RP6 Efficiency Advice

The Northern Ireland Utility Regulator (UR)

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Final Report

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Executive Summary

Cambridge Economic Policy Associates (CEPA) has been engaged by the Utility Regulator (UR) to develop benchmarking models for Northern Ireland Electricity Networks Ltd (NIE Networks) historic distribution expenditure.

As part of its next price control (RP6), UR would like to use benchmarking models to assess the efficiency of NIE Networks' distribution expenditure proposed under its business plan. Benchmarking is a standard technique used by regulators to assess expenditure and to set efficiency challenges for regulated companies. It was used by Ofgem during their most recent price control determinations for electricity distribution companies (RIIO-ED1) as well as the UR and the Competition Commission (CC) in the previous price control for NIE Networks (RP5).

This report presents a range of models that we have developed following our methodology. These models can be used by the UR as the basis for setting efficiency. We have tested various levels of cost aggregation, but have found that the operating expenditure (opex) is most reliable. Given the precedent of benchmarking in the UK, we have also re-estimated models that have been used in the past by both the CC (RP5) and Ofgem (RIIO-ED1) as part of their benchmarking assessments and considered whether these are the best options for RP6.

We also considered the effects of adjusting for connection costs prior to modelling. The decision to use a pre/ post allocation approach is ultimately one for the UR. But to facilitate that decision Table 1 below summarises the advantages/ disadvantages of each approach.

Table 1: Advantages/ disadvantages of pre/ post allocation modelling

	Pre-allocation models	Post-allocation models
Advantages	• Allows flexibility on the assumptions of the allocation rates going forward. • Does not allocate costs between activities which reduces the risk of distortions in the modelling.	• Does not require the regulator to determine the share of opex to be allocated to connections. • Focuses the analysis on regulated costs.
Disadvantages	• Requires post-modelling adjustment, increasing the number of regulatory decisions.	• Requires allocation of costs between connections and other activities, which could introduce distortions in the modelling. • Requires policing of the costs allocated between activities.

Source: CEPA analysis

Given the potential trade-offs in using pre/ post allocation models, we tested the performance of our preferred set of models and the CC's RP5 models, both on a pre-allocation and post-allocation basis. As summarised in the Table 2 below, we consider that overall the identified models perform well on both a pre and post allocation basis and could be used to assess NIE Networks' efficiency for RP6. The only exceptions to this are the pre-allocation version of our business support model, which marginally fails the RESET test (gives an indication of whether there are any omitted non-linearities in the model); and the pre- and post-allocation versions of our disaggregated faults model, which fails the pooling (determines whether or not the data is appropriate for pooling) and normality (tests whether the error term is normally distributed) tests.

Table 1: Performance of independently developed models and CC's RP5 models

	Pre-allocation models	Post-allocation models
Model performance		
IMFT and Indirects (IMFT)	Performs well	Performs well
Network Operating Costs (NOCs)	Performs well	Performs well
Closely Associated Indirects (CAI)	Performs well	Performs well
Business support	Performs correctly. Marginally fails the RESET test.	Performs well
Tree cutting	Performs well	Performs well
Faults (LV HV OHL faults)	Performs averagely. Marginally fails the pooling test.	Performs averagely. Marginally fails the pooling test.
Performance of CC's RP5 models		
IMFT and Indirects (M4)	Performs well	Performs well
IMFT and Indirects (M6)	Performs well	Performs well

Source: CEPA analysis

The key findings are that:

- Length and network density are both key drivers of IMFT and Indirect costs for DNOs. Length captures network scale and network density captures the rural vs. urban divide.
- Across different input sensitivities we have run, the parameter estimates of the models stay statistically significant and similar in magnitude.
- NIE Networks' efficiency gap against the upper quartile company is relatively smaller across all years (2013 to 2016) on a post-allocation basis than on a pre-allocation basis. On a pre-allocation basis, NIE Networks' efficiency gap for IMFT and Indirects, in our base case model, ranges from 3% to 15%. The equivalent range on a post-allocation basis is lower, ranging from -2% to 10%.
- Many of the input sensitivities tested in our analysis make NIE Networks look more efficient compared to the base case models. Based on this, it may be worth considering which set of input assumptions is preferred by the UR, or if different sensitivities should be weighted together when setting the catch-up efficiency target.

1. INTRODUCTION

Cambridge Economic Policy Associates (CEPA) has been engaged by the Utility Regulator (UR) to develop benchmarking models for Northern Ireland Electricity Networks Ltd (NIE Networks) historic distribution expenditure.

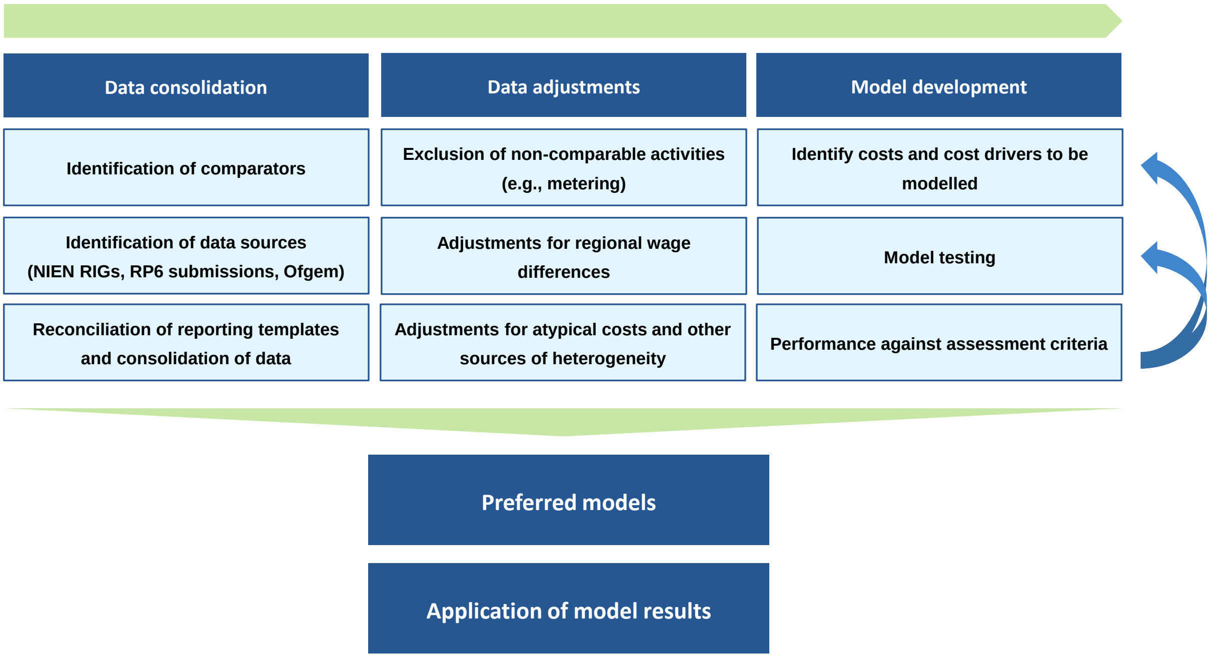
The rest of this report sets out our approach and recommendations and is structured as follows:

- Section 2 sets out our methodology including the adjustments we have made to the data and our approach to model development/ refinement.
- Section 3 summarises our baseline model estimation results and sensitivity analysis.
- Section 4 presents our efficiency gap analysis based on our preferred set of models.
- Section 5 re-runs the benchmarking models run by the CC at RP5 and Ofgem at RIIO-ED1, and presents efficiency gap analysis based on these models.
- Section 6 sets out our preferred models.

2. METHODOLOGY

This section sets out the methodology used in developing and refining our benchmarking models. We conducted our analysis only on historic data, incorporating the most recent regulatory returns by both NIE Networks and GB DNOs. We conducted an independent model development and refinement process and replicated models used by Ofgem and the CC in previous determinations using historic data only. This methodology is summarised at a high-level in Figure 2.1.

Figure 2.1: High-level approach to model development



Source: CEPA analysis

2.1. Historic comparator data

We have identified GB DNOs as potential comparators to NIE Networks, in line with the approach taken by the CC at RP5. We therefore have a total of 15 companies in our analysis (14 GB companies plus NIE Networks). Their names and acronyms are provided in Annex A.

We have obtained historic data for NIE Networks from two sources: NIE Networks' RP6 submission and NIE Networks' 2016 Regulatory Instructions and Guidance (RIGs). For GB DNOs we used historic data from their 2015/16 RIIO-ED1 RIGs submissions, provided by Ofgem. We also had access to previous submissions from DPCR5, which generally aligned better with NIE Networks' reporting. However, in discussion with NIAUR, we chose to use the most recent RIIO-ED1 RIGs to reflect revisions to historic data made by companies since DPCR5 and to provide an extra year of data compared to using only DPCR5 RIGs. In particular, based on Ofgem's updated RIIO-ED1 guidance, the RIIO-ED1 RIGs contained material re-allocations of costs (compared to DPCR5 RIGs) between opex and capex (for example, between fault repairs and asset replacement). Therefore, we considered the RIIO-ED1 RIGs to be more accurate measures of costs for GB DNOs.

The total available sample is summarised in Table 2.1 below.

Table 2.1: Summary of available dataset

Company	Companies	Historical data available	Observations
NIE Networks	1	4 years	4
GB DNOs	14	6 years	84

However, although we had access to six years of historical GB DNO data, we decided to use only the four most recent years of GB data in our analysis. We made this decision because we preferred to use a balanced panel rather than an unbalanced panel. Both Ofgem at RIIO-ED1 and CC at RP5 also used a balanced panel. However, we acknowledge that adding additional observations to the benchmarking data set may improve the explanatory power of the model. Taking this into account, we have tested this as a sensitivity in sub-section 3.4.[1]

2.2. Data adjustments

We have proposed a number of adjustments to the data to account for differences in the scope of activities / assets, atypical costs, DNO-specific costs and other regional factors. These adjustments are important to avoid company heterogeneity being misconstrued as inefficiency (that is, differences between companies not related to inefficiency). In doing this, we have considered the adjustments that were made to costs by the CC during the RP5 referral and the adjustments made by Ofgem at RIIO-ED1. We set out the adjustments we have made and their rationale in the following sub-sections.

2.2.1. Regional labour adjustment

We have adjusted for differences in the regional cost of labour between DNOs. We have produced a standalone report that details our approach and proposed regional wage adjustment (RWA), but we summarise the key aspects of this analysis here.

Since our approach is more aligned with Ofgem's RIIO-ED1 analysis, we recognise that there are differences in our approach compared to that proposed by NIE Networks for RP6 and CC at RP5. Therefore, we conduct sensitivities around the two assumptions that are most contentious:

1. *Relevant SOC codes*. We have chosen 2-digit SOC codes, but also test 3 and 4-digit codes based on weightings used by the CC at RP5.
2. *Local labour adjustment*. As a base case we do not make an adjustment for the share of labour that is incurred locally, since we have not been able to identify the evidence

[1] The outcome of this sensitivity provides evidence that including the additional two years of GB DNO data does not improve the explanatory power of the IMFT and Indirects preferred model.

used by Ofgem to develop these adjustments. However, we recognise that this may influence the comparative efficiency of NIE Networks and conduct two sensitivities:

a. First, we use Ofgem's assumptions on the share of labour that is incurred locally for all companies in the data set (including NIE Networks). The respective local labour shares for Inspections, Maintenance, Faults and Tree Cutting (IMFT), Closely Associated Indirects (CAI) and Network Operating Costs (NOCs) are presented in Annex B.

b. Second, we apply the local labour adjustments to GB DNOs only (that is, excluding NIE Networks).

The results of these sensitivity analyses are set out in Sections 3 and 4.

2.2.2. Gross versus net cost benchmarking

Gross costs are those costs that are incurred by DNOs before netting off customer contributions / income. Net costs are those which subtract customer contribution costs.

Both Ofgem (RIIO-ED1) and the CC (RP5) did their benchmarking at a gross cost level. We agree with this approach as it focuses the benchmarking on expenditure that is incurred by the company without conflating it with income. Looking at gross costs helps to preserve the relationship between expenditure and cost drivers which could otherwise be skewed by differing levels of customer contributions if net costs are used. Consequently, we conduct our benchmarking at a gross cost level.

2.2.3. Re-allocation of costs - connections

Every year a share of indirect opex costs incurred by NIE Networks are allocated to the connections activities (outside of the target of the regulatory framework). This could have implications for benchmarking since the way in which these costs are allocated could affect the efficiency of the regulated costs.

Looking at the total amount of indirect costs allocated to connections for NIE Networks compared to GB DNOs, NIE Networks looks to be allocating a relatively high proportion (Figure 2.2 below ✂), with a step-up in the allocation rate in 2014/15. This was justified by NIE Networks as being due to a ramp-up in connection work. This means that conducting our benchmarking on a post-allocation basis would improve NIE Networks' efficiency performance, because a larger share of its indirect costs would be excluded from the assessment.

Figure 2.2: Indirect costs allocated to connections plus connections income related to indirects, as a share of gross indirect costs[2] ✂

Source: CEPA analysis

To account for these effects on our benchmarking, the models can be developed pre and post allocation. The choice between these options can generate material differences in estimated efficiency depending on companies' allocation rates. At RP5 the CC tested models that controlled for indirect costs that are related to connections (that is, post-allocation models), as well as models which ignored this allocation (that is, pre-allocation models). After taking the advantages and disadvantages of both approaches into account, the CC decided to put a 100% weighting on post-allocation models.

The advantages of using one approach over the other are summarised in Table 2.2 below.

Table 2.2: Advantages/ disadvantages of pre/ post allocation models

Approach	Advantages	Disadvantages
Pre-allocation	• It allows flexibility on the assumptions of the allocation rates going forward. The regulator could depart from historic rates to account for future characteristics of the expenditure. • It does not allocate costs between activities which reduces the risk of a distortion in the relationship between costs and explanatory variables.	• It requires the regulator to determine the share to be allocated going forward. Therefore, increasing the number of regulatory decisions. • It requires modelling both regulated and unregulated costs.

[2] Figure redacted to protect data confidentiality.

Approach	Advantages	Disadvantages
Post-allocation	• It does not require the regulator to determine the share of opex to be allocated to connections. • It focuses the analysis on regulated costs.	• It requires allocation of costs between connections and other activities. That allocation could introduce distortions in the relationship between cost drivers and the costs not allocated to connections, unless it is possible to separate between the costs truly generated by the different activities. • It requires the policing of the costs allocated between activities.

Following the CC, we also consider that there is merit in evaluating both options.

One challenge we have identified when setting the post allocation costs is that GB DNOs' and NIE Networks' reporting templates have different reporting lines to capture these allocations. Some of them reflect connections income that offsets indirect costs and some reflect an allocation of costs from indirects to connections. It was unclear to us whether the income that is allocated from connections charges to indirect costs reflects the actual indirect costs incurred for connections, since under Ofgem's templates connections income also includes margins. However, in discussions with NIE Networks, the company argued that the income lines in their reporting template were in fact related to indirect costs. Therefore, to be consistent with NIE Networks' treatment in their reporting template we also netted off income from GB DNOs' indirect costs when conducting our post-allocation models.[3]

2.2.4. Re-allocation of costs – other

In CC's RP5 determination it was identified that NIE Networks' vehicle costs differed from those of GB DNOs in that NIE Networks leases all its vehicles, while GB DNOs have a mixture of leasing/ buying. At RIIO-ED1, Ofgem decided to assess vehicle leasing costs (captured under CAI) and vehicle purchasing costs (captured under non-op capex) together to be 'blind' to the choice of purchasing / leasing taken by DNOs. We have taken a similar approach and included DNO non-op capex spending related to vehicles in CAI.

[3] For GB DNOs, this captured three lines in their C1 matrix reporting template: '*Allocation of Income relating to closely associated indirects, Business support costs and Non-op capex*' (C1 matrix, row 60); '*Indirect activity allocations to Connections outside of price control*' (C1 matrix, row 69); and '*Indirect activity allocation to Connections within the price control*' (C1 matrix, row 109).
For NIE Networks, this captured four lines in their C1 matrix: '*Allocation of Income relating to non-op capex and Business support costs*'; '*Allocation of Income relating to closely associated indirects*'; '*Indirect Activity Allocations to Connections (RAB related)*'; and '*Indirect Activity Allocations to Part Funded Connections (RAB related)*'

We have undertaken an equivalent allocation for non-operational capex (non-op capex) property expenditure and added it to business support property management costs. This was the approach taken by Ofgem at the RIIO-ED1 fast-track determination. At the RIIO-ED1 slow-track these two areas were split out. We consider that there may be some trade-offs between the two categories (for example, purchasing versus renting office space) and so we assess them together as part of business support.

We have not, however, added IT & Telecoms non-op capex into business support given its lumpy nature over time. As a result, the UR has commissioned Gemserv to assess IT & Telecoms separately.

2.2.5. Adjustments for differences in scope

There are three key differences we have identified and adjusted for in the data related to differences in the scope of assets owned and maintained by NIE Networks and GB DNOs:

- **Key difference 1:** GB DNOs operate high voltage (132kV) lines, whereas NIE Networks' higher voltage (110kV) assets are kept in the transmission business:
    - *Solution:* We have allocated costs attributable to NIE Networks' 110kv transmission assets to their distribution business across each of the categories in the C1 matrix.
        - This has been done based on an allocation provided by NIE Networks in its RP6 reporting packs. We have not verified this allocation.
        - On the cost-driver side we have also re-allocated the relevant 110kV assets to the distribution business. This includes all 110kV assets set out in the V1 asset register in NIE Networks' reporting templates.
        - We have not included costs associated with NIE Networks' 275kV transmission assets in our analysis because, unlike in Northern Ireland, electricity transmission is operated by separate Transmission Operators in GB. As a result, GB DNOs do not incur any costs associated with 275kV assets.
- **Key difference 2:** The voltage on NIE Networks is 110kV, which is different to GB (132kV).
    - *Solution:* We have assumed that NIE Networks 110kV assets are comparable to the 132kV assets in GB. Therefore, we have not adjusted any of the costs or the asset numbers for the different voltages. This was the approach taken at RP5 by the CC.
- **Key difference 3:** Differences in scope of work undertaken, the main one being that NIE Networks incur costs associated with metering, but GB DNOs do not.

    - *Solution:* We have excluded metering costs and indirect costs associated with metering, from NIE Networks costs in all our modelling. We also excluded costs reported by GB DNOs related to non-distribution activities (row 78 of GB DNO C1 matrix).

2.2.6. Adjustments for atypical costs

Atypical costs are those that are one-off costs not representative of normal business conditions. NIE Networks has identified two such atypical costs in its historic data: those costs related to the CC referral for RP5 and those related with network policy costs associated with the North-South interconnector. We have adjusted for both based on the values provided by NIE Networks.

Also, costs related to faults repair activities for severe weather incidents are reported separately to other faults costs in NIE Networks' reporting templates. We have excluded these costs from our benchmarking since severe weather incidents will not affect all companies equally and are uncontrollable.

2.2.7. DNO-specific costs

There are some costs that are incurred by a single, or small number, of DNOs and are to some extent uncontrollable. Excluding these costs is important to ensure that they are not construed as inefficiency in the benchmarking.

Ofgem made several adjustments to DNO costs during the course of RIIO-ED1, which we have used for our analysis in RP6. This includes costs which Ofgem referred to as 'regional factors' as well as other individual cost elements which it excluded in its modelling on the basis that they were not-comparable across DNOs:

- Regional factors are included for three DNOs:
    - LPN. The most relevant normalisations are under I&M (for substation flooding, additional security costs, tunnel repair and network strategy), faults (cable damage, additional security costs and network strategy) and CAI (parking fines, cable damage, HV faults, HV plant charges, additional security costs, tunnel repair and network strategy).
    - SSEH. The most relevant normalisation was for CAI (depot staff).
    - SPWM. The most relevant normalisation was for I&M related to its meshed network. We have also made equivalent adjustments to SPMW assets (as done by Ofgem) on the cost driver side.
- Street-works. Related to new street-works costs, these were excluded from RIIO-ED1 totex benchmarking as they were deemed not to be comparable across DNOs. These are costs related to permits, permit penalties, condition costs and lane rentals.

- ETR 132 tree cutting costs. These were included in Ofgem's totex models (as they are related to overhead line length), but excluded from its tree cutting model. Some GB DNOs do not incur these costs and NIE Networks incurred very minimal costs attributable to ETR 132 tree cutting. Hence, we considered that these costs were not comparable for benchmarking and so excluded them from our analysis.

The treatment of wayleaves payments is an area where we took a different approach from Ofgem in terms of our opex modelling and aligned with the CC in its treatment of these costs at RP5. However, given there is the potential for this adjustment to have a material impact we have conducted a sensitivity on it (set out in Section 3). We summarise these approaches and the rationale for our own, below.

Wayleaves payments were included in Ofgem's totex models since they are related to overhead line supports, which are captured in Mean Equivalent Asset Value (MEAV)).[4] But they were excluded from Ofgem's CAI model and assessed separately in its bottom-up assessment.

We have not excluded wayleaves payments from our analysis, taking the view that both Ofgem and the CC considered these costs could be compared, even though the cost drivers differed. NIE Networks has submitted a paper in relation to wayleaves, noting again (as at RP5) the trade-offs they face between aligning the rates with Scottish Power, administrative costs and goodwill. We have not identified any new arguments (from those at RP5) in that paper in relation to historic wayleaves payments and so have aligned our approach with the CC's determination.

2.3. Approach to model development and refinement

Following our high-level model development methodology we have conducted an iterative process of model refinement that considered variations in:

- disaggregation of models (for example, different cost categories);
- cost drivers;
- estimation method; and
- functional form of the cost function.

We briefly discuss each of these below, as well as the model selection criteria which we used to arrive at our preferred set of models.

2.3.1. Disaggregation of models

Our main focus has been on testing middle-up models (that is, total direct opex, total load-related capex) as well as some more disaggregated models used by Ofgem (for example, faults

[4] A measure of the value of a company's assets, and captures the overall size and complexity of the network.

and tree cutting). We also tested totex models but these may be less appropriate due to the limited capex time series. The different 'levels' of models we have tested/run are:

- **Disaggregated models.** We run the faults and tree cutting disaggregated models used by Ofgem in RIIO-ED1.
- **Middle-up models.** Our definition of middle-up models is split by activity and opex/capex but not at the most disaggregated level. For RP6 these would be:
  - Load-related.
  - Non-load related.
  - Network investment – core.
  - Network investment – non-core.
  - Network operating costs (NOCs).
  - Business support.
  - Closely associated indirects (CAI).
  - Overall capex.
  - Overall opex (IMFT and Indirects).
- **Top-down totex models (capex + opex)** that have the sum of all comparable costs on the left-hand side.

Annex C provides a breakdown of the cost categories that are included under the different levels of cost used in our econometric models.

2.3.2. Cost drivers

In terms of cost drivers for models, common ones that are often used or tested for electricity distribution and to which we had access, are set out in Table 2.3 below.

Table 2.3: Cost drivers

Drivers	Rationale
Customer numbers	Number of customers connected (that is, connections). This is a scale variable as it is a measure of total consumer base.
Energy throughput	This is an output measure and related to both scale of network and network usage.
Network length	Total length of lines, not including dual circuits. This is a scale variable as it measures total network length.
Network density	Captures rural vs. urban divide.
Peak demand	This is a scale variable as it is a proxy for maximum system capacity. It is also an output variable as it is a measure of yearly peak demand.

Drivers	Rationale
MEAV	Measures the overall size and complexity of the network.
Composite scale variables (CSV)	Used by CC and Ofgem, a CSV weights various cost drivers together. We use two versions, one based on Ofgem's top-down totex model and one based on the CSV used by the CC.
Spans cut & spans inspected	Directly linked to the number of trees cut and inspected.
Total number of faults	Drives fault expenditure.
MACRO CSV	Top-down totex cost driver used by Ofgem in RIIO-ED1. This is a CSV which places a weighting on MEAV and customer numbers. The weights are identified by running a regression of totex on MEAV and customer numbers.
Customer minutes lost (CML) and number of customer interruptions (CI)	Quality of service indicators capturing interruptions to end-customers.

2.3.3. Estimation methods

Pooled ordinary least squares (POLS) is a common regression technique used by regulators for econometric benchmarking. Ofgem used OLS models in the final determination for RIIO-ED1, as did the CC at RP5. POLS does not make any assumptions around the panel structure of the data and so treats each observation as an individual company (even though we have observations for companies over several years). However, we do consider there is a benefit in testing GLS (random effects) models that recognise the panel structure of the data and place more weight on the variation within companies to determine the coefficients. Ofwat has used this approach in its recent price control along with OLS and Ofgem tested GLS during RIIO-ED1 (though only used OLS).

Also, we use cluster robust standard errors when estimating the standard error of coefficients. This helps control systematic differences in the variance of the error term between companies and is useful in a POLS context that otherwise does not take account of the fact that the sample is made from multiple cross-sections. Not controlling for within-cluster (that is, within company) correlation of the error term could lead to misleading test results for statistical significance, so we consider it appropriate to use cluster robust errors in our POLS models.

2.3.4. Functional form

We have tested Cobb-Douglas and squared functional forms. The latter allows for cost elasticities to vary across companies.

2.4. Model refinement

We have run several models and taken the 'general-to-specific' approach to refining the set of viable cost drivers used in the models. This approach starts from a specification that includes several cost drivers and progressively omits cost drivers based on statistical significance and logical criteria.

In refining our models we have applied a number of statistical diagnostic tests to ensure that our model specifications and estimation methods are appropriate for the data being examined. We have adopted the following assessment criteria for developing and refining our models.

1. **Statistical performance**:
    - Parameter significance. The parameter estimates should be statistically significant (from zero) to, at least, 10% level of significance.
    - Statistical performance of the models, capturing a number of tests:
        - **Normality tests**. For small sample sizes a normally distributed error term is required in order for tests of statistical significant to be valid.
        - **Ramsey RESET**. This test gives an indication of whether there are any omitted non-linearities in the model. If so, then the model specification would need to be corrected to account for non-linear components.
        - **Pooling test**. For POLS models, this test determines whether or not the data is appropriate for pooling.
2. **Model robustness** – sensitivity to changes in data (for example, input assumptions/ companies):
    - We tested the robustness to dropping NIE Networks as well as testing different panel lengths.
    - We also tested the sensitivity of models to different regional wage adjustments (for example, using 3- and 4-digit SOC codes); different cost exclusions (for example, wayleaves payments) and whether or not we make assumptions around the proportion of labour that does not have to be procured from the local labour market.
3. **Logical criteria** – this criterion assesses the sensibility of model results, in terms of their economic and engineering interpretation. This includes the sign/ magnitude of parameter estimates.

3. MODEL ESTIMATION RESULTS

This section sets out results of the different models chosen through our model selection process. We set out the results of our independent model development and, when different, those used by the CC and Ofgem.

3.1. Independent model development

Presenting the full range of models tested would be impractical since there were several dozen permutations developed. Therefore, this sub-section focuses on how we arrived at our preferred models.

The most common cost drivers used in this exercise are indicators of company scale; namely network length, the CSV and MEAV. We found the density variable to be significant in the IMFT and Indirects and NOCs models, but not in the CAI or Business support models. As part of this exercise, we also tested alternative specifications that included squared terms for the cost driver (allowing for economies of scale and density to vary across the industry). However, these models failed the statistical robustness criterion as they produced insignificant coefficient estimates.

In some cases, there were possible alternative cost drivers that were available that were also statistically significant. For the opex models with one variable (CAI and Business support) we chose the CSV as the cost driver (comprising customer numbers, units distributed and network length (the same CSV used by the CC at RP5)), but MEAV was also a credible and robust option. Our rationale for choosing the CSV instead of MEAV for the business support and CAI models was based on:

- Precedent from RP5. The CC used models with the same CSV.
- The MEAV has been created based on expert views of unit costs from RIIO-ED1 and thus has some degree of discretion on how it is calculated. While the weights of the CSV require discretion, their components (customer numbers, network length and units distributed) have regulatory precedent and are individually reliable.

On balance, we went with the CSV but note that these models could also be used with the MEAV if desired. We show these potential alternatives for both pre- and post-allocation models in Annex D.

For capex models, we used MEAV as it is more reflective of the types of assets owned and therefore the type of capex incurred.

On a pre-allocation basis, we also tested the inclusion of asset additions as an additional explanatory variable in the IMFT and Indirects, CAI and business support models, recognising that both the scale of the network and the workload on that network (for example, new connections activity) are likely to drive these costs. However, asset additions was not significant at a 5% level in any of the models. As a result, we omitted asset additions from our baseline models.[5]

Table 3.1 and Table 3.2 below present the models we found to be the most robust for each cost categorisation, and the corresponding pooled OLS regressions results for these models (random effects/ GLS results are shown in Annex E) on a pre- and post-allocation basis. These models were run under our base case assumptions discussed in sub-section 2.2. We focused primarily on developing opex models and, as we discuss further below, have more confidence in these. However, we also tested capex and totex models and include the specifications that produced significant parameter estimates in the tables.

[5] These estimation results are provided in Annex F.

Table 3.1: Pre-allocation OLS estimation results. All explanatory and dependent variables are in natural logarithm. [6]

	IMFT and Indirects	NOCs	CAI	Business Support	Tree Cutting	LV HV OHL Faults	Capex	Load Related Capex	Non-Load Related Capex	Totex
Length	0.846***	1.067***								
Density	0.449***	0.737***								
CSV			0.744***	0.586***						
Spans Cut					0.550**					
LV HV OHL Faults						0.883***				
MEAV							0.767***	1.088**	0.702***	
MACRO CSV										0.822***
Constant	-5.922***	- 10.402***	-4.535***	-3.390***	-3.448*	-5.434***	-7.782**	-14.333*	-7.056**	-7.714***
RESET	0.122	0.395	0.862	**0.077**	0.425	0.161	0.310	0.893	0.178	0.325
Normality	0.372	0.134	0.276	**0.059**	**0.042**	**0.029**	0.690	0.380	0.240	0.576
Pooling	0.928	0.981	0.669	0.994	0.960	**0.096**	0.201	0.267	0.457	0.325
N	60	60	60	60	56	56	60	60	60	60
R^2	0.846	0.737	0.757	0.622	0.243	0.493	0.359	0.269	0.295	0.694

Source: CEPA analysis

[6] * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Statistical diagnostic test results in bold indicate the test has failed.

Table 3.2: Post-allocation OLS estimation results. All explanatory and dependent variables are in natural logarithm. [7]

	IMFT and Indirects	NOCs	CAI	Business Support	Tree Cutting	LV HV OHL Faults	Capex	Load Related Capex	Non-Load Related Capex	Totex
Length	0.888***	1.067***								
Density	0.475***	0.737***								
CSV			0.793***	0.604***						
Spans Cut					0.550**					
LV HV OHL Faults						0.883***				
MEAV							0.740***	0.884**	0.702***	
MACRO CSV										0.821***
Constant	-6.581***	-10.402***	-5.302***	-3.734***	-3.448*	-5.434***	-7.189**	-10.550*	-7.056**	-7.722***
RESET	0.224	0.395	0.760	0.225	0.425	0.161	0.436	0.995	0.178	0.315
Normality	0.713	0.134	0.994	0.135	**0.042**	**0.029**	0.732	0.138	0.24	0.608
Pooling	0.924	0.981	0.718	0.993	0.960	**0.096**	0.286	0.500	0.457	0.319
N	60	60	60	60	56	56	60	60	60	60
R^2	0.800	0.737	0.652	0.554	0.243	0.493	0.424	0.323	0.295	0.698

Source: CEPA analysis

[7] * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Statistical diagnostic test results in bold indicate the test has failed.

3.2. Interpreting the models

This sub-section focuses on the interpretation and statistical significance of the parameter estimates presented in Table 3.1 and Table 3.2. As the main focus of this exercise was to assess the relative efficiency of NIE Networks' IMFT and Indirects costs, we focus our interpretation of model results for IMFT and Indirects, NOCs, CAI and Business Support models.

All the models presented in the tables have a log-log model specification. As a result, the parameter estimates can be interpreted as elasticities; that is, a percentage change in costs for a percentage change in the cost driver. All estimated elasticities are appropriate in terms of magnitude (between zero and one) and all are statistically significant at a 10% significance level for both pre-allocation and post-allocation estimation results.

Estimated coefficients in the post-allocation models are slightly higher in magnitude for IMFT and Indirects, CAI and Business Support than in the pre-allocation models. This implies that the elasticity between indirect connections costs and network length is lower than between the other indirect costs (not attributed to connections) and network length. We may expect indirect costs associated with connections to be more related to connections workload than the scale of the company. If this is the case then this result is not surprising.

For the IMFT and Indirects model, both modelling approaches show that a 1% increase in network length leads to a smaller than 1% increase in costs (0.85% in the pre-allocation model and 0.89% in the post-allocation model). This implies that economies of scale are possible. Turning to network density, ex ante, the impact of network density on costs is ambiguous. On one hand, costs may decrease with density (increase with sparsity) as a company may need a higher number of staff/assets to provide a defined level of service in sparse areas. On the other hand, costs may increase with density (decrease with sparsity) as working in highly populated (urban) areas is more complex as it is likely to require, among other things, a more detailed consideration of the deployment of other utilities. The estimated parameter on network density suggests that a 1% increase in density leads to a 0.45% (0.48%) increase in costs in the pre-allocation (post-allocation) model.

For NOCs, we also selected length and density as our preferred model specification, and the parameter estimates are higher in magnitude than in the IMFT and Indirects model. This implies that the elasticity between NOCs and length / density is greater than the elasticity between Business Support / CAI and length / density. This is supported by the fact that the length and density model specification was rejected for Business Support or CAI costs within our independent model selection process.

Turning to CAI and Business Support costs, a CSV was chosen as the only cost driver in our preferred models. The CAI pre-allocation (post-allocation) model indicates that a 1% increase in the CSV will lead to a 0.74% (0.79%) increase in CAI costs; implying that economies of scale are possible. The Business Support pre-allocation (post-allocation) model indicates that a 1%

increase in the CSV will lead to a 0.59% (0.60%) increase in Business Support costs; which also implies that economies of scale are possible.

3.3. Statistical diagnostic testing

This sub-section discusses the statistic diagnostic test results for our preferred set of models on a pre- and post-allocation basis. The results of these tests played a significant role in our model selection process as they help to assess the validity of each model. The tests we have performed are:

- **Ramsay RESET**: Which gives an indication of whether there are any omitted non-linearities in the model. If this test fails it provides a strong indication that the model is mis-specified. For this reason, we placed a relatively high weight on the outcome of this test within our model selection process.
- **Normality test:** For small sample sizes a normally distributed error term is required in order for tests of statistical significance to be valid. However, the assumption of normality is not required for models to have other desirable statistical properties (for example, unbiasedness and consistency). Therefore, we have placed a lower weight on this test result when determining whether models pass the statistical criterion.
- **Pooling test:** This test determines whether or not the data is appropriate for pooling. If this test fails then this would be an indication that using panel data estimation methods is not appropriate.

All of our preferred models pass the RESET test with the exception of the business support model, which fails at a 10% level of significance on a pre-allocation basis. However, the RESET test does pass at the 5% level of significance. This result means that, on a pre-allocation basis, there is the possibility that the model is mis-specified.

Following on from this, the test for normality of the regression residuals fails for the business support, tree cutting and faults models on a pre-allocation basis; and fails for the tree cutting and faults models on a post-allocation basis. In these cases caution should be applied when examining the statistical significance of the estimated parameters given the usual t-statistic assumes the data came from normally distributed population. But this does not change the overall performance of the model.

The pooling test was passed in all our short-listed models with the exception of the faults model, where we reject the null hypothesis that data can be pooled across time at a 10% level of significance. Based on this result, it may not be advisable to estimate the disaggregated faults model using panel data estimation methods.

3.4. Model robustness

As set out in Table 3.3, we tested models against a number of sensitivities to see how the models performed against changing inputs.

Table 3.3: Sensitivities tested

No.	Sensitivity
1	Using full historic Ofgem RIIO-ED1 panel
2	Using DPCR5 RIGs for GB DNOs
3	Including an adjustment for local labour
4	Only apply local labour adjustment to GB DNOs
5	RWA using three-digit SOC codes
6	RWA using four-digit SOC codes
7	Excluding NIE Networks from the sample
8	Excluding wayleaves costs

We performed these sensitivities for each of the OLS models. For brevity, Table 3.4 and Table 3.5 below only present the results of these sensitivities for the IMFT and Indirects model on a pre- and post-allocation basis. However, the results are similar for other models (and are provided in Annex G).

Table 3.4: IMFT and Indirects OLS sensitivities tested (pre-allocation) [8]

Cost Driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks	Excluding Wayleave Payments
Length	0.846***	0.854***	0.840***	0.843***	0.837***	0.839***	0.752***	0.844***	0.858***
Density	0.449***	0.453***	0.415***	0.495***	0.470***	0.459***	0.411***	0.435***	0.470***
Constant	-5.922***	-6.025***	-5.756***	-6.047***	-5.900***	-5.872***	-4.719***	-5.840***	-6.103***
RESET	0.122	0.159	0.198	**0.078**	**0.075**	0.144	**0.096**	0.142	0.14
Normality	0.372	0.387	0.186	0.418	0.485	0.37	0.123	0.292	0.305
Pooling	0.928	0.992	0.938	0.851	0.842	0.915	0.932	0.942	0.944
N	60	88	60	60	60	60	60	56	60
R^2	0.846	0.835	0.848	0.882	0.879	0.853	0.813	0.821	0.842

Source: CEPA analysis

[8] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated parameters in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

Table 3.5: IMFT and Indirects OLS sensitivities tested (post-allocation) [9]

Cost Driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks	Excluding Wayleave Payments
Length	0.888***	0.874***	0.883***	0.884***	1.066***	0.794***	0.793***	0.875***	0.901***
Density	0.475***	0.455***	0.421***	0.518***	0.495***	0.485***	0.437***	0.415**	0.501***
Constant	-6.581***	-6.372***	-6.373***	-6.700***	-6.562***	-6.531***	-5.376***	-6.221***	-6.802***
RESET	0.224	0.284	0.282	0.125	0.144	0.247	0.182	0.309	0.231
Normality	0.713	0.304	0.453	0.798	0.855	0.673	0.413	0.24	0.595
Pooling	0.924	0.939	0.969	0.863	0.844	0.915	0.919	0.998	0.951
N	60	88	60	60	60	60	60	56	60
R^2	0.8	0.781	0.79	0.836	0.837	0.805	0.768	0.766	0.79

Source: CEPA analysis

[9] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated parameters in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

These tables show that across the different sensitivities the parameter estimates stay statistically significant and are similar in magnitude when estimating the models either on a pre- or post-allocation basis. However, for the IMFT and Indirects model on a pre-allocation basis, the RESET test result indicates that we reject the null hypothesis that the functional form is correctly specified at a 10% significance level, but not at a 5% significance level, when using Ofgem's local labour adjustment and when using the four-digit SOC RWA. Therefore, we recommend interpreting this model with caution under these sets of assumptions since the test result indicates the model may be mis-specified. Otherwise, the models continue to pass the diagnostic tests under other sensitivities.

Interestingly, the sensitivity which utilises the full ED1 dataset has a lower explanatory power than our baseline model that uses a balanced panel, with R^2 decreasing from 0.846 (0.800) to 0.835 (0.781) on a pre-allocation (post-allocation) basis.

The 4-digit SOC sensitivity has the biggest impact on the estimated coefficients on length and density, with the elasticity between length / density and IMFT and Indirect costs decreasing significantly. On a pre-allocation (post-allocation) basis the elasticity between length and IMFT and Indirects decreases from 0.846 (0.888) in our baseline to 0.752 (0.793) when using 4-digit SOC codes to calculate the regional wage adjustment factors. Similarly, on a pre-allocation (post-allocation) basis the elasticity between density and IMFT and Indirects decreases from 0.449 (0.475) in our base case to 0.411 (0.437) when using 4-digit SOC codes.

This result reiterates our previously raised concerns with using 4-digit SOC codes when estimating regional wage adjustment factors. In particular, we found that the use of these SOC codes would require the use of both unreliable data[10] and data that is potentially heavily influenced by one single company, which, as indicated by the CC in its RP5 final determination, is likely to be NIE Networks.[11] As a result, it appears that the use of 4-digit SOC weightings would not provide robust findings, and this is supported by our model estimation results when using them.[12]

[10] At the 4-digit level, there is a large share of the adjustment that is categorised as disclosive in 2012 and 2013, as well as circa 20% classified as unreliable in 2014.

[11] CMA (2014) Northern Ireland Electricity Limited price determination: Final determination. Paragraph 8.216

[12] NIE Networks appear to be less efficient using the 4-digit SOC approach than using a 2-digit SOC approach (see below for more details).

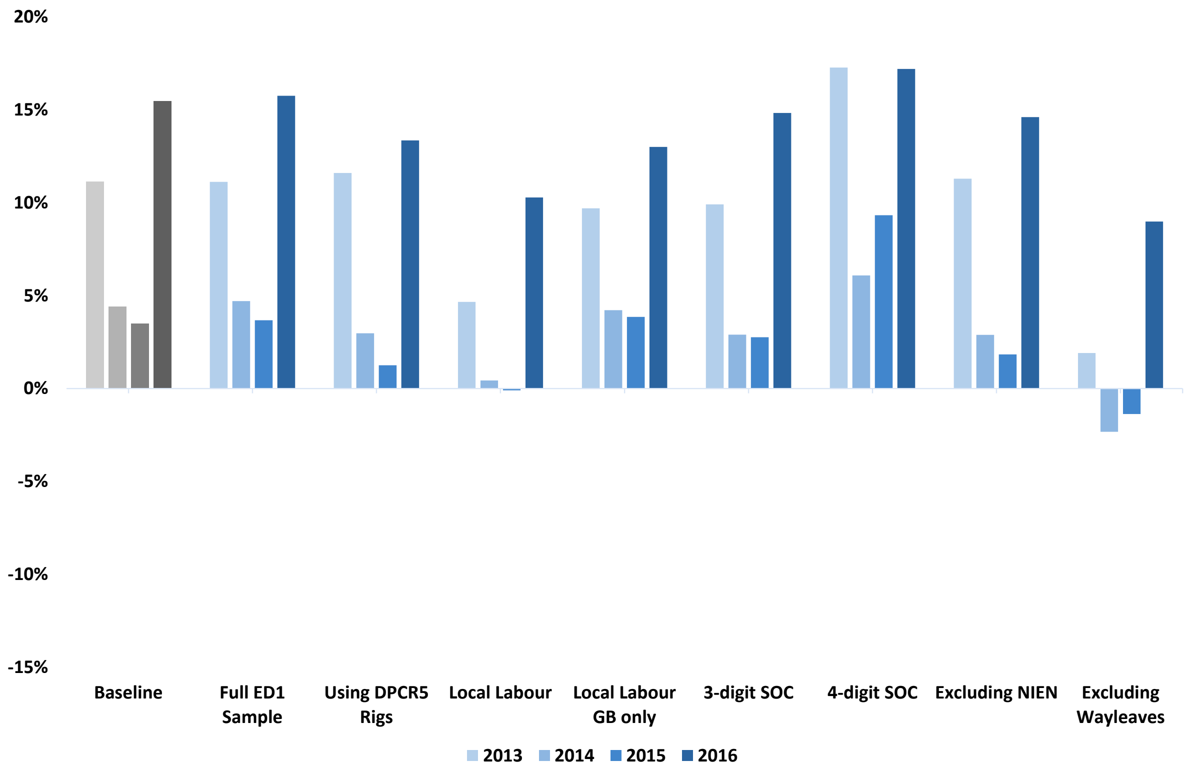
4. Efficiency Gap Analysis

This section assesses how NIE Networks performs under our preferred POLS models above. For illustrative purposes this section shows NIE Networks' efficiency gap compared to the upper quartile company, which we have rounded to be the fourth placed company. As a result, the fourth placed company will have a zero efficiency gap.[13]

4.1. Pre and post allocation results

Figures 4.1 and 4.2 below show the estimated annual efficiency gaps for NIE Networks from our IMFT and Indirects models (pre / post-allocation) (efficiency gaps for other models are provided in Annex H), in which positive values indicate inefficiency relative to the benchmark. Following guidance from UR, we have shown efficiency gaps for each year, but average efficiency gaps should also be considered, since there can be some volatility between years as POLS does not place any structure on the variation of company efficiency over time.

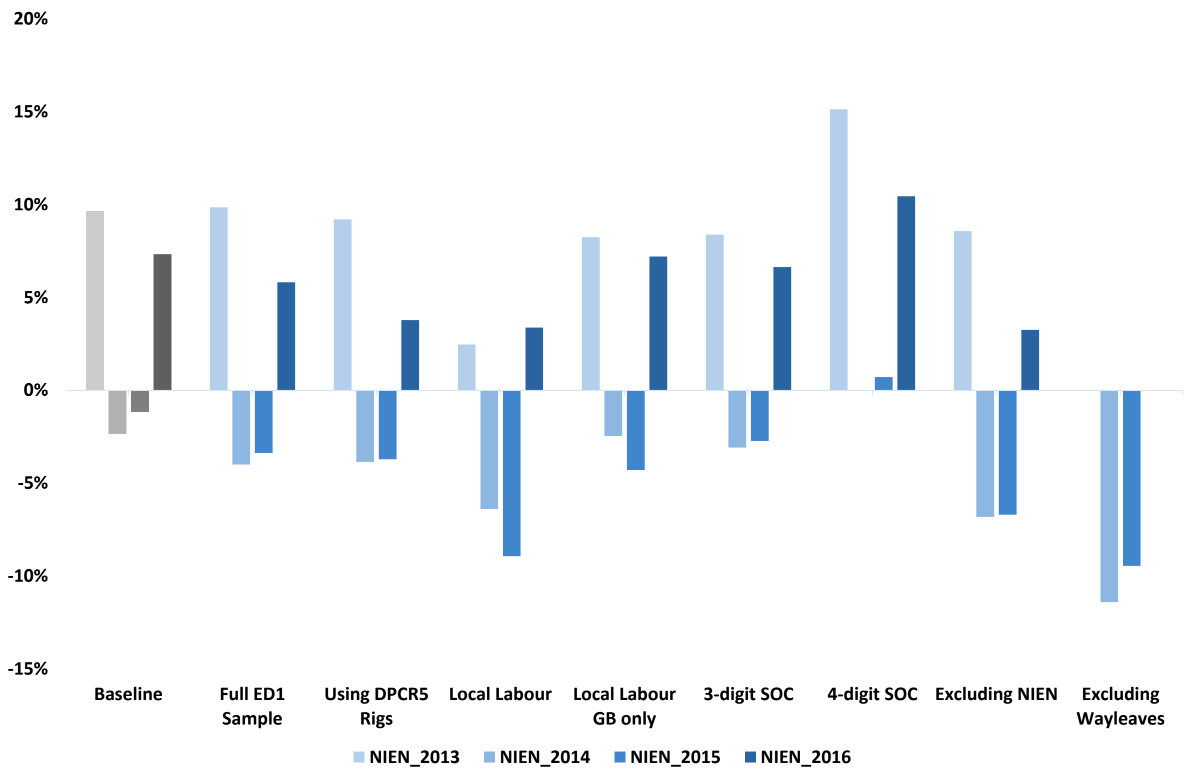
Figure 4.1: Efficiency gaps from IMFT and Indirects model (pre-allocation)



Source: CEPA analysis

[13] We have estimated efficiency gaps for other companies and for alternative benchmarks (fifth placed company and upper decile) but do not present these here. The efficiency gaps presented in this report are calculated as 1 – (efficiency score of upper quartile company / efficiency score of NIE Networks). This reflects the percentage change in NIE Networks' efficiency score required to reach the upper quartile efficiency score.

Figure 4.2: Efficiency gaps from IMFT and Indirects model (post-allocation)[14]



Source: CEPA analysis

NIE Networks efficiency gap is relatively smaller across all years (2013 to 2016) on a post-allocation basis than pre-allocation. On a pre-allocation basis, NIE Networks' efficiency gap for IMFT and Indirects in our baseline scenario ranges from 3% to 15%. The equivalent range on a post-allocation basis is lower, ranging from -2% to 10%. The advantages and disadvantages of using either of these approaches has been discussed above.

In Annex H we present efficiency gap analysis for NOCs, CAI and business support models, which can be combined to cover the same costs as our IMFT and Indirects model. These charts show that NIE Networks tend to be relatively efficient in NOCs, but relatively inefficient at an overall IMFT and Indirect model, which is driven by their relative inefficiency estimated in CAI and business support models.

In addition, when considering efficiencies, it is also important to understand the potential effects of the different sensitivities. The sensitivities that have the greatest impact on NIE Networks' efficiency gap across all models are:

- Ofgem's local labour adjustment;
- granularity of ASHE SOC codes; and
- the exclusion of wayleave payments.

[14] NIE Networks are the upper quartile company on a post-allocation basis under the 4-digit SOC sensitivity in 2015 and under the wayleaves sensitivity in 2013. As a result, there is no efficiency gap.

These effects are explained in the following sub-sections.

4.2. Ofgem's local labour adjustment

Some labour costs do not necessarily have to be sourced locally, that is, within the region the DNO operates; as the role being performed can be conducted remotely. Examples may include call centres which, in theory, can be located anywhere in the world providing a sufficiently skilled labour force is available. Hence, all else being equal, if we assume DNOs are profit maximising firms all DNOs should locate business support activities in the lowest cost region of the world where a sufficiently skilled labour force is available. As a result, for the proportion of labour costs that do not need to be incurred locally, competitive pressures should eliminate price differentials across companies.

At RIIO-ED1, Ofgem accounted for this by applying a percentage to the amount of labour costs that needed to be carried out locally. Percentages varied across different cost categories, ranging from 0% to 88% of labour costs. The percentages were informed by submissions from the DNOs regulated by Ofgem. The CC does not appear to have considered this at RP5, but instead appears to have applied the RWA to the entirety of indirect labour costs. At RP6, the decision to introduce Ofgem's local labour adjustment, or an alternative local labour adjustment, is a decision to be considered by the regulator. Thus, we have outlined our thoughts on this issue below.

To ensure that, when possible, our analysis is consistent with Ofgem's approach, we aimed to replicate the work it undertook to develop its data adjustments at RIIO-ED1. However, we were unable to find the exact source of Ofgem's assumptions with regards to its local labour adjustment. As a result, we were unable to duplicate Ofgem's analysis that would have supported us when assessing the suitability of the adjustment for Northern Ireland.

Overall, we consider that it is difficult to pinpoint the total proportion of labour that can realistically be procured nationally (or internationally) by DNOs as there are many factors to take into account that include:

- This is likely to be an asymmetric effect. Companies operating in expensive areas would have incentives to acquire these services outside of their area. On the contrary, those operating in cheaper areas (such as Northern Ireland) are less likely to go to a national market where they would face higher costs.
- The decision to relocate certain activities outside of the DNO's operational region will not only be the result of differences in wages but there could be other considerations. Examples of these factors may include: the existence of cheaper regions inside of the area served by the DNO; joint provision of services across DNOs in the same group; political pressure to keep jobs in the area or degree of control required by the company over the provision of these services; and quality of service incentives.

Taking these factors into account, it appears that DNOs could have limited incentives to source labour outside of their operational region, hence reducing the local labour adjustment required.

It is important to note, however, that if a proportion of a DNO's labour costs are not sourced locally, an approach that assumes that all cost are regional would 'over-adjust' the costs of the company. This will mean that for companies operating in a cheap area, the adjustment would also be applied to the costs of services sourced outside of their region. Given that, for these services, the company would be paying the same price as the other DNOs, the costs entering into the benchmarking model would appear to be more expensive after the application of the RWA than they would otherwise.

To illustrate this effect the table below shows a numerical example of how costs would be adjusted for different companies. For simplicity, we assume that Company A operates in an average cost area and it receives no adjustment while Company B operates in a cheap area and its costs are adjusted by 1.25 before they enter into the econometric analysis.

Table 4.1: Worked example of applying a RWA to non-local costs

	Source of the services	Actual costs	RWA applied only to regional costs	RWA applied to all costs
Company A	Regional	1,000	1,000	1,000
	National	100	100	100
	Total cost	1,100	1,100	1,100
Company B	Regional	800	1,000 (800*1.25)	1,000 (800*1.25)
	National	100	100	125 (100*1.25)
	Total cost	900	1,100	1,125

This shows that when the regulator applies the adjustment to all costs (including those that are being acquired at the same price than Company A), Company B will seem to be less efficient (that is, relatively higher cost).

Lacking a robust approach for the development of this adjustment, we also considered the possibility of using Ofgem corrections for Northern Ireland. However, given the characteristics of operating in Northern Ireland, it appears reasonable to assume that NIE Networks would acquire less services in other regions than the GB's DNOs.

As a result, we would recommend not to apply this adjustment to NIE Networks costs, and we have not applied the local labour adjustment in our preferred set of models. However, we have run a sensitivity across all our models where we apply Ofgem's local labour adjustment in full (NIE Networks and GB DNOs). This makes NIE Networks look more efficient, which is not surprising because under this sensitivity we apply the RWA to a smaller proportion of total IMFT and Indirects costs. That is, when we do not apply the local labour adjustment we apply the RWA to 100% of labour costs incurred by the companies, but when we apply the local labour adjustment this percentage decreases significantly. For example, the proportion of NIE

Networks' IMFT and Indirect labour costs we apply the RWA to decreases from 100% to approximately 42% when we apply the local labour adjustment. As a result, we adjust NIE Networks' costs upwards less than under the baseline models for the purpose of benchmarking.

Following guidance from the UR, we have also run a separate sensitivity where we only apply the local labour adjustment to GB DNOs and not to NIE Networks. The result is that NIE Networks' efficiency gap is somewhere in between our baseline, where we do not apply the local labour adjustment, and the local labour adjustment sensitivity.

4.3. Granularity of SOC codes

A key decision when calculating the regional wage model was the granularity of the ASHE SOC code we would choose. We arrived at the decision to use 2-digit SOC codes rather than 3-digit or 4-digit SOC codes for reasons we explain in our separate RWA paper.

Using 3-digit SOC codes makes NIE Networks look more efficient because the RWA applied to NIE Networks costs is absolutely and relatively lower than when using 2-digit SOC codes (the baseline scenario). In contrast, using 4-digit SOC codes makes NIE Networks look less efficient because the RWA for NIE Networks is absolutely and relatively larger than in the baseline scenario. This because of two reasons:

- the *absolute* value of NIE Networks' RWA factor is greatest using 4-digit SOC codes, and
- the *relative* difference between NIE Networks' RWA factor and GB DNO RWA factor is greatest when using 4-digit SOC codes.

As a result, for benchmarking purposes, absolutely and relatively, NIE Networks' costs are adjusted upwards by the greatest amount when using 4-digit SOC codes. This is explained in more detail in our RWA paper.[15] It is important to note that moving from a 2-digit SOC approach to a 3-digit SOC approach would not make any material difference to the efficiency gap. Whereas moving to a 4-digit SOC approach would make NIE Networks look less efficient.

4.4. Excluding wayleaves

NIE Networks looks relatively more efficient in this analysis because it has relatively high wayleave payments costs compared to GB DNOs. Therefore, when removing these costs from all companies NIE Networks' costs are reduced by more (proportionately) than GB DNOs.

[15] CEPA, 2017. Regional wage adjustment.

5. Regulatory Precedent – CC RP5 and Ofgem RIIO-ED1

To ensure that we consider the relevant precedent, we have re-run the CC's preferred models for benchmarking IMFT and Indirects expenditure at RP5, and Ofgem's tree cutting, faults, CAI and top-down totex models used at RIIO-ED1, using the base case assumptions set out in sub-section 2.2. The latter also provides a useful comparison and sense-check to the analysis conducted by NERA for NIE Networks, whose approach to benchmarking NIE Networks' IMFT and Indirect costs was centred around Ofgem's benchmarking approach taken in RIIO-ED1.[16]

5.1. CC models (RP5)

We used the base case assumptions set out in sub-section 2.2 and re-ran the CC's preferred models for benchmarking IMFT and Indirects expenditure at RP5. As with the CC, this was run on a pre- and post-allocation basis.

Model coefficients, diagnostic tests and performance against our selection criteria are shown in Table 5.1 (pre-allocation) and Table 5.2 (post allocation). The models were estimated using OLS and for four years of data.

Table 5.1: Results of CC models M4 and M6 (pre-allocation) [17]

Cost Driver	CC Model M4	CC Model M6
	(IMFT and Indirects)	(IMFT and Indirects per Customer)
CSV	0.858***	
Length per Customer		0.559***
Time dummy (2014)	0.053***	0.048**
Time dummy (2015)	0.034**	0.024*
Time dummy (2016)	**0.030**	**0.016**
Constant	-5.019***	-7.588***
RESET	0.273	0.219
Normality	0.198	0.748
Pooling	1.000	1.000
N	60	60
R^2	0.835	0.690

Source: CEPA analysis

[16] This approach benchmarks DNO forecasts of expenditure against the comparator set rather than the UR's preference to examine NIE Networks' historical efficiency.

[17] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated parameters in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

Table 5.2: Results of CC models M4 and M6 (post-allocation) [18]

Cost Driver	CC Model M4 (IMFT and Indirects)	CC Model M6 (IMFT and Indirects per Customer)
CSV	0.902***	
Length per Customer		0.531***
Time dummy (2014)	0.070***	0.065***
Time dummy (2015)	0.041**	**0.03**
Time dummy (2016)	**0.021**	**0.007**
Constant	-5.638***	-7.807***
RESET	0.273	0.220
Normality	0.508	0.499
Pooling	1	1
N	60	60
R^2	0.790	0.592

Source: CEPA analysis

Given the results above, it appears that CC's models M4 and M6 could still be viable for estimating efficiency for RP6. While the explanatory power of our length and density model is higher (see Table 3.1), both CC models produce statistically significant parameter estimates with intuitive signs and magnitudes on a pre- and post-allocation basis. The only explanatory variables that are statistically insignificant are the 2015 (M6 model only) and 2016 time dummies. This is not detrimental to the model as this simply means that the 2015 or/and 2016 intercepts are not statistically significantly different from the 2013 intercept. In addition, both CC models on a pre- and post-allocation basis pass all statistical tests and so perform well against the statistical performance criterion.

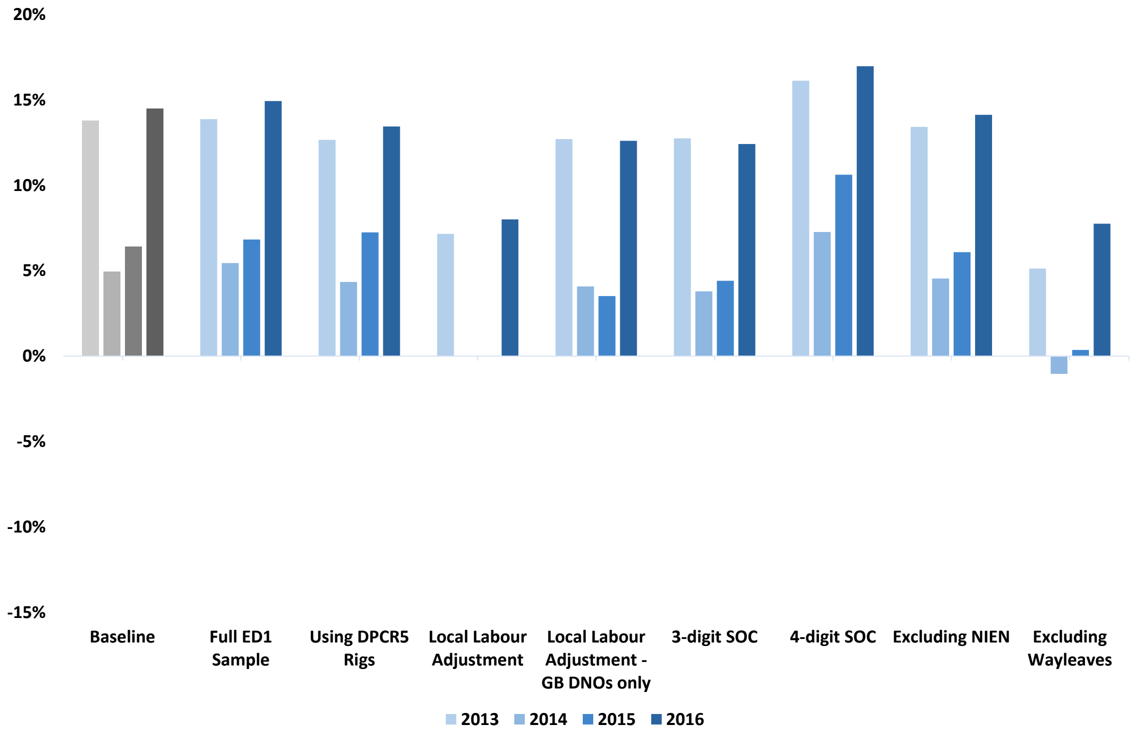
On a note of caution, we recommend that these models should not be used to forecast the costs of an efficient company as we would not be in a position to estimate an annual year dummy going forward. As a result, we would have to make the assumption that the intercept for every year in the forecast period is not significantly different from the base year intercept (2012/13). This is quite a significant assumption because as it is shown in Table 5.1 and Table 5.2 this was not the correct assumption in 2014 and 2015.

As with our preferred models, we have also considered NIE Networks' efficiency levels on a pre- and post-allocation basis, and across the different sensitivities run in sub-section 3.4.

[18] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated parameters in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

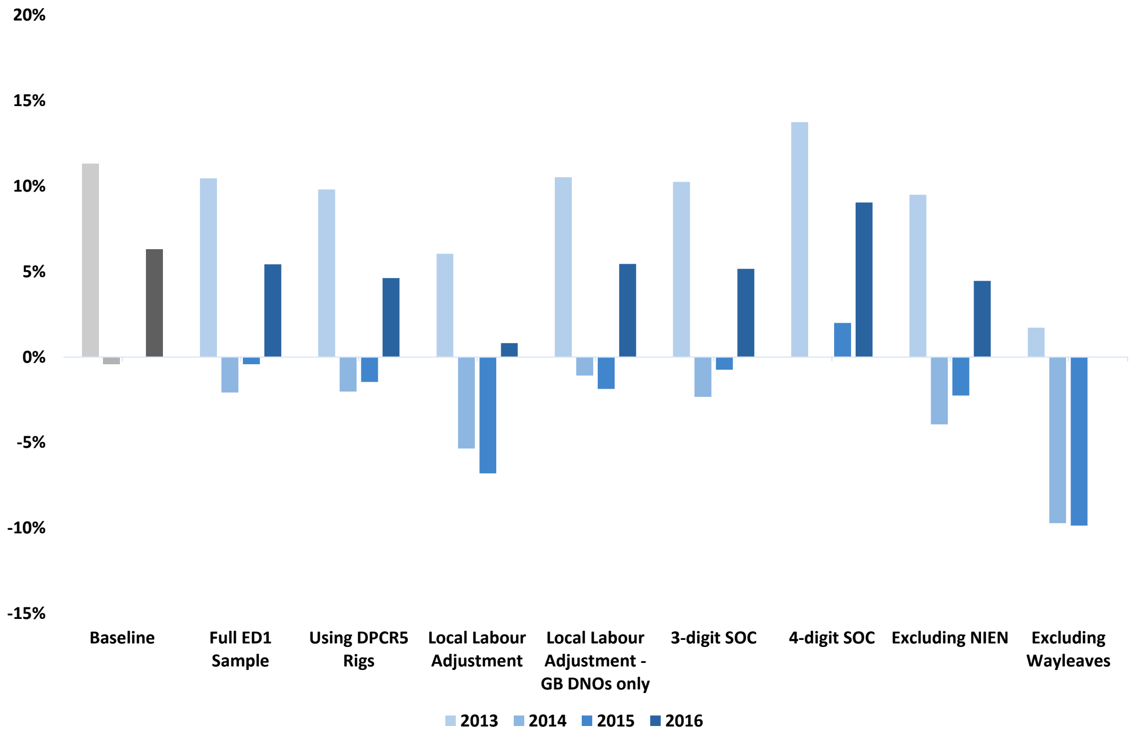
Figure 5.1 to Figure 5.4 show that NIE Networks' efficiency gap varies over time, which is not surprising given OLS does not impose any assumptions on the structure of efficiency. As we found in our independent model development, NIE Networks appear more efficient in the post-allocation modelling results. Overall, the identified efficiency gaps for NIE Networks from the CC M4 and M6 models are of a similar magnitude to our preferred model specification. As in our independent model development, NIE Networks perform best when we apply the local labour adjustment in full (applied to GB DNOs and NIE Networks) or when we exclude wayleaves payments.

Figure 5.1: Efficiency gaps from CC model M4 (pre-allocation)



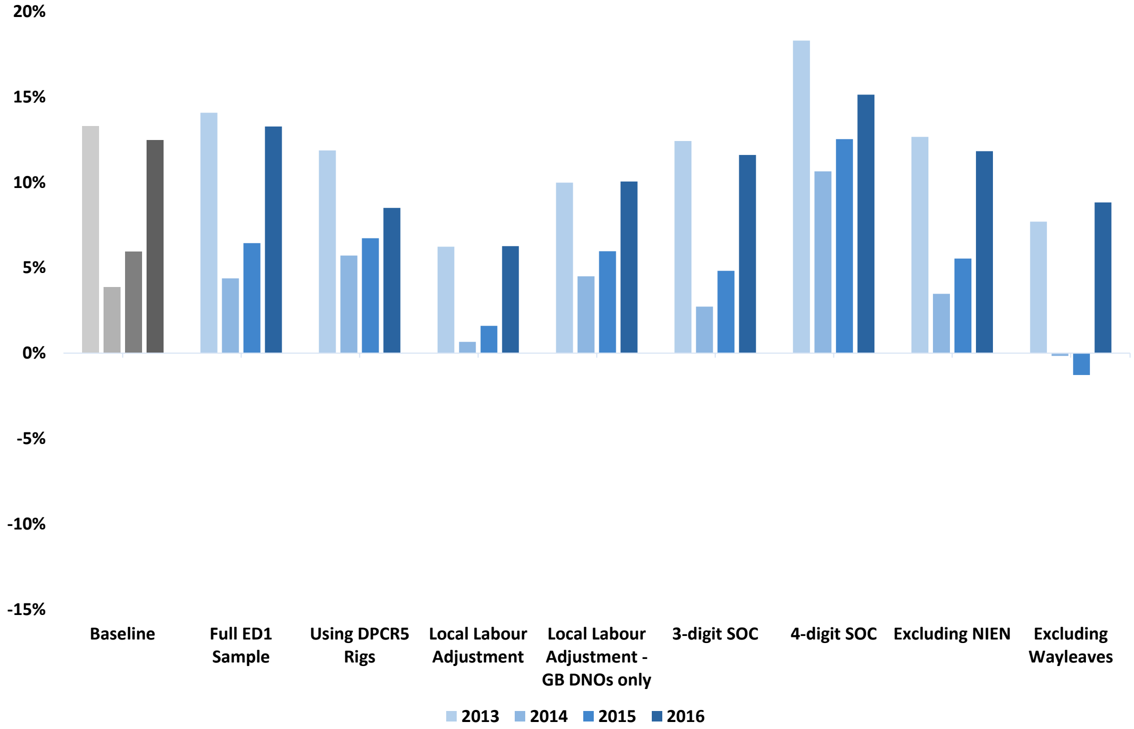
Source: CEPA analysis

Figure 5.2: Efficiency gaps from CC model M4 (post-allocation)



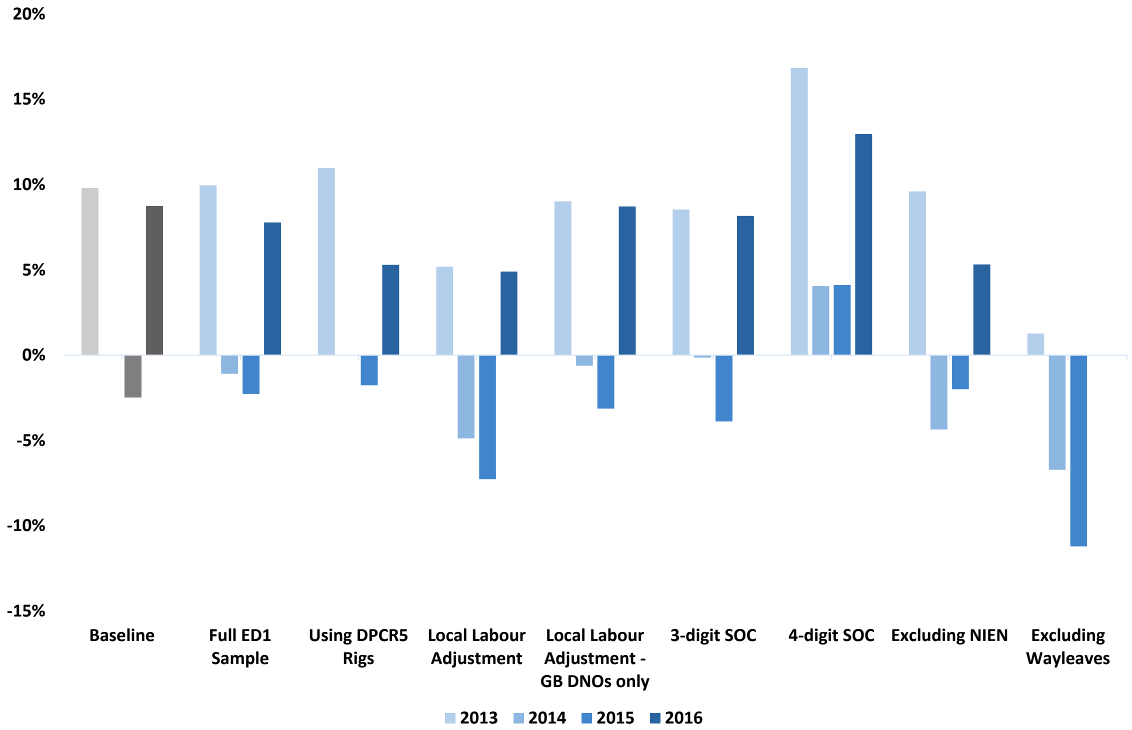
Source: CEPA analysis

Figure 5.3: Efficiency gaps from CC model M6 (pre-allocation)



Source: CEPA analysis

Figure 5.4: Efficiency gaps from CC model M6 (post-allocation)



Source: CEPA analysis

5.1.1. Conclusion

Our analysis of the CC's models from RP5 shows that they produce similar results to our independently developed models, and so could be used as alternatives. However, if the models were to be used to forecast costs of an efficient company by plugging in forecast cost drivers into the estimated equation, we would advise against using the CC models because the time trends in the CC models do not extend beyond 2015/16 and so would not be factored into forecast costs. As a result, we would have to make the assumption that the intercept for every year in the forecast period is not significantly different from the base year intercept (2012/13). This is quite a significant assumption because as it is shown in Table 5.1 and Table 5.2 this was not the correct assumption in 2014 and 2015. Furthermore, our independently developed IMFT and Indirects model captures density in the same model, whereas the CC models capture these effects separately.

However, if the models are to be used for setting a base year adjustment based on historic efficiency instead of forecasting costs using forecast cost drivers, then we would consider the CC's models as reasonable alternatives to our independently derived models.

5.2. Ofgem models (RIIO-ED1)

Using the base case assumptions set out in sub-section 2.2, we have rerun Ofgem's econometric cost models used in RIIO-ED1 for tree cutting, LV, HV, OHL faults, CAI, and top-down totex.

It should be noted that Ofgem's CAI variable at RIIO-ED1 had a different grouping of costs than we have assumed in our other CAI modelling. Ofgem excluded vehicles costs and operational training costs from its CAI modelling and included network policy costs (classed as business support). We have not made these same adjustments in our modelling. Also, Ofgem excluded wayleaves in the CAI model. As described in sub-section 2.2 we have not made this adjustment.

Given Ofgem only conducted its econometric analysis on a pre-allocation basis, we have replicated Ofgem's modelling on a pre-allocation basis but not on a post-allocation basis. For brevity, we only re-run these models under our preferred model assumptions. Model coefficients, diagnostic tests and performance against our selection criteria are shown in Table 5.3 below. These models were estimated using pooled OLS and four years of data.

Table 5.3: Ofgem Models (RIIO-ED1) [19]

Cost Driver	Tree Cutting	LV HV OHL Faults	Top-down Totex	CAI
Spans Cut	0.510**			
Spans Inspected	**0.047**			
LV HV OHL Faults		0.883***		
MACRO CSV			0.822***	
MEAV				0.783***
Asset Additions				**-0.046**
Constant	-3.562*	-5.434***	-7.714***	-8.164***
RESET	0.497	0.161	0.325	0.120
Normality	**0.034**	**0.029**	0.576	0.162
Pooling	0.939	**0.096**	0.325	0.788
N	56	56	60	60
R^2	0.249	0.493	0.694	0.661

Source: CEPA analysis

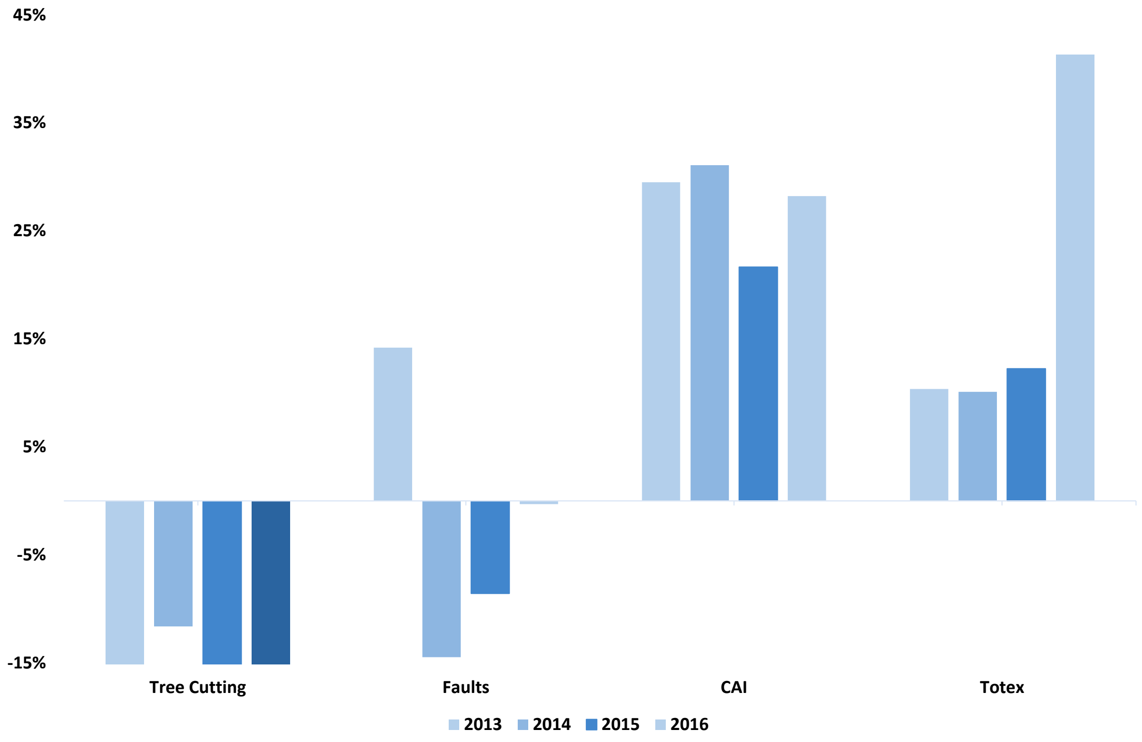
[19] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated parameters in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

Based on these results we find that:

- Tree cutting and CAI models do not pass our selection criteria because they contain statistically insignificant explanatory variables (spans inspected and asset additions, respectively) and so it would be unadvisable to use them.
- The faults model pooling test result suggests that we reject the null hypothesis that the same coefficients apply across all individuals at a 10% significance level. This suggests that pooling the data may not be advised. The normality test also fails. Furthermore, the model covers a relatively narrow definition of costs that may be of limited use if a disaggregated approach to cost assessment is not being used.
- The totex model passes all diagnostic tests and produces a parameter estimate on MACRO CSV that is sensible in magnitude and statistically significant.

Below we check whether the resulting efficiency gaps are reasonable for the Ofgem models and consider what this says about the validity of the model. Figure 5.5 shows that NIE Networks' efficiency gap varies over time, which is not surprising given OLS does not impose any assumptions on the structure of efficiency.

Figure 5.5: Efficiency gaps from Ofgem RIIO-ED1 models (pre-allocation)



Source: CEPA analysis

As we highlighted in our independent modelling of tree cutting costs, NIE Networks perform well in terms of tree cutting. The only difference between Ofgem's tree cutting model and CEPA's tree cutting model is the inclusion of spans inspected in the former. We excluded this variable as it was statistically insignificant and there was evidence of multicollinearity between spans cut and spans inspected. NIE Networks are slightly more efficient in the case of the Ofgem tree cutting model than in the CEPA tree cutting model, but the results are very similar.

For faults, NIE Networks appears to be relatively efficient compared to the upper quartile company in the last three years. Even though we have excluded costs excluded from severe weather, the higher efficiency gap recorded in 2013 may have been caused by the 1-in-20 severe weather event witnessed in 2013.[20]

Turning to Ofgem's CAI model, which has a slightly different definition of costs than in CEPA's CAI model, NIE Networks performs quite poorly, with the efficiency gap ranging from 28% to 45%. NIE Networks is slightly less efficient in the Ofgem CAI model than in the CEPA CAI model.

For totex, NIE Networks' efficiency gap is quite stable with the exception of the final year when NIE Networks' efficiency gap jumps from 14% in 2015 to 70% in 2016. This may be caused by the increase in connection activity undertaken in 2016, which the model may not capture given it does not contain an asset additions variable.

[20] This model is identical to our independent modelling of faults costs on a pre-allocation basis.

6. PREFERRED MODELS

Our independent model development process has developed robust opex models aimed at estimating the operational efficiency of NIE Networks over the RP5 period. Capex models in general produce quite extreme results, which is likely in part due to the lumpy nature of capex.[21] After an initial analysis, and following the guidance of UR, we focused our efforts on opex models and, as such, the capex models are not robust and we would not recommend their use.

We have also looked at the performance of CC's RP5 models and Ofgem's RIIO-ED1 models, which have mixed performance, as well as potential alternative drivers for our independently developed models. In Table 6.1 we set out our preferred models and their performance under both pre and post allocation approaches to dealing with indirect costs associated with connections.

Table 6.1: Recommended models

Modelled cost	Cost driver(s)	Performance against selection criteria	
		Pre-allocation	Post-allocation
IMFT and Indirects	Network length Network density	Performs well	Performs well
NOCs (i.e. opex)	Network length Network density	Performs well	Performs well
Tree cutting	Spans cut	Performs well	Performs well
LV HV OHL faults	LV HV OH faults (excluding switching events)	Performs well	Performs well
CAI	Composite scale variable (CSV)	Performs well	Performs well
Business support	Composite scale variable (CSV)	Performs correctly. Marginally fails the RESET test.	Performs well

[21] IT & Telecoms non-op capex is also lumpy over time, and as such was excluded from benchmarking and separately assessed by the UR.

Table 6.2 sets out the performance of potential alternative models (including CC's RP5 models).

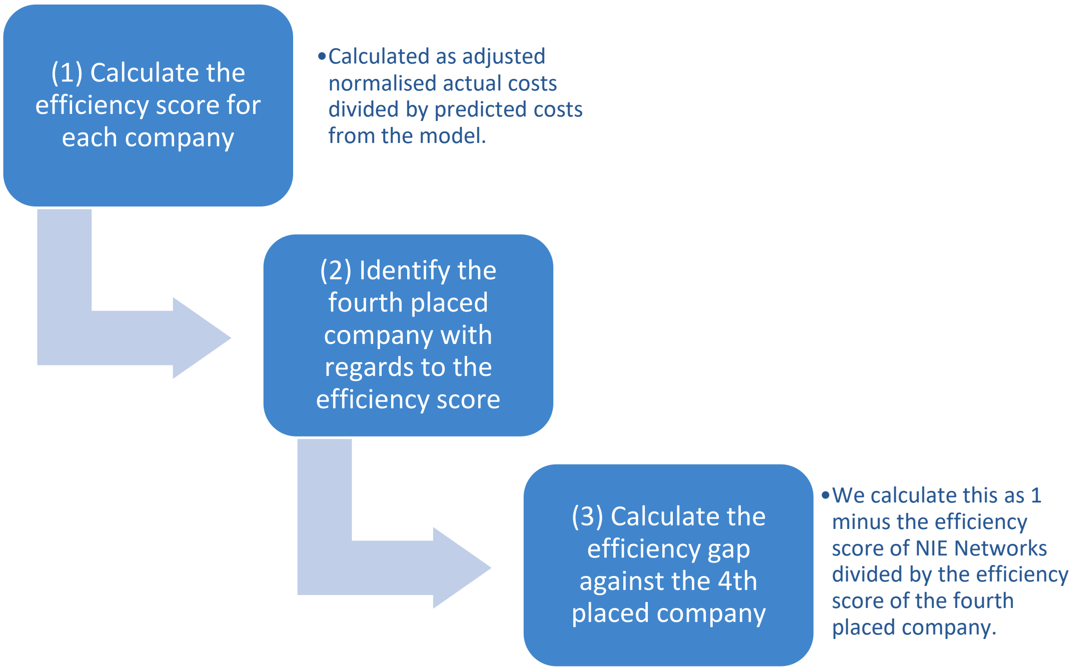
Table 6.2: Potential alternative models

Modelled cost	Cost driver(s)	Performance against selection criteria	
		Pre-allocation	Post-allocation
IMFT and Indirects (CC's model M6)	CSV, time dummies	Performs well	Performs well
IMFT and Indirects CC's model M4)	Length/ customer, time dummies	Performs well	Performs well
IMFT and Indirects	MEAV	Performs well	Performs well
NOCs (i.e. opex)	MEAV	Performs well	Performs well
CAI	MEAV	Performs well	Performs well
Business support	MEAV	Performs correctly. Marginally fails the RESET test.	Performs well

Many of the sensitivities tested in our analysis make NIE Networks look more efficient compared to the base case models. Based on this, it may be worth considering which set of input assumptions is preferred by the UR, or if different sensitivities should be weighted together when setting the catch-up efficiency target.

In this paper, we have calculated annual efficiency gaps (against the 4th ranked company) for individual models. Our three step method for doing this is illustrated in Figure 6.1:

Figure 6.1: Calculating the efficiency gap against the 4th ranked company



However, we note that there are different options for:

- Setting the efficient frontier. We have shown results assuming the upper quartile efficient company in the sample as the efficient frontier.[22] Other options we have calculated are the fifth placed company and upper decile. We have not presented these here. The ultimate choice of benchmark should be considered in tandem with other elements of cost assessment, such as the scope and size of special factor claims.
- Number of years used in the efficiency gap calculation. Efficiency gaps can be calculated over one or more years. Ofgem and Ofwat have recently based their efficiency gaps on several years of data.
- Combining different models. Efficiency gaps can be calculated for individual models, or can be calculated based on triangulated modelled costs, if several models are selected (for example, by averaging different models). Ofgem and Ofwat have recently based their efficiency gaps on triangulated values. We have identified some potential trade-offs between models and would therefore recommend that the UR consider the scope for triangulation of model results.

[22] We have rounded this up to the fourth most efficient company. The upper quartile company is 3.75. Similarly, for the top decile company we have rounded upwards to the second most efficient company. The top decile company is 1.5.

ANNEX A LIST OF GB COMPARATOR COMPANIES

Table A.1: Comparator companies in GB

DNO acronym	DNO
ENWL	Electricity North West
NPGN	Northern Powergrid (Northeast)
NPGY	Northern Powergrid (Yorkshire)
WMID	Western Power Distribution (West Midlands)
EMID	Western Power Distribution (East Midlands)
SWales	Western Power Distribution (South Wales)
SWest	Western Power Distribution (South West)
LPN	London Power Networks
SPN	South Eastern Power Networks
EPN	Eastern Power Networks
SPD	SP Distribution
SPMW	SP Manweb
SSEH	Scottish Hydro Electric Power Distribution
SSES	Southern Electric Power Distribution
NIE Networks	Northern Ireland Electricity

ANNEX B OFGEM’S SHARE OF LABOUR LOCATED LOCALLY ASSUMPTIONS

Table B.1: Ofgem’s share of labour located locally assumptions and notional labour weights [23] ✂

Table B.2: Proportion of NIE Networks’ gross IMFT and Indirect labour costs the RWA is applied to using Ofgem local labour weights

Year	% of IMFT and Indirect labour Costs
2013	42%
2014	42%
2015	43%
2016	43%

[23] Data has been redacted to protect data confidentiality.

ANNEX C COST CATEGORIES USED IN REGRESSIONS

Below we indicate the cost categories, as reported in NIE Networks / GB C1 matrices and accompanying cost and volumes spreadsheets, that are included under each type of cost modelled in the regression models. 'TRUE' indicates that a cost is included under a category, while 'FALSE' indicates that it has not been included.

Table C.1: Cost category breakdown

Cost type	Cost category	IMFT & indirects	NOCs	Tree cutting	LV HV OHL Faults	CAI	Business Support	Load related capex	Non-load related capex	Capex	Totex
Load Related	Connections - Sole Use	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE
	Connections - Shared Use	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE
	Reinforcement	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE
Non Load Capex (excluding Non-op Capex)	Diversions	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
	ESQCR	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
	Asset Replacement	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
	Refurbishment	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
	Civil Works	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
	Legal & Safety	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
	Flooding	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
	Operational IT & Telecoms	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
	Environmental Reporting	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
Network Operating Costs	NOCs other	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
	Inspections & Maintenance	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
	Tree Cutting	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
	Trouble Call (excl. severe weather)	TRUE	TRUE	FALSE	Partially	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
	ONIs	TRUE	TRUE	FALSE	Partially	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
NABC	Primary NABC	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
	Other NABC	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Re-openers	Change of Law (COL) items	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Non GB DNO	Meter Reading	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
	Metering Services	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
	Market Opening	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Closely Associated Indirects	Network Design & Engineering	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE
	Project Management	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE
	Engineering Mgt & Clerical Support	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE
	System Mapping	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE
	Control Centre	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE
	Call Centre	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE
	Stores	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE
	Operational Training	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE
	Vehicles & Transport	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE
Business Support Costs	Network Policy	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE
	HR & Non-operational Training	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE
	Finance & Regulation	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE
	CEO	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE
	IT & Telecoms	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE
	Property Mgt	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE
Non Op Capex	Vehicles	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
	Small Tools, Equipment, Plant & Machinery	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
	Non-Operational Property	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
	IT & Telecoms	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

ANNEX D MEAV MODEL SENSITIVITIES

Table D.1: Alternative OLS models using MEAV as a cost driver (Pre-allocation) [24]

Cost Driver	IMFT and Indirects	NOCs	CAI	Business Support	Totex
MEAV	0.848***	1.144***	0.734***	0.609***	0.822***
Constant	-8.647***	-14.424***	-7.685***	-6.359***	-7.713***
RESET	0.464	0.692	0.667	**0.031**	0.325
Normality	0.457	**0.000**	0.12	0.324	0.576
Pooling	0.906	0.922	0.869	0.996	0.325
N	60	60	60	60	60
R^2	0.822	0.675	0.746	0.680	0.694

Table D.2: Alternative OLS models using MEAV as a cost driver (Post-allocation) [25]

Cost Driver	IMFT and Indirects	NOCs	CAI	Business Support	Totex
MEAV	0.892***	1.144***	0.784***	0.630***	0.819***
Constant	-9.469***	-14.424***	-8.689***	-6.845***	-7.671***
RESET	0.402	0.692	0.781	0.229	0.322
Normality	0.541	**0.000**	0.44	0.499	0.606
Pooling	0.858	0.922	0.83	0.992	0.320
N	60	60	60	60	60
R^2	0.778	0.675	0.646	0.612	0.698

[24] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated parameters in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

[25] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated parameters in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

ANNEX E RANDOM EFFECT MODELS

Table E.1 overleaf shows the results of the independently developed models when estimated using random effects (GLS). We have not dedicated as much time to analysing these results, in particular around assessing their performance on other statistical diagnostic tests. Therefore we present only the estimated coefficients and their statistical significance. In general, the coefficients remain statistically significant and of a sensible sign/ magnitude. While we have not recommended these models as part of our short-listed modelling suite, they may be worth investigating further in future price reviews.

Table E.1: Estimation results for short-listed models, using random effects (GLS) estimation (pre-allocation) [26]

	IMFT and Indirects	NOCs	CAI	Business Support	Tree Cutting	LV HV OHL Faults	Capex	Load Related Capex	Non-Load Related Capex	Totex
Length	0.846***	1.027***								
Density	0.450***	0.743***								
CSV			0.738***	0.596***						
Spans Cut					0.524***					
LV HV OHL Faults						1.174***				
MEAV							0.681***	1.048**	0.555***	
MACRO CSV										0.775***
Constant	-5.923***	-9.980***	-4.461***	-3.508***	-3.195**	-7.694***	-6.405**	-13.702**	-4.718*	-6.964***
RESET	0.121	0.395	0.862	**0.078**	0.425	0.177	0.310	0.893	0.178	0.325
Normality	0.370	0.134	0.276	**0.075**	**0.042**	**0.033**	0.690	0.380	0.240	0.573
Pooling	0.928	0.981	0.669	0.994	0.960	**0.088**	0.201	0.267	0.457	0.323
N	60	60	60	60	56	56	60	60	60	60
LM [27]	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.000

Source: CEPA analysis

[26] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Statistical diagnostic test results in bold indicate the test has failed.

[27] The Breusch-Pagan Lagrangian multiplier test for random effects. The null hypothesis is that is no variation in unobserved fixed effects across DNOs. If we reject the null hypothesis (which we do for every model) this supports the use of random effects over POLS.

Table E.2: Estimation results for short-listed models, using random effects (GLS) estimation (post-allocation) [28]

	IMFT and Indirects	NOCs	CAI	Business Support	Tree Cutting	LV HV OHL Faults	Capex	Load Related Capex	Non-Load Related Capex	Totex
Length	0.879***	1.027***								
Density	0.479***	0.743***								
CSV			0.784***	0.610***						
Spans Cut					0.524***					
LV HV OHL Faults						1.174***				
MEAV							0.663***	0.855**	0.555***	
MACRO CSV										0.774***
Constant	-6.501***	-9.980***	-5.196***	-3.810***	-3.195**	-7.694***	-5.966**	-10.084*	-4.718*	-6.964***
RESET	0.221	0.395	0.760	0.218	0.425	0.161	0.438	0.995	0.178	0.315
Normality	0.716	0.134	0.994	0.179	**0.042**	**0.029**	0.732	0.138	0.240	0.606
Pooling	0.922	0.981	0.718	0.992	0.960	**0.096**	0.286	0.499	0.457	0.318
N	60	60	60	60	56	56	60	60	60	60
LM [29]	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: CEPA analysis

[28] All explanatory and dependent variables are in natural logarithm. All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated parameters in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

[29] The Breusch-Pagan Lagrangian multiplier test for random effects. The null hypothesis is that is no variation in unobserved fixed effects across DNOs. If we reject the null hypothesis (which we do for every model) this supports the use of random effects over POLS.

ANNEX F ASSET ADDITIONