (log)	0.191***	0.165***	0.173***	0.149***
MEAV (%)	74.9%	63.0%	68.1%	57.2%
Customers (log)	0.0639**	0.0967***	0.0810***	0.111***
Customers (%)	25.1%	37.0%	31.9%	42.8%
Constant	5.425***	5.426***	5.429***	5.431***
Adj. R2	0.786	0.802	0.786	0.796

The weight on MEAV materially reduces when pre-modelling adjustments are **not** made

The model fit improves without wage adjustments, indicating that the components of the CSV are better able to capture differences in expenditure between the DNOs and over time

- the top-down CSV is generally better able to capture differences in expenditure when pre-modelling adjustments are not made
- the sensitivity of the CSV weights to the pre-modelling adjustments indicates that the adjustments could be highly correlated with MEAV and/or customer numbers
- regional adjustments require careful application and validation to ensure that they do not skew results towards particular companies

Regional adjustments—wage and density

1. Background and industry engagement
2. Empirical analysis
3. **Observations and recommendations**

Regional adjustments—wage and density
Observations and recommendations

- it appears difficult to account for regional wages directly within the model in a way that yields statistically significant and operationally intuitive coefficients
  - there could potentially be grounds for Ofgem to investigate alternative approaches to accounting for regional wage adjustments directly in the modelling process
  - if alternative methods do not yield robust and intuitive results, pre- or post-modelling adjustments may be needed (provided that these adjustments are robustly evidenced)

- density can be accounted for in the model directly, but not in isolation
  - for the coefficient on density to be consistently both positive and statistically significant, intra-regional variations have to be captured through the Gini index
  - it might be inappropriate to dedicate two cost drivers to capture one characteristic if other important characteristics (e.g. outcomes) are unaccounted for

- the magnitude and significance of wages and density depend on the other cost drivers included in the model
  - in this context, further consideration of uniform pre-modelling adjustments may be necessary
  - multiple methods of pre-modelling, within modelling and post-modelling adjustments should be fully explored to ensure that the results are not skewed towards particular companies

5. Cost driver analysis—MEAV

Cost driver analysis—MEAV

1. Background and industry engagement
2. Empirical analysis
3. Observations and recommendations

Cost driver analysis—MEAV
Background

MEAV is the weighted sum of asset volumes, defined as per the following equation:

$$MEAV = \sum_a n_a v_a$$

Where n_a is the number of assets of type a and v_a is the weight of such an asset. The weight, v, is informed by expert judgement but based on the DNOs' data

MEAV was given a material weight in the TOTEX modelling at ED1, accounting for 75% and 70% of the top-down and bottom-up CSV, respectively. As an asset-based measure of output, it is partially within management control. In theory, the impact of this endogeneity on the model estimates can be empirically tested through instrumental variables

Cost driver analysis—MEAV
Industry views: does MEAV drive expenditure?

The MEAV:

- *does* drive expenditure—there is a relatively strong correlation between TOTEX and MEAV
  - it also captures topographical features and network complexity, to some extent
  - it is a particularly strong cost driver of some elements of the cost base (e.g. faults)
- is a ‘blunt instrument’ because it does not account for:
  - network condition and any work done on the network
  - unmetered connections
  - mandated activities and investments (e.g. PCBs)
  - environmental factors that cause the asset to be more/less costs to operate in different areas
- is biased towards certain asset structures
  - LV networks are overly accounted for
  - it assumed that underground networks cost more, which is not the case for all cost lines
- the ‘bluntness’ and biases may average

Furthermore, there is uncertainty about the raw data that feeds into the MEAV calculations:

- MEAV reporting should be harmonised across DNOs and any data errors or inconsistences should be corrected
- the data uncertainty is endemic in the measure, which mitigates the use of the variable in cost benchmarking
- material improvements are needed on the data (e.g. re-evaluating which assets are to be included in the measure)

Cost driver analysis—MEAV
Industry views: is MEAV endogenous?

- companies with historically large MEAVs received higher funding which they have been able to invest in growing the network, resulting in an even higher MEAV for these companies at the next price control
  - ‘one price control begets another’
  - the MEAV could lead to DNOs ‘gold-plating’ assets
    - *but* DNOs are unlikely to incur the expenditure necessary for MEAV to be meaningfully impacted
  - the risk element is relatively new in ED1
- the use of MEAV biases the assessment in favour of asset-based solutions
  - this does not reflect operational measures that DNOs incur in order to avoid adding assets to the network (e.g. flexibility)
  - this is not necessarily bad—asset-based solutions are essentially a one-off expenditure, while flexible solutions require ongoing expenditure, and the asset bias is not inappropriate in this context
- the discussion regarding the endogeneity of MEAV is largely academic
  - the MEAV is a function of a DNO’s inherited asset base and the assets it needs to deliver consumer outcomes
  - much of the asset base is static; the MEAV is unlikely to move significantly from year to year
    - increases to the MEAV from investment (or forfeiture of future MEAV from flexible solutions) are minimal

Oxera comment

Much of the critique of the MEAV appears to relate to its importance in ED1 such that other factors were possibly inadequately captured

Cost driver analysis—MEAV

1 Background and industry engagement

2 **Empirical analysis**

3 Observations and recommendations

Cost driver analysis—MEAV
What we have tested

Generic uncertainty in the measure

Monte Carlo simulations, to assess the impact of uncertainty in the asset and weight measures on companies' efficiency performance

Specific uncertainty relating to LV connections

Making adjustments to the LV service data to bring it broadly in line with customer numbers

Specific uncertainty relating to data issues

Making adjustments to the MEAV data to 'correct' for large structural changes in the measure. This is addressed in the 'ED1 replication' section.

- the main issue that the DNOs had with the use of MEAV related to:
  - data uncertainty
  - structural breaks that may be potential data issues
  - giving MEAV excessive weight in the analysis
- this section models specific types of data uncertainty and potential data issues
  - the weight on MEAV is addressed throughout this pack
- while known data inconsistencies and any errors should always be corrected, modelling the impact of the uncertainty can be used to inform, for example:
  - the weight attached to MEAV in the analysis
  - the weight on model outputs (with and without MEAV) in triangulation
  - the appropriate efficiency benchmark
- if data uncertainty is endemic in the MEAV measure, then the analysis should be validated with alternative cost drivers
- note that we have not assessed whether the asset weights are appropriate—Ofgem should carefully examine its expert view of unit costs to ensure they are appropriate for ED2.

Cost driver analysis—MEAV
Sources of uncertainty

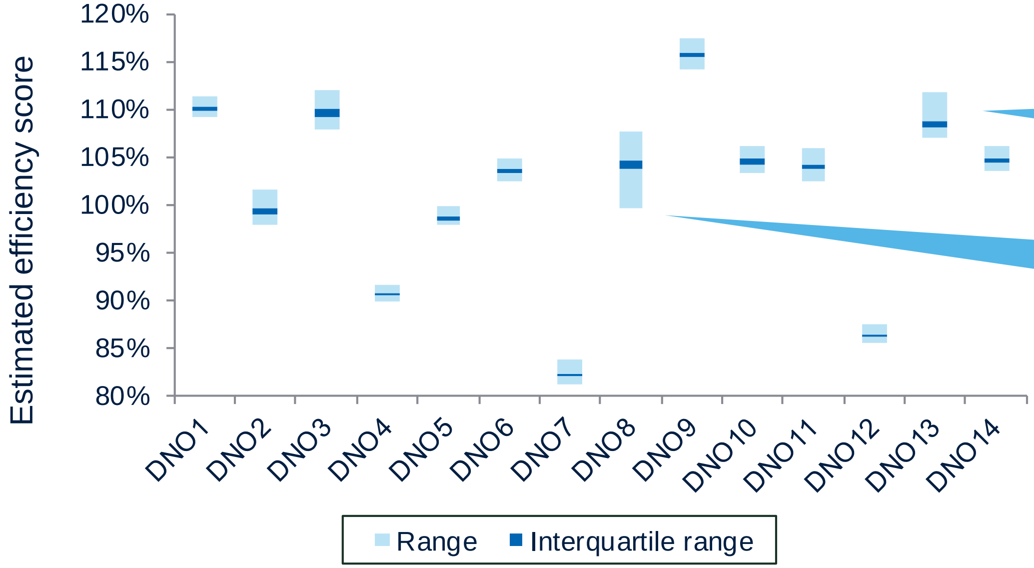
$$MEAV = \sum_a n_a v_a$$

Where n_a is the number of assets of type a and v_a is the weight of such an asset. The weight, v, is informed by expert judgement but based on DNOs' data

Identify asset groups	Assign cost weights	Apply to volume data
• Are all (and only) relevant asset groups considered?	• Are the weights appropriate?	• Is the volume data measured correctly?

We have tested the sensitivity of the results to uncertainty in how the cost weight is estimated by running a Monte Carlo analysis assuming a ±25% uncertainty margin (where noise is simulated, here symmetrically, and added to the data)

Cost driver analysis—MEAV
Modelling generic uncertainty

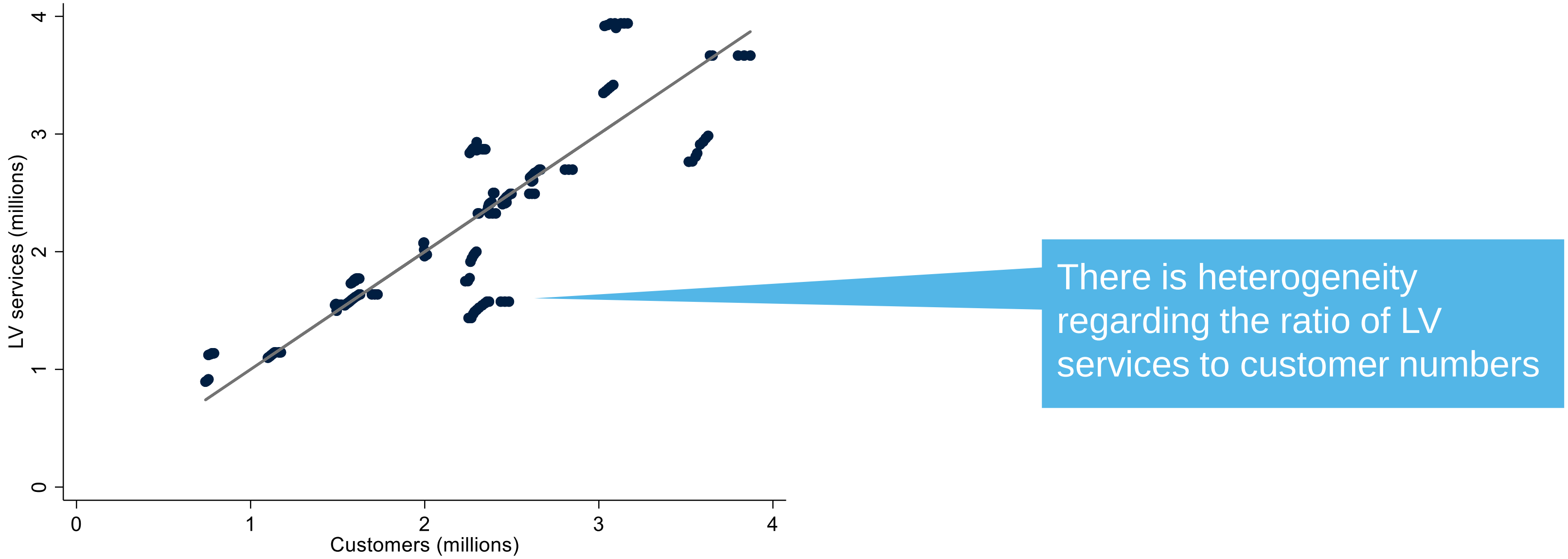


The range in estimated efficiency scores is narrow for most DNOs

Even the DNO with the largest range has a relatively narrow interquartile range

- there are a large number of (disaggregated) asset classes—the ‘uncertainty’ components added to each asset weight might cancel out when aggregated, causing the narrow range of efficiency scores
- a more targeted approach to modelling uncertainty—e.g. specific to each asset class and possibly asymmetrically distributed—should be investigated
- Monte Carlo analysis can be used to assess the impact of uncertainty any constructed measure, including CSVs

Cost driver analysis—MEAV
LV connections



- there is a view that the ratio of LV services to customers varied across DNOs, and stated that they believed that this was driven by inconsistencies in reporting and measurement
  - an alternative view is that there are operational reasons why the ratio could differ, so the ratio cannot provide meaningful insights into reporting
- as a sensitivity, we adjust the MEAV data such that LV services match the number of customers
  - this would only improve the modelling if a 1:1 relationship is expected, and if customer numbers were measured with more certainty than LV services

Cost driver analysis—MEAV

LV connections: impact on cost models

Variables	MEAV only		Top-down CSV		Bottom-up CSV	
	No adjustment	Adjusted	No adjustment	Adjusted	No adjustment	Adjusted
MEAV (log)	0.811***	0.802***				
Macro CSV (log)			0.773***	0.799***		
BU CSV (log)					0.860***	0.856***
Time trend	-0.0118**	-0.0103**	-0.0109**	-0.0102**	-0.00826*	-0.00719
Constant	16.24*	13.29	15.32	13.28	17.46*	15.31*
Adj. R2	0.794	0.801	0.799	0.801	0.815	0.822
RESET	0.0702	0.00791	0.00644	0.00488	0.0123	0.0184
Link	-2.024	-1.520	-1.097	-1.457	-3.154	-2.659
Chow (DPCR5)	0.000416	0.00129	0.000732	0.00132	0.00340	0.00734

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

The change in coefficient on the CSVs is marginal, and not consistent across different models

Model fit and other statistical diagnostics are largely unchanged after data is adjusted

Cost driver analysis—MEAV

LV connections: impact on efficiency rankings

MEAV only		Top-down CSV		Bottom-up CSV	
No adjustment	Adjusted	No adjustment	Adjusted	No adjustment	Adjusted
1	1	1	1	1	1
2	5	2	2	2	2
3	6	3	6	3	4
4	4	4	4	4	6
5	3	5	3	5	7
6	9	6	7	6	5
7	2	7	8	7	8
8	7	8	9	8	3
9	8	9	5	9	9
10	10	10	11	10	10
11	11	11	10	11	11
12	12	12	12	12	12
13	13	13	13	13	13
14	14	14	14	14	14

Note: The period used to estimate the cost function is 2011–20 while the period used to estimate efficiency rankings is 2016–20.

- while the divergence between LV services and connections may be the result of legitimate operational reasons, the analysis indicates that this issue can have a material impact on some DNOs' performance
- as with all data, Ofgem should perform sense checks and engage with DNOs to ensure that asset data is reported correctly and consistently

There is uncertainty regarding which companies are top performers (e.g. ranked 5 and above)

The difference between the 'adjusted' and 'unadjusted' analysis is smaller in the bottom-up CSV

DNOs at the top and bottom of the efficiency rankings are largely insensitive to the MEAV adjustment

Cost driver analysis—MEAV

1 Background and industry engagement

2 Empirical analysis

3 Observations and recommendations

Cost driver analysis—MEAV
Observations

- cost models are not particularly sensitive to potential uncertainties that we have detected in the MEAV measure, but DNO efficiency rankings can be sensitive
  - the coefficients on the cost driver does not change materially under adjustments to the MEAV data, nor do the statistical diagnostics considered

- the impact of any MEAV uncertainty may be reduced when it is included in a CSV
  - moderating weight on MEAV might mitigate the impact of data uncertainty for this variable, although this may introduce other sources of uncertainty if the other variables are measured with noise
  - sensitivity analysis is needed to ensure that the results are robust to small changes

- the current analysis takes the assets and their respective weights as given
  - Ofgem should work to update the asset weights to reflect the costs associated with each asset class
  - additional or different asset classes could be included in the measure (if appropriate from operational and data-quality perspectives)
  - if other assets are included in the MEAV measure (as was defined at ED1), then care must be taken to maintain the correspondence between costs and cost drivers

6. Cost driver analysis—individual cost drivers

Cost driver analysis—individual cost drivers

1. Background and industry engagement
2. Empirical analysis
3. Observations and recommendations

Individual cost drivers
Industry views: ED1 fast-track drivers

Cost driver	Advantages	Disadvantages
Network length	• generally a good measure of scale and can capture some aspects of network complexity • incorporates legacy network design to some extent	• measured inconsistently across DNOs and not clearly defined • endogenous and depends on network design and reinforcement decisions • does not account for network characteristics (e.g. subsea cable) • might not capture costs associated with shorter (denser) networks
Units distributed and peak load	• customer-centric measure of output that should be an underlying driver of scale • largely exogenous to management decisions • some explanatory power for reinforcement requirements	• as a high-level variable, it does not account for volatility in volume growth and volume decline (‘churn’) within each DNO’s operating region, both of which are associated with costs • capacity is not a driver of ongoing costs (once installed, there are few ongoing costs) • does not take into account correlation to network length • peak load may become endogenous in ED2 as networks manage demand through DSO activity • could potentially be measured inconsistently across DNOs
Customer numbers	• customer-centric measure of output that should be an underlying driver of scale • exogenous to management decisions	• customer numbers do not take into account network usage or legacy network configurations • cost-to-serve is highly variable depending on network

One DNO noted that none of these drivers accounts for the actual work that the DNOs have to do, nor the associated investment

Another DNO noted that it would be inappropriate to include drivers that explicitly capture the activities undertaken on the network

Cost driver analysis—individual cost drivers

1. Background and industry engagement
2. **Empirical analysis**
3. Observations and recommendations

Individual cost drivers
What we have tested

Individual performance

- testing the cost drivers one by one allows us to explore which one has the best overall explanatory power
- the individual analysis also allows us to explore how sensitive the performances of the DNOs are to the choice of cost driver
- note: models accounting for only one cost driver are unlikely to be robust enough to be used to set allowances for ED2

Combined performance

- testing multiple cost drivers in a single model allows us to explore the impact of multi-collinearity, and to see which combination of cost drivers has the best explanatory power
- models with multiple cost drivers will typically be able to account for more operating characteristics
- note: as the cost drivers are highly correlated with each other, some of the tested models are likely to have unintuitive coefficients

If it is not possible to capture all relevant industry characteristics in a single model, a more prudent approach could be to use multiple models, possibly at different levels of aggregation, to assess the DNOs' efficiency and triangulate the results.

Individual cost drivers
Scale variables: individual performance

Variables	MEAV (log)	Total faults (log)	Units distributed (log)	ONIs faults (log)	Peak load (log)	Total length (log)	Customers (log)
Cost driver	0.811***	0.656***	0.590***	0.471***	0.599***	0.799***	0.609***
Time trend	-0.0118**	-0.000277	0.000578	-0.00572	0.000384	-0.00766	-0.00842*
Constant	16.24*	-0.170	-1.562	12.21	-0.257	12.14	13.57
Adj. R2	0.794	0.663	0.690	0.552	0.719	0.593	0.728
RESET	0.0702	0.0598	0.00623	0.0115	0.0951	0.183	0.0248
Link	-2.024	-1.956	0.512	0.00148	0.365	0.669	2.477
Chow (DPCR5)	0.000113	0.0593	0.00144	0.00139	0.000437	0.00279	0.000154

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

- MEAV appears to be the best *single* cost driver for explaining TOTEX in terms of model fit, followed by customer numbers and units distributed
  - this is not surprising—*in theory*, MEAV may capture the costs associated with a wide range of assets
  - MEAV is a measure of costs, so the relationship between MEAV and TOTEX could be *tautological*—i.e. an input–input model, where the interpretation of regression outputs becomes unclear
  - this would not necessarily negate the use of asset-based measures as cost drivers, but would require corroboration with the results from other model specifications

Individual cost drivers

Scale variables: individual performance

MEAV (log)	Units distributed (log)	Total faults (log)	ONIs faults (log)	Peak load (log)	Total length (log)	Customers (log)
1	3	1	2	2	5	2
2	12	6	8	12	1	12
3	5	2	6	6	8	6
4	4	10	7	5	6	4
5	8	9	9	9	4	8
6	9	8	13	8	10	9
7	1	11	3	1	14	1
8	6	7	4	4	3	5
9	2	4	1	3	2	3
10	10	14	14	10	7	11
11	7	5	5	7	9	7
12	11	12	12	11	11	10
13	13	13	11	13	13	14
14	14	3	10	14	12	13

Efficiency rankings based on individual cost drivers tend to be **very volatile**.

There is *some* stability across *some* of the cost drivers for a few DNOs

Note: The period used to estimate the cost function is 2011–20 while the period used to estimate efficiency rankings is 2016–20.

- . the DNOs’ efficiency rankings appear highly sensitive to the cost driver being considered
- while there appears to be some correlation in DNOs’ performance between certain cost drivers (e.g. peak load and units distributed, customers and network length), it is not strong

Individual cost drivers

Scale variables: combined performance

Variables	Ofgem (MEAV and customers)	Customers, length and total faults	MEAV, customers and length	Customers and length	Length, faults and units distributed	Length, faults and peak load
MEAV (log)	0.642***		0.434			
Customers (log)	0.143	0.397***	0.225	0.437***		
Units distributed (log)					0.355***	
Network length (log)		0.296***	0.144	0.363***	0.299***	0.254**
Peak load (log)						0.370***
Total faults (log)		0.0995			0.165*	0.174**
Time trend	-0.0112**	-0.00725	-0.0103*	-0.00841*	-0.00112	-0.000983
Constant	15.56	10.12	14.33	12.09	-0.629	-0.0248
Adj. R2	0.798	0.793	0.799	0.792	0.804	0.807
RESET	0.00525	0.00660	0.000428	0.000777	0.0146	0.0252
Link	-1.430	-1.453	-1.753	-1.607	-2.285	-1.912
Chow (DPCR 5)	8.45e-05	1.94e-06	2.86e-06	7.75e-08	0.000141	0.000100
VIF	7.059	5.201	25.90	1.897	4.464	4.365

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

- the analysis highlights the difficulty with finding alternatives to the ED1 models
- it can be challenging for the econometric models to account for more than two or three cost drivers (even with a larger dataset), making CSVs an important tool in the analysis

Individual cost drivers

Scale variables: combined performance

Ofgem (MEAV and customers)	Customers, length, faults	MEAV, customers, length	Customers, length	Length, faults, units distributed	Length, faults, peak load
1	1	1	1	1	1
2	5	4	7	6	6
3	6	3	5	8	7
4	7	6	6	3	3
5	2	2	2	2	2
6	10	8	10	9	9
7	8	9	8	7	5
8	3	5	3	4	4
9	4	7	4	5	8
10	9	10	9	11	10
11	11	11	11	10	11
12	12	12	12	12	12
13	14	14	14	14	14
14	13	13	13	13	13

Efficiency rankings based on combinations of cost drivers tend to be **dependent on the choice** of cost drivers used

This is only a small difference in the DNOs' performance between units distributed and peak load

The bottom of the efficiency rankings is largely invariant to which cost drivers are used

Note: The period used to estimate the cost function is 2011–20 while the period used to estimate efficiency rankings is 2016–20.

- performance is more stable when considering models with multiple drivers than when considering models with a single cost driver

Cost driver analysis—individual cost drivers

1. Background and industry engagement
2. Empirical analysis
3. **Observations and recommendations**

Individual cost driver analysis
Observations and recommendations

- MEAV is the single best cost driver when modelling historical data in terms of model fit, but this does not necessarily mean that it is the only cost driver of importance
  - MEAV is defined in terms of costs and assets, so the relationship may be tautological
  - models with or without MEAV may help to validate, corroborate or triangulate outcomes
  - consideration of multiple models may lead to more robust results

- it is difficult to estimate ‘sensible’ models with multiple cost drivers, likely due to collinearity issues
  - this indicates that alternatives to top-down benchmarking with multiple drivers may be required, for example, through CSV construction or activity-level analysis
  - using multiple models to assess DNOs’ expenditure and triangulating outcomes could also mitigate this problem

- high-level cost drivers considered in previous price reviews remain relevant from statistical and operational perspectives on ED1 outturn data (i.e. over 2016–20)
  - these drivers include MEAV, customer numbers, network length and units distributed
  - other cost drivers (such as outcome measures and drivers of ‘Net Zero’) are discussed elsewhere
  - all analysis needs to be updated with new data (e.g. 2020/21 outturn and ED2 business plan data) for further validation

7. Cost driver analysis—CSV construction

Cost driver analysis—CSV construction

1. Background and industry engagement
2. Empirical analysis
3. Observations and recommendations

CSV construction
Background

- combining variables into a CSV can mitigate some of the issues associated with modelling several, highly correlated, cost drivers
  - the approach to combining cost drivers should be defensible and justified with robust economic, operational and statistical evidence
  - CSV is not a panacea and comes with its own limitations. Sensitivity analysis and cross-checks are important to ensure that the results are robust
- when assessing DNOs' expenditure, Ofgem has considered three approaches:

Simple average CSVs

A simple average of customer numbers, units distributed and network length was used as the CSV in the fast-track determinations

Top-down CSVs

Defined as the weighted sum of the MEAV and customer numbers, where the weights were estimated via regression analysis

Bottom-up CSVs

Estimated by mapping one relevant cost driver to each cost line

CSV construction
Industry views: disaggregated view of cost drivers (I)

Expenditure	Modelling approach and relevant cost drivers
Reinforcement & connections	• reinforcement is driven by company-specific factors (e.g. EV uptake) and should be separated from the TOTEX assessment • history and current utilisation levels are poor indicators of future spend requirements • reinforcement decisions can be triggered by decisions of the TSO, and high-level drivers such as units distributed will not capture this • forecast demand could be measured through load indices but the data is immature • there are several emerging factors relevant to driving reinforcement expenditure (DSO, net zero) that are not easy to measure or estimate
Tree-cutting	• spans cut and spans inspected are not appropriate drivers of tree-cutting expenditure as they are endogenous and bias the assessment in favour of specific solutions • spans affected and the length of the overhead network are reasonable cost drivers • environmental variables (such as the amount of forestry in an operating region) *might* be an appropriate driver of costs • a function of overhead line network length, and also affected by tree coverage (and species mix) and, at the margin, differences in growth rates
Troublecall	• faults are an endogenous driver, but the clearest short-term driver (network investment to significantly change fault rates is unlikely to be cost-effective) • troublecall could be broken down into separate cost categories with different drivers • can be affected by previous TOTEX allowances (i.e. if companies receive higher TOTEX allowances in ED1, they are likely to have fewer faults as there has been more reinforcement on the networks)

CSV construction

Industry views: disaggregated view of cost drivers (II)

Expenditure	Modelling approach and relevant cost drivers
ONIs	• ONIs faults and population density are relevant cost drivers • smart meter activity is a key driver, as is, increasingly, the penetration and usage of smart devices
Business support & CAIs	• MEAV is an *inappropriate* driver, but there are not many alternatives. MEAV attaches different weights to different assets, even though indirect costs (e.g. project management) are similar • there is an unclear distinction between direct and indirect expenditure in the context of outsourcing, so modelling at a TOTEX level (or 'middle-up' level) can alleviate some allocation concerns • indirect costs are driven by costs elsewhere, so everything is interlinked; total network length might make sense but will be incomplete • CAI can be split into two categories—costs associated with: (i) having a network (e.g. control rooms); and (ii) workload (e.g. design and project management). General scale (e.g. MEAV, customer numbers) can proxy the former, while the latter is a function of all other cost categories

Ofgem's approach to mapping and weighting at ED1 was inappropriate as the selected cost drivers could not adequately explain the variations in the respective cost lines. Unless better cost drivers can be identified, this limits the use of bottom-up and middle-up modelling

Oxera comment:

DNOs generally appear to be critical of assigning a MEAV to cost categories as the default option (i.e. if no other cost categories can be identified). If a bottom-up CSV is constructed, more work is required to identify (and quantify) relevant drivers for these categories

Cost driver analysis—CSV construction

1. Background and industry engagement
2. Empirical analysis
3. Observations and recommendations

CSV construction

What we tested

Top-down approaches		Bottom-up approaches		
Simple averages	**Weights based on regression analysis**	**Single driver mapping**	**Multiple driver mapping**	**Hybrid approach**
Mitigates multicollinearity, but assumes that the cost impact of each driver is the same	More material drivers of expenditure may receive a larger weight, but there are the same issues of collinearity for controlling for each driver separately	Less significant drivers of expenditure can be captured using a more granular CSV, but only one driver is mapped to each cost line	Multiple drivers can be mapped to each cost line, but the cost impact of each driver on each cost is assumed to be equal	Weights are derived using cost driver analysis at the activity level

Alternative approaches, such as DEA and PCA have more attractive features and can be used to construct a CSV. These were not tested as part of this study

CSV construction
Simple average CSVs

Variables	Ofgem (customers, length, units distributed)	Customers, length, faults	MEAV, customers, length	Customers, length	Length, faults, units distributed	Length, faults and peak load
CSV (log)	0.812***	0.759***	0.796***	0.821***	0.816***	0.819***
Time trend	-0.00123	-0.00464	-0.00522	-0.00956*	-0.00839*	-0.00105
Constant	0.209	5.852	6.719	13.35	11.97	-0.683
Adj. R2	0.800	0.788	0.783	0.800	0.792	0.799
RESET	0.0626	0.616	0.0445	0.000336	0.000700	0.0648
LINK	-2.576	-0.329	-2.074	-2.207	-2.120	-2.662
Chow (DPCR5)	0.00342	0.000858	0.00324	0.000262	0.000485	0.00797

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

- the fast-track CSV generally (marginally) outperforms alternative CSVs in terms of model fit, while other diagnostics are broadly similar
- despite the simple nature of the CSV construction, the model fit is broadly comparable to Ofgem’s ED1 models estimated with the updated data
  - Top-down adjusted R-squared: 0.796
  - Bottom-up adjusted R-squared: 0.812

CSV construction

Simple average CSVs

Ofgem (Customers, length, units distributed)	Customers, length, faults	MEAV, customers, length	Customers, length	Length, faults, units distributed	Length, faults, peak load
1	10	8	6	7	7
2	1	1	1	1	1
3	5	6	4	5	6
4	2	2	2	2	2
5	3	3	3	4	3
6	7	4	5	8	8
7	4	5	7	3	5
8	6	9	9	6	4
9	9	11	10	10	10
10	12	10	11	11	11
11	13	12	12	12	12
12	8	7	8	9	9
13	11	13	13	13	13
14	14	14	14	14	14

Efficiency rankings based on simple average CSVs of cost drivers are **generally less dependent** on the combination of cost drivers used

The DNOs towards the top and bottom of the rankings **tend** to be more stable, but this is not universal

Note: The period used to estimate the cost function is 2011–20 while the period used to estimate efficiency rankings is 2016–20.

CSV construction

Regression-based weights: MEAV and one other driver

Variables	MEAV, customers	MEAV, units distributed	MEAV, length	MEAV, peak load	MEAV, total faults
CSV (log)	0.773***	0.775***	0.812***	0.762***	0.808***
Time trend	-0.0109**	-0.00799	-0.0118**	-0.00738	-0.00901*
Constant	15.32	10.31	16.22*	9.887	11.81
Adj. R2	0.799	0.796	0.794	0.797	0.797
RESET	0.00644	0.000997	0.0700	0.00119	0.0566
LINK	-1.097	-1.228	-2.034	-0.994	-2.506
Chow (DPCR5)	0.000118	0.000209	0.000114	0.000115	0.000462

The coefficient on the CSV is generally closer to 1 (e.g. closer to constant returns to scale) when not using customer numbers

TD drivers are sometimes better at passing diagnostic tests.

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

- in this table, we construct top-down CSVs according to Ofgem's methodology, but using a cost driver different from customer numbers, in addition to MEAV
  - the model fit and statistical diagnostics are broadly similar
  - the coefficient is generally closer to 1, indicating that the effect of scale economies is less pronounced when alternative drivers are included

CSV construction

Regression-based weights: MEAV and one other driver

Variables	MEAV, customers	MEAV, units distributed	MEAV, length	MEAV, peak load	MEAV, total faults
MEAV (log)	0.191***	0.193***	0.249***	0.182***	0.202***
MEAV %	74.9%	75.1%	99.6%	70.1%	78.6%
Cost driver (log)	0.0639**	0.0643***	0.000893	0.0773***	0.0550**
Cost driver %	25.1%	24.9%	0.4%	29.9%	21.4%
Constant	5.425***	5.427***	5.425***	5.430***	5.426***
Adj. R2	0.786	0.790	0.779	0.792	0.789

MEAV tends to dominate the CSV if it is the only other cost driver

The weight on the alternative cost driver can become negligible (likely due to multi-collinearity).

The model fit for an alternative top-down CSV with positive weightings is broadly comparable to Ofgem's

- top-down CSV constructed with **MEAV and an alternative cost driver** are equally able to capture differences in expenditure
- an alternative cost driver comprises an insignificant percentage of the top-down CSVs

CSV construction

Regression-based weights: MEAV and one other driver

Ofgem (MEAV, customers)	MEAV, units distributed	MEAV, length	MEAV, peak load	MEAV, total faults
1	1	1	1	1
2	2	7	2	9
3	3	3	4	2
4	4	4	3	6
5	5	5	6	3
6	8	8	7	7
7	7	9	8	8
8	6	6	5	5
9	9	2	9	4
10	10	11	10	10
11	11	10	11	11
12	12	12	12	12
13	13	13	13	14
14	14	14	14	13

Controlling for network length or total faults has the most impact on the efficiency rankings, relative to Ofgem's ED1 approach

The efficiency rankings are broadly stable when considering MEAV plus one other driver

This is **not surprising** given that the **MEAV dominates in nearly all CSVs**

Note: The period used to estimate the cost function is 2011–20 while the period used to estimate efficiency rankings is 2016–20.

CSV construction

Regression-based weights: alternative drivers

Variables	Ofgem (MEAV and customers)	Customers, length and total faults	MEAV, customers and length	Customers and length	Length, faults and units distributed	Length, faults and peak load
CSV (log)	0.773***	0.762***	0.784***	0.765***	0.790***	0.769***
Time trend	-0.0109**	-0.00698	-0.00978*	-0.00845*	-0.000491	-0.000433
Constant	15.32	9.846	13.85	12.36	-1.533	-0.704
Adj. R2	0.799	0.794	0.800	0.790	0.803	0.807
RESET	0.00644	0.827	0.00759	0.393	0.580	0.440
LINK	-1.097	-0.567	-1.167	-0.550	-1.381	-1.155
Chow (DPCR5)	0.000118	0.000959	0.000197	0.000364	0.00544	0.00197

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

- it is possible to construct CSVs without the MEAV that outperform models with the MEAV, although the difference is marginal
  - this highlights the difficulty of finding drivers that clearly dominate the MEAV when it comes to explaining TOTEX
- the coefficient on the time trend is volatile and typically statistically insignificant
  - any statements about the productivity achieved by the sector gleaned through the time trend could be sensitive to the model selected

CSV construction
Regression-based weights: alternative drivers

Variables	Ofgem (MEAV and customers)	Customers, length and total faults	MEAV, customers and length	Customers and length	Length, faults and units distributed	Length, faults and peak load
MEAV (%)	74.9%		40.0%			
Customers (%)	25.1%	56.0%	40.3%	63.6%		
Units distributed (%)					50.8%	
Total length (%)		27.7%	19.7%	36.4%	28.6%	24.3%
Peak load (%)						54.0%
Total faults (%)		16.3%			20.6%	21.7%
Adj. R2	0.786	0.789	0.790	0.786	0.805	0.805

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

- MEAV can have a less dominant weight if it is combined with more than one other driver
- for most combinations of drivers, the weighted average is not too dissimilar from a simple (unweighted) average. Deriving weights from regression analysis may potentially have drawbacks, in that:
  - the regression may add unnecessary noise and volatility to the weights
  - regression analysis may generate unnecessary complexity without adding insights that are clear and intuitive

CSV construction

Regression-based weights: alternative drivers

Ofgem (MEAV and customers)	Customers, length and total faults	MEAV, customers and length	Customers and length	Length, faults and units distributed	Length, faults and peak load
1	1	1	1	2	1
2	4	3	2	1	2
3	6	6	7	5	5
4	7	4	6	8	7
5	2	2	4	3	4
6	3	5	3	6	3
7	5	7	5	4	8
8	9	8	9	7	6
9	11	9	11	11	11
10	8	10	8	9	9
11	10	11	10	10	10
12	12	12	12	12	12
13	14	14	14	14	14
14	13	13	13	13	13

Note: The period used to estimate the cost function is 2011–20 while the period used to estimate efficiency rankings is 2016–20.

Most top-down CSVs constructed with the Ofgem approach using alternative cost drivers tend to be relatively strongly correlated with each other

The top and bottom of the efficiency rankings are broadly stable across different models

CSV construction

Bottom-up CSVs: alternative mappings (weights)

Cost drivers	Ofgem CSV composition	Alternative 1 composition	Alternative 2 composition	Alternative 3 composition
MEAV	70.3%	17.5%	34.4%	64.3%
Units distributed	12.1%	36.2%	3.7%	6.6%
Overhead length	1.3%	1.2%	1.6%	1.2%
Total faults	9.4%	30.1%	9.7%	13.1%
Total length	2.7%	4.5%	43.9%	4.5%
Customers	0.0%	2.2%	4.8%	2.6%
ONI faults	1.8%	4.7%	2.0%	4.1%
Spans cut	2.3%	3.6%	0.0%	3.5%

We present three alternatives to Ofgem's CSV mapping:

Alternative 1 For every cost line, we use the cost driver that gives the highest adj. R2 value

Alternative 2 We change the cost lines for five cost drivers, in line with DNOs' views taken from the interviews

Alternative 3 We follow the approach in Alternative 1, but avoid using faults or ONIs faults, except where every alternative gives a negative adj. R2, or it is used for a cost line by Ofgem.

There may be incentive issues with giving too great a weight to faults.

CSV construction

Bottom-up CSVs: alternative mappings

Cost area	Cost driver used by Ofgem	Cost driver that maximises R2	% of Totex
cai	TotMEAV_excRLM_Other	TotMEAV_excRLM_Other	23.0%
asset_replacement	TotMEAV_excRLM_Other	faults_total	17.3%
business_support	TotMEAV_excRLM_Other	TotMEAV_excRLM_Other	11.7%
trouble_call	faults_total	faults_total	10.1%
reinforcement	units_dist	units_dist	5.9%
im	TotMEAV_excRLM_Other	faults_total	3.9%
connections	units_dist	units_dist	3.4%
tree_cutting	spans_cut	ohllvhv	3.0%
onis	onis_faults	customers	2.5%
diversions	length_total	faults_total	2.4%
refurbishment	TotMEAV_excRLM_Other	faults_total	2.4%
non_op_capex_adjusted	TotMEAV_excRLM_Other	spans_cut	2.3%
civil_works	TotMEAV_excRLM_Other	onis_faults	1.6%
esqcr	ohllvhv	ohllvhv	1.5%
legal_safety	TotMEAV_excRLM_Other	onis_faults	1.2%
hvp_gr	units_dist	units_dist	0.8%
hvp_ar	units_dist	units_dist	0.3%
nocs_other	TotMEAV_excRLM_Other	n.a.	0.3%
tcp	units_dist	onis_faults	0.2%
sw_1in20	ohllvhv	units_dist	0.2%
hvp_bt21cn	units_dist	faults_total	0.2%
black_start	TotMEAV_excRLM_Other	faults_total	0.2%
hvp_flr	units_dist	length_total	0.1%
hvp_ls	units_dist	spans_cut	0.1%
diversions_rail	length_total	n.a.	0.0%
qos	customers	n.a.	0.0%
hvp_other	units_dist	n.a.	0.0%

The most material cost lines are CAI, asset replacement, trouble call and reinforcement, which together make up over half of TOTEX.

Of these, only asset replacement's cost driver changes under the approach of maximising model fit (from MEAV total faults)

As the approach is data-driven, some mappings may not be operationally intuitive—a middle ground between Ofgem's operational mapping and this data-driven mapping may be needed.

One cost line has nonzero values only from forecast data (i.e., 2021-2023), which are not used in the results presented here.

Three cost lines in Ofgem's do-file either do not exist in Ofgem's dataset, or have only zero values.

CSV construction

Bottom-up CSVs: alternative mappings

Variables	Ofgem CSV	Alternative CSV 1	Alternative CSV 2	Alternative CSV 3
CSV (log)	0.860***	0.841***	0.877***	0.885***
Time trend	-0.00826*	-0.00440	-0.00717	-0.00614
Constant	17.46*	9.752	15.18	13.03
Adj. R2	0.815	0.778	0.734	0.663
RESET	0.0123	0.00315	0.121	0.0633
LINK	-3.154	-3.464	-2.447	-1.158
Chow (DPCR5)	0.000305	0.0909	0.0207	0.0351

Note: Modelling period 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices.

- Ofgem’s CSV generally outperforms the alternative mappings in terms of model fit
- the observation that mapping based on granular model fit (alternative 1) does not improve the TOTEX model fit indicates that such an approach may not be clearly preferable to Ofgem’s current approach of identifying operationally intuitive drivers
- the statistical tests generally support exploring alternative functional forms with BU CSV

CSV construction

Bottom-up CSVs: alternative mapping efficiency

Ofgem	Alternative BU CSV1	Alternative BU CSV2	Alternative BU CSV3
1	1	3	5
2	2	2	3
3	5	1	1
4	3	7	8
5	4	6	4
6	9	8	11
7	6	5	2
8	11	13	14
9	7	4	6
10	13	9	12
11	10	10	9
12	12	11	10
13	8	12	7
14	14	14	13

There is some stability at the top and bottom of the efficiency rankings

Several DNOs' performances are highly sensitive to the exact mapping—given this sensitivity, the mapping should be supported by robust operational, economic and statistical evidence. Sensitivity analysis regarding the mapping and weights should also be conducted.

Note: The period used to estimate the cost function is 2011–20 while the period used to estimate efficiency rankings is 2016–20.

CSV construction
Bottom-up CSVs: multiple mappings (weights)

- Ofgem’s current bottom-up approach is broadly equivalent to estimating a single regression for each activity* without a constant

$$Expenditure_i = \beta Cost\ driver_i + \varepsilon_i$$

- several cost drivers could influence costs for some activities, and the selection of one cost driver over another could be somewhat arbitrary
- it is possible to account for several cost drivers for each activity with methods equivalent to the top-down CSV construction i.e.
  - a simple average
  - regression based weights
- these, alongside other approaches such as DEA and PCA, could be explored for ED2 to allow for a more detailed assessment of DNOs’ expenditure

*As Ofgem applies the median unit cost instead of the mean unit cost, the implied estimation approach is Least Absolute Deviations (LAD) rather than OLS. LAD, like the median, is less influenced by outliers in the sample. This approach can be maintained in alternative bottom-up CSV constructions.

Cost driver analysis—CSV construction

1 Background and industry engagement

2 Empirical analysis

3 Observations and recommendations

CSV construction
Observations and recommendations

- CSVs do not need to account for the MEAV in order to produce ‘sensible’ results with good model fit
  - models such as these can be used in combination with (or as a cross-check on) models that control for the MEAV

- there is no material difference in the statistical quality of models using a unweighted average of cost drivers and those where the weights are informed by regression analysis
  - unweighted averages should not be excluded ex ante if this remains the case

- Ofgem does not necessarily need to be limited by ED1 and GD2 precedent when developing CSVs
  - extending Ofgem’s current methods and undertaking sensitivity analysis can offer additional insights and should be considered
  - different methods, such as PCA and DEA, could also potentially be explored

7. Cost driver analysis—controlling for outcomes

Cost driver analysis—controlling for outcomes

1. **Background and industry engagement**
2. **Empirical analysis**
3. **Observations and recommendations**

Controlling for outcomes

Overview

Advantages

- **Perverse incentives**
  Failing to account for service quality could allow companies to reduce expenditure at the expense of service quality
- **Omitted variable bias**
  If service quality is a material driver of expenditure, failing to account for it in the econometric models will result in biased coefficients and cost predictions

Oxera has argued in submissions to several regulators that the relationship between costs and service quality must be analytically modelled when setting cost allowances, and that such analysis is particularly necessary when the regulator sets challenging service targets.

Indeed, the academic literature clearly shows that efficiency scores estimated from economic cost models that ignore key factors, such as service quality, can be biased. Several EU regulators pursue an analytically integrated approach.

Disadvantages

- **Perverse incentives**
  Controlling for service quality could encourage companies to reduce service quality to achieve a higher allowance if the incentives are not appropriately calibrated
- **Endogeneity bias**
  Service quality is within management control and the coefficient may therefore be biased

Having ruled that there are costs associated with improving or maintaining some measures of service quality, the CMA made adjustments to the cost assessment in some cases. However, it stopped short of accounting for it explicitly in the modelling due to concerns regarding endogeneity.

More sophisticated modelling techniques that can mitigate or avoid the endogeneity issue can be explored as part of ED2.

Controlling for outcomes

Industry views: controlling for outcomes in principle

- cost assessment has historically not taken sufficient account of differences in quality/performance as a differentiating factor between DNOs
  - there is a policy-driven step change, and the regulatory cost assessment should be ‘at-tune’ with government policy
  - the cost/quality balance is driven by stakeholder input, engagement, and sign-off, as per Ofgem’s explicit guidance
- companies have different starting points, based on different appetites for risk, and this should be accounted for
  - simply controlling for outcomes will not drive improvements in the industry—how are poorly performing companies to be funded to achieve the desired level of outcomes?
  - costs associated with improving outcomes can materially differ across DNOs depending on weather conditions and other regional factors
- care must be taken to ensure that the outputs of an integrated model are incentive-compatible
  - incentives already exist to improve/maintain outcomes—incorporating outcomes in cost determination could result in a double-count
- it may be difficult to agree upon consistent qualitative measures and the link of qualitative measures to costs has not been proven

Oxera comment:

DNOs generally agree that outcome variables should (at least) be considered in the cost assessment model. However, the DNOs also identify several limitations and caveats

Controlling for outcomes

Industry views: controlling for outcomes in practice

Customer-centric outcomes

- customer satisfaction is inappropriate as data is noisy
- CI and CML are good measures of reliability
  - these measures make sense only for 12 of the 14 DNOs
- CI and CML depend heavily on the density or sparsity of the region
  - the fault rate may be a better variable for capturing this effect
- network losses could be modelled
- the costs associated with improving customer outcomes differ across DNOs

Asset health and condition

- CNAIM and NARMs are good starting points for measures of asset condition
  - there isn't a 1:1 relationship between NARMs and costs
  - placing reliance on this measure could result in micro-management and remove a significant aspect of efficiency incentives
- the data is relatively new, immature and cannot be backdated, making historical cost modelling difficult
- the quality of relevant data may vary across time and across DNOs (data may also be under the control of DNOs)
- the categorisation of assets to health index bands is subjective
- risk that poor stewardship of assets results in higher cost allowance

Cost driver analysis—controlling for outcomes

1 Background and industry engagement

2 Empirical analysis

3 Observations and recommendations

Controlling for outcomes
What we tested

1. Customer reliability

- customer minutes lost (CML) and customer interruptions (CIs)
- the lower the value of the cost driver, the better the service quality
  ➔ **the incentive-compatible coefficient should be negative**

2. Asset age

- the proportion of overage assets and the MEAV-weighted proportion of overage assets
- older networks generally require more maintenance and replacement activity
  ➔ **the expected coefficient is positive**

3. Fault rate

- the fault rate per MEAV and the fault rate per length of network
- the lower the value of the cost driver, the better the service quality
  ➔ **the incentive-compatible coefficient should be negative**
- *However,* the fault rate is already included in the BU CSV where the cost-impact is positive

4. Customer satisfaction

- overall customer satisfaction score based on survey evidence
- the higher the value of the cost driver, the better the service quality
  ➔ **the incentive-compatible coefficient should be positive**

Controlling for outcomes
Reliability measures

Variables	Top-down		Bottom-up	
	CML	**CI**	**CML**	**CI**
Macro CSV	0.776***	0.778***		
BU CSV (log)			0.860***	0.860***
CML	0.00105		0.000158	
CI		0.00121		0.000421
Time trend	-0.00771**	-0.00735**	-0.00778*	-0.00702*
Constant	8.816	8.020	16.48**	14.93**
Adj. R2	0.802	0.808	0.814	0.815
RESET	0.00206	0.000320	0.0110	0.00395
Link	-1.334	-1.530	-3.160	-3.220
Chow (DPCR5)	7.37e-05	0.000389	0.000106	0.000452
VIF	1.235	1.124	1.232	1.121

Note: Modelling period is 2016–20 (70 observations). Expenditure is expressed in 2012/13 prices. We do not present the efficiency rankings for these models as the coefficients are not incentive-compatible.

All coefficients on network reliability measures are **statistically insignificant**

Positive coefficients indicate that DNOs with more interruptions require more expenditure—this could cause **perverse incentives**

- controlling for service quality in this way does not lead to statistically robust and incentive-compatible models
- alternative econometric approaches (e.g. SFA) could be adopted
- monetising measures of service quality and estimating a pre-modelling or post-modelling adjustment could mitigate the issue of unintuitive coefficients. In some cases, outputs could be adjusted
- non-econometric methods, such as DEA, may be better suited to dealing with a complex relationship in a small dataset

Controlling for outcomes
Causes of the inconsistency?

The relationship between service quality and expenditure is complex and could differ between the short run and long run

Long-run effect:

Negative relationship between supply interruptions and expenditure

Higher historical expenditure → Better-maintained network → Fewer faults and supply interruptions

Short-run effect:

Positive relationship between supply interruptions and expenditure

More faults and supply interruptions → Increased maintenance activity → Higher in-period expenditure

The long-run (incentive-compatible) effect could be captured with an appropriately long-run measure of service quality e.g. average historical performance

Controlling for outcomes
Reliability measures: long-run average

Variables	Top-down		Bottom-up	
	CML	**CI**	**CML**	**CI**
Macro CSV	0.777***	0.779***		
BU CSV (log)			0.860***	0.860***
CML (long-run average)	0.00154		0.000104	
CI (long-run average)		0.00145		0.000383
Time trend	-0.0109**	-0.0109**	-0.00826*	-0.00826*
Constant	15.25	15.23	17.45*	17.44*
Adj. R2	0.802	0.808	0.814	0.814
RESET	0.00105	2.56e-05	0.00974	0.00276
Link	-1.581	-1.840	-3.168	-3.275
Chow (DPCR5)	1.20e-05	6.89e-06	7.66e-05	4.77e-05
VIF	1.008	1.008	1	1

Note: Modelling period is 2016–20 (70 observations). Expenditure is expressed in 2012/13 prices. We do not present the efficiency rankings for these models as the coefficients are not incentive-compatible.

- controlling for average service quality does not appear to lead to more robust models
- the analysis could be corroborated with alternative methods such as DEA, monetising quality etc. alongside operational insights

Controlling for outcomes
Asset age variables

Variables	Top-down		Bottom-up	
	Asset age	Overage assets	Asset age	Overage assets
Macro CSV	0.856***	0.863***		
BU CSV (log)			0.907***	0.951***
Asset age (MEAV-weighted)	-0.000581		0.00555	
Proportion of overage assets (MEAV-weighted)		-0.105**		-0.0960
Time trend	-0.0104**	-0.0105**	-0.00742*	-0.00751*
Constant	12.91	12.88	15.06*	15.28*
Adj. R2	0.855	0.864	0.865	0.865
RESET	0.0851	0.546	0.0732	0.0164
Link	-0.638	0.0441	-2.011	-2.682
Chow (DPCR5)	1.31e-05	0.000815	5.19e-05	0.00538
VIF	1.257	1.017	1.144	1.013

Note: Modelling period is 2011–20 (140 observations). Expenditure is expressed in 2012/13 prices. We do not present the efficiency rankings for these models as the coefficients are not incentive-compatible.

MEAV-weighted asset age does not appear to be a helpful regressor as it is generally statistically insignificant and volatile

The proportion of overaged assets weighted by the MEAV indicates that DNOs with older assets tend to incur lower costs

- the regression may be biased because of simultaneity: replacing an overaged asset is a significant current expenditure, but may lower future spending
- OLS may not be able to distinguish these two effects: overaged assets *were caused by* lower past expenditure, but *will be causing* higher future expenditure
- the incorporation of forecast data could mitigate this issue

Controlling for outcomes
Fault rate and customer satisfaction

Variables	Top-down		Bottom-up	
	Faults per km	**Customer satisfaction**	**Faults per km**	**Customer satisfaction**
Macro CSV	0.764***	0.775***		
BU CSV (log)			0.854***	0.850***
Faults per length (log)	0.0346		0.0223	
Customer satisfaction		0.247***		0.192**
Time trend	-0.0105*	-0.0331**	-0.00801	-0.0254*
Constant	14.64	57.90**	17.00	50.46*
Adj. R2	0.798	0.819	0.814	0.855
RESET	0.00544	0.000152	0.00655	0.00405
Link	-0.978	-1.653	-3.086	-3.247
VIF	1.239	2.016	1.244	1.916

Note: Modelling period is 2011–20 for (140 observations) faults per km and 2016–20 (70 observations) for customer satisfaction. Expenditure is expressed in 2012/13 prices.

The fault rate is positive and statistically insignificant

The positive coefficient on customer satisfaction indicates that DNOs with more satisfied customers tend to incur higher costs

The coefficients on some outcome variables appear directionally intuitive. However, the magnitude must also be validated against operational expectations.

Controlling for outcomes

Fault rate and customer satisfaction

Top-down			Bottom-up		
Ofgem	Faults per km	Customer satisfaction	Ofgem	Faults per km	Customer satisfaction
1	1	1	1	1	1
2	2	3	2	2	3
3	3	7	3	5	2
4	4	9	4	3	5
5	5	4	5	4	9
6	6	6	6	6	10
7	8	2	7	8	4
8	7	12	8	7	7
9	9	5	9	9	6
10	10	10	10	10	8
11	11	8	11	11	12
12	12	11	12	12	11
13	13	13	13	13	13
14	14	14	14	14	14

Note: The period used to estimate the cost function is 2011–20 for faults per km and 2016–20 for customer satisfaction. The period used to estimate efficiency rankings is 2016–20 for both.

Efficiency rankings are volatile when measures of customer satisfaction are included in the analysis

DNOs at the top and bottom of the rankings tend to display little sensitivity in modelling outcomes

Cost driver analysis—controlling for outcomes

1. Background and industry engagement
2. Empirical analysis
3. **Observations and recommendations**

Controlling for outcomes
Observations and recommendations

- it may be possible to account for outcomes in the cost assessment by simply including them in the econometric model
  - coefficients on some outcome variables are of the correct (incentive-compatible) sign and are statistically significant
  - care must be taken to avoid over- or under-compensating for any one outcome measure, and to avoid having too many regressors—a ‘Composite Outcome Variable’ could be constructed to account for this

- accounting for outcomes can have an impact on the rankings of some DNOs
  - DNOs may be mis-identified as inefficient if they provide a higher quality of service

- if inclusion does not work, simple transformations (e.g. taking a long-run average) to the data may improve the quality of the model
  - alternative estimation approaches (e.g. SFA, DEA, PCA) should also be tested
  - it may be useful to also explore additional transformations (e.g. constructing monetised measures of service quality and adjusting expenditure or outputs)

8. Cost driver analysis—other potential drivers at ED2

Cost driver analysis—other potential drivers at ED2

1. Background and industry engagement
2. Empirical analysis
3. Observations and recommendations

Other potential drivers at ED2
Background

- for the cost models to be used to assess business plan expenditure, they must be able to explain differences in costs **in ED2**
  - they must be able to explain differences in costs **between DNOs** and **over time**
- if possible, the models should capture changes in:
  - regulatory requirements
  - DNO technology
  - operating environments
  - input prices

If these cannot be captured in the cost models then:

- the historical cost models may be unable to robustly assess ED2 expenditure
- activities/expenditure may need to be removed from the TOTEX benchmarked cost and assessed separately

Other potential drivers at ED2

Industry views: net zero

Drivers of net zero

- **excess capacity** (i.e. utilisation) will be a driver of the investments required to meet future demand
- number (and type of) **LCT connections** may explain differences in DNOs' observed costs

Regional variation

- the **target date differs** across the UK, so not all DNOs face the same pressure
- **sources of renewable** energy differ across regions, and different renewables are associated with different costs
- different DNOs have differing levels of **ambition** to meet targets
- regional variation could be addressed through uncertainty mechanisms

Modelling uncertainty

- there is a significant amount of uncertainty surrounding the costs and target dates associated with net zero
- this should be subject to **uncertainty mechanisms and re-openers** as well as cost benchmarking
- a common (centralised) forecasting approach might allow for net zero to be captured in a TOTEX model

Impact on prices

- surge in industry-wide activity leads **to price increases** as DNOs compete for the same technology and workers
- decarbonisation initiatives in some cities
- (e.g. banning fossil-fuel vehicles) **directly increase costs**
- flexible solutions may result in lower CAPEX costs but higher operating costs—**the OPEX/CAPEX trade-off should be modelled**

Other potential drivers at ED2
Industry views: other cost increases (I)

- there is a renewed focus on cyber security for the DNOs, which will lead to an increase in IT investment
  - there could be some high-level driver of this investment activity (e.g. current age of servers), but there is no consistent data for these drivers and the exact relationship between the drivers and investment is unclear
  - given the lack of drivers and significant uncertainty in the expenditure, it would make the most sense to address this outside of the cost assessment (e.g. through uncertainty mechanisms and re-openers)
- DSO functionality will lead to increased expenditure (e.g. through increased IT investment) to meet price control deliverables
  - as the exact expenditure requirements are unclear, this might be better assessed outside of the TOTEX modelling
  - DNOs and DSOs are intrinsically linked, and the company breakdown of which expenditure is DNO and which is DSO is likely to vary—i.e. data allocation may not be comparable/consistently drawn
  - DSO functionality leads to new ways of controlling costs
    - it is more important for regulatory cost benchmarking to be ‘technology neutral’

Other potential drivers at ED2

Industry views: other cost increases (I)

- future investment programmes are driven by the requirement to comply with legislation across health, safety, environmental and other statutory instruments
  - the investment needed to manage these requirements varies across DNOs depending on:
    - historical investment decisions (some pre-dating privatisation)
    - network topography and geography
    - climate effects
  - examples include PCB legislation and ESQCR
- there is considerable risk with TOTEX modelling in the face of such uncertainties
  - backward-looking benchmarks fail to capture the step-change in requirements
  - forward-looking benchmarks rest on DNO forecasts, which may be highly uncertain and not comparable across DNOs
  - where work requirements are driven by legislation, there is a rationale for costs to be excluded from the TOTEX assessment
  - the industry is still in the early stages of transition
    - arguments relating to future uncertainty may be more relevant for ED3 than ED2

Cost driver analysis—other potential drivers at ED2

1. Background and industry engagement
2. Empirical analysis
3. Observations and recommendations

Other potential drivers at ED2
What we tested

Drivers of net zero

- we have access to data on LCT connections
- we have been unable to test the use of excess capacity due to data limitations

This is a conceptually promising cost driver that should be explored in future work

Other ED2 changes

- these are more difficult to model as few tangible cost drivers were found in engagements with the industry
- e.g. costs associated with DSO functionality and cyber security

If appropriate cost drivers cannot be found, these costs may need to be removed from the modelled cost base and either assessed separately (e.g. with technical assessments) or passed through if deemed outside of management control with possible uncertainty mechanisms to ensure control of costs

Other potential drivers at ED2
Low-carbon technologies

Variables	Top-down			Bottom-up		
	Size of LCT primary connections	Size of LCT secondary connections	Size of LCT total connections	Size of LCT primary connections	Size of LCT secondary connections	Size of LCT total connections
Macro CSV	0.708***	0.663***	0.704***			
BU CSV (log)				0.816***	0.766***	0.820***
LCT (MW)	-0.000112	0.000671	-3.60e-05	-0.000239**	0.000406	-0.000176
Time trend	-0.0106	0.00202	-0.00802	-0.0141	0.000187	-0.0137
Constant	15.62	-9.088	10.56	29.40	0.869	28.64
Adj. R2	0.789	0.796	0.787	0.845	0.838	0.841
RESET	2.11e-05	5.46e-05	1.28e-05	0.268	0.0224	0.197
Link	-0.456	-1.022	-0.733	-1.494	-2.610	-1.750
VIF	1.313	1.488	1.525	1.347	1.532	1.594

Note: Modelling period is 2016–20 (70 observations). Expenditure is expressed in 2012/13 prices.

Coefficients on LCT measures are generally **statistically insignificant**

Coefficients are often **negative and unintuitive**

- LCT connections do not appear to work well in the econometric models
- this is largely robust to how LCT connections are modelled (e.g. alternative functional forms)

Other potential drivers at ED2

Low-carbon technologies: potential causes of the unintuitive results

1. Smaller dataset

- LCT data is available only from 2015
- this significantly reduces the size of the dataset relative to those used for other models

2. Historical variation

- there is not much historical variation in LCT connections compared to other variables
- this makes estimating coefficients through regression difficult

3. Future importance

- there is an operational argument that LCT connections will be a *material* driver of *future* costs
- it is unclear whether LCT connections have been a driver of expenditure in ED1

4. Incremental impact

- the cost of LCT connections may be small relative to other factors (e.g. scale)
- difficult to capture small incremental impacts in top-down econometric models, especially where the method used cannot separate noise from signal

Other potential drivers at ED2

Low-carbon technologies: potential solutions

Use forward-looking data			Bottom-up CSV mapping
1. Smaller dataset	2. Historical variation	3. Future importance	4. Incremental impact
Incorporate data from ED2 to increase the size of the dataset	The uptake of LCTs may be more variable in ED2, which increases variation in the data	The incorporation of forward-looking data explicitly models the expected cost impact	Less significant drivers of expenditure can be captured using a more granular CSV

Other potential drivers at ED2
Low-carbon technologies: bottom-up CSV

Variables	Ofgem's BU CSV	Asset replacement, single LCT line	Asset replacement and reinforcement, single LCT line	Asset replacement, multiple lines	Asset replacement and reinforcement, multiple lines
BU CSV (log)	0.795***	0.681***	0.632***	0.769***	0.751***
Time trend	-0.00514	0.0332**	0.0366**	0.0166	0.0206*
Constant	11.52	-65.30**	-71.94**	-32.24	-40.24*
Adj. R2	0.838	0.643	0.582	0.782	0.759
RESET	0.0567	0.232	0.260	0.0290	0.0704
Link	-2.674	-1.519	-0.733	-3.052	-2.697

Note: Modelling period is 2016–20 (70 observations). Expenditure is expressed in 2012/13 prices.

- above, bottom-up CSVs have been constructed by mapping LCT connections to specific cost lines
- the model fit is typically worse, especially where LCT connections *replace* another cost driver
  - this may be because LCT connections are not (yet) a material driver of expenditure compared to other cost drivers

Other potential drivers at ED2

Low-carbon technologies: bottom-up CSV

Ofgem BU CSV	Asset replacement, single LCT line	Asset replacement and reinforcement, single LCT line	Asset replacement, multiple lines	Asset replacement and reinforcement, multiple lines
1	3	3	3	3
2	1	1	1	1
3	4	4	4	4
4	2	2	2	2
5	7	9	6	6
6	5	5	5	5
7	8	8	7	7
8	6	6	8	8
9	12	12	11	11
10	9	7	9	9
11	11	11	10	10
12	13	13	13	13
13	10	10	12	12
14	14	14	14	14

Including LCT connections has some impact on the efficiency rankings in most scenarios

DNOs at the top and bottom of the rankings tend to display little sensitivity in modelling outcomes

Note: The period used to estimate the cost function is 2016–20, as is the period used to estimate efficiency rankings.

Cost driver analysis—other potential drivers at ED2

1. Background and industry engagement
2. Empirical analysis
3. **Observations and recommendations**

Other potential drivers at ED2
Observations and recommendations

- as there are several anticipated changes in the regulatory and operational environments that DNOs face in ED2, a simple extrapolation of historical cost models is likely to be inappropriate
  - these include ‘Net Zero’ policy objectives (including distributed generation); a renewed focus on cyber security; the introduction/expansion of ‘DSO functionality’; and other investments to comply with legislation (e.g. health and safety)

- it is difficult to estimate robust models with LCT connections using historical data
  - the incorporation of ED2 business plan data should be explored to address some of the issues associated with LCT drivers (and other future drivers of costs)
  - other drivers, such as excess capacity, can be important to consider

- we were unable to identify drivers of DSO functionality as part of our industry engagement
  - if no drivers can be identified and DSO functionality (and other future costs) is material, this may need to be assessed outside of the TOTEX models
  - careful treatment of the modelling and benchmark periods and potential structural changes might accommodate some new expenditure—some approaches might only pick up such expenditure if as all DNOs face similar and proportionate cost pressures

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Appendix

1. Further background
2. Data descriptions
3. Other analysis

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1. Appendix—further background

Further Background

Why benchmarking? What are the issues?

Starting point

- DSOs are ‘natural monopolies’
- no competition: little incentive to improve efficiency (in theory!)

Solution

- relative cost benchmarking, to simulate competition
- costs should be no higher than those of **comparable** firms

Problem

- DSOs are different (in scale, topography, ambition…)
- differences have to be accounted for to ensure comparability

Further Background

Problem: addressing differences between DNOs

Pre-modelling

- cost adjustments
- cost exclusions
- output adjustments

Modelling

- cost drivers
- functional form
- estimation approach

Post-modelling

- cost adjustments
- second-stage corrections
- benchmark correction

Further Background
Cost driver categories

Costs

Factor prices (labour and capital)
- relevant for local markets (often labour markets)
- in ED1 (and Ofgem's approach generally)—pre-modelling adjustments

Factor quantities (assets)
- often used in activity-based modelling
- problematic if inefficiency is related to over-usage of resources (endogenous cost drivers)

Outputs
- demand or scale factors (e.g. no. of customers, load, maintenance…)
- RIIO outcomes (e.g. safety, customer satisfaction…)

Context
- factors affecting the complexity of the production process (outturn and future)
- often environmental factors (forestation, soil, customer density…)
- change in in generation structure (e.g. decentralised renewables)

Further Background
ED1 approach: level of analysis

- to assess expenditure at RIIO-ED1, Ofgem used three types of model, including two TOTEX (total expenditure) models and several activity-level models
- the final allowances were derived from the weighted average of cost allowances across the different models

TOTEX top-down (25%)

- expenditure is assessed on a TOTEX basis with some cost exclusions
- the cost driver is a composite scale variable (CSV) defined as the weighted average of the modern equivalent asset value (MEAV) and customer numbers
- the weights are derived using regression analysis

TOTEX bottom-up (25%)

- expenditure is assessed on a TOTEX basis with some cost exclusions
- the cost driver is a CSV defined as the weighted average of units distributed, total network length, LV and HV overhead line length, MEAV, customer numbers, spans cut, total faults, and total ONIs
- the weights are derived by mapping each cost driver to a cost line

Disaggregated activity-level analysis (50%)

- expenditure is assessed at the activity level before being aggregated to a TOTEX allowance
- a combination of regression analysis, unit cost ratios and engineering assessments is used to assess expenditure

Further Background

ED1 approach: model estimation approach

- Ofgem used pooled ordinary least squares (OLS) with a time trend to fit the following model for each of the regressions:

$$y_{i,t} = B_1 + B_2 x_{1,i,t} + B_3 x_{2,i,t} + B_4 t + u_{i,t}$$

- where y is the outcome being assessed (e.g. TOTEX), x_1 and x_2 are explanatory variables (e.g. the CSV for a regression), and t is the time trend. All variables except for the time trend are logged
- TOTEX has been adjusted to account for contextual factors such as density, sparsity and regional wages

2. Appendix—data description

Data description
Cost and Volumes Reporting Packs

- from the cost and volumes reporting pack, we have access to data regarding the following variables:
  - MEAV (2010–23)
  - Customer numbers (2006–20)
  - Units distributed (2006–20)
  - Network length (2010–20)
  - Expenditure (2011–20)
  - Peak demand (2010–20)
  - Spans cut (2010–20)
  - Total faults (2010–20)
  - ONIs faults (2010–20)
  - Customer Interruptions (2011–20)
  - Customer Minutes Lost (2011–20)
  - Asset age (2020)

Most variables from the cost and volumes reporting packs are available for the full outturn period

Data description

Environment and Innovation Reporting Pack

- the Environment and Innovation Reporting Packs are used to construct data on Low Carbon Technology (LCT) connections
- the data is split by:
  - primary vs secondary network
  - volume (number of connections) vs size (MW)
  - type of connection
    - Heat Pumps
    - EV slow charge
    - EV fast charge
    - PVs (G83)
    - Other DG (G83)
    - DG (non-G83)
- this data is publicly available, but only exists for ED1 outturn (2016–20)

Data description
RIIO-ED1 Annual Returns

- the RIIO-ED1 annual report supplementary data file is used to collect data regarding:
  - customer satisfaction
  - distribution losses
- the data is only available for the outturn ED1 period (2016–20)

3. Appendix—other analysis

Controlling for outcomes
Reliability measures

Variables	Top-down		Bottom-up	
	CML	CI	CML	CI
Macro CSV	0.776***	0.778***		
BU CSV (log)			0.860***	0.860***
CML	0.00105		0.000158	
CI		0.00121		0.000421
Time trend	-0.00771**	-0.00735**	-0.00778*	-0.00702*
Constant	8.816	8.020	16.48**	14.93**
Adj. R2	0.802	0.808	0.814	0.815
RESET	0.00206	0.000320	0.0110	0.00395
Link	-1.334	-1.530	-3.160	-3.220
Chow (DPCR5)	7.37e-05	0.000389	0.000106	0.000452
VIF	1.235	1.124	1.232	1.121

Period in regression: 2011–20. 140 observations.

All coefficients on network reliability measures are **statistically insignificant**

Positive coefficients indicate that DNOs with more interruptions require more expenditure—this could cause **perverse incentives**

- controlling for service quality in this way does not lead to statistically robust models
- alternative econometric approaches (e.g. SFA) could be adopted
- monetising measures of service quality and estimating a pre-modelling or post-modelling adjustment could mitigate the issue of a negative coefficient
- non-econometric methods may better suit the analysis of complex relationships in a small dataset

Controlling for outcomes
Reliability measures

Top-down			Bottom-up		
Ofgem	CML	CI	Ofgem	CML	CI
1	1	1	1	1	1
2	3	7	8	8	9
3	6	8	4	5	5
4	2	2	6	6	6
5	9	9	2	2	4
6	4	4	9	9	8
7	8	6	7	7	7
8	5	3	5	4	3
9	7	5	3	3	2
10	11	12	11	11	11
11	10	10	10	10	10
12	12	11	12	12	12
13	13	14	14	14	14
14	14	13	13	13	13

Note: The period used to estimate the cost function is 2016–20, as is the period used to estimate efficiency rankings.

Efficiency rankings are somewhat volatile for DNOs in the middle of the table when CML and CI are included in the analysis

DNOs at the top and bottom of the rankings tend to display little sensitivity to reliability measures

Controlling for outcomes
Reliability measures: long-run average

Variables	Top-down		Bottom-up	
	CML	CI	CML	CI
Macro CSV	0.777***	0.779***		
BU CSV (log)			0.860***	0.860***
CML (long-run average)	0.00154		0.000104	
CI (long-run average)		0.00145		0.000383
Time trend	-0.0109**	-0.0109**	-0.00826*	-0.00826*
Constant	15.25	15.23	17.45*	17.44*
Adj. R2	0.802	0.808	0.814	0.814
RESET	0.00105	2.56e-05	0.00974	0.00276
Link	-1.581	-1.840	-3.168	-3.275
Chow (DPCR5)	1.20e-05	6.89e-06	7.66e-05	4.77e-05
VIF	1.008	1.008	1	1

Period in regression: 2011–20. 140 observations.

Coefficients are consistently positive, which is in line with operational expectations and incentives. When only ED1 data is considered, some become statistically significant.

- controlling for average service quality does not appear to lead to more robust models
- is the magnitude of the coefficients plausible? Results should be corroborated with alternative methods such as DEA, monetising quality etc. alongside operational insights

Controlling for outcomes

Reliability measures: long-run average

Top-down			Bottom-up		
Ofgem	CML average	CI average	Ofgem	CML average	CI average
1	1	1	1	1	1
2	3	7	8	8	9
3	6	8	4	5	5
4	2	2	6	6	6
5	9	9	2	2	4
6	4	4	9	9	8
7	8	6	7	7	7
8	5	3	5	4	3
9	7	5	3	3	2
10	11	12	11	11	11
11	10	10	10	10	10
12	12	11	12	12	12
13	13	14	14	14	14
14	14	13	13	13	13

Note: The period used to estimate the cost function is 2016–20, as is the period used to estimate efficiency rankings.

Efficiency rankings display slightly less volatility when the long-run averages of CML and CI are included in the analysis

Controlling for outcomes
Asset age variables

Variables	Top-down		Bottom-up	
	Asset age	Overage assets	Asset age	Overage assets
Macro CSV	0.856***	0.863***		
BU CSV (log)			0.907***	0.951***
Asset age (MEAV-weighted)	-0.000581		0.00555	
Proportion of overage assets (MEAV-weighted)		-0.105**		-0.0960
Time trend	-0.0104**	-0.0105**	-0.00742*	-0.00751*
Constant	12.91	12.88	15.06*	15.28*
Adj. R2	0.855	0.864	0.865	0.865
RESET	0.0851	0.546	0.0732	0.0164
Link	-0.638	0.0441	-2.011	-2.682
Chow (DPCR5)	1.31e-05	0.000815	5.19e-05	0.00538
VIF	1.257	1.017	1.144	1.013

Period in regression: 2011–20. 140 observations.

MEAV-weighted asset age does not appear to be a helpful regressor as it is statistically insignificant and volatile

The proportion of overaged assets weighted by the MEAV indicates that DNOs with older assets tend to incur lower costs

- the regression may be biased because of simultaneity: replacing an overaged asset is a significant current expenditure, but lowers future spending
- OLS may not be able to distinguish these two effects: overaged assets *were caused by* lower past expenditure, but *will be causing* higher future expenditure
- the incorporation of forecast data or alternative modelling approaches could mitigate this issue

Controlling for outcomes
Asset age variables

Top-down			Bottom-up		
Ofgem	Asset age	Overage assets	Ofgem	Asset age	Overage assets
1	1	1	1	1	2
2	5	6	8	4	5
3	3	5	4	3	3
4	4	4	6	8	10
5	2	2	2	2	1
6	7	7	9	5	6
7	9	9	7	9	9
8	6	3	5	6	4
9	10	8	3	11	8
10	11	11	11	10	12
11	8	10	10	7	7
12	12	12	12	12	11
13	13	14	14	13	14
14	14	13	13	14	13

Efficiency rankings are somewhat volatile when measures of asset age are included in the analysis

DNOs at the top and bottom of the rankings tend to display little sensitivity to asset age measures

Note: The period used to estimate the cost function is 2016–20, as is the period used to estimate efficiency rankings.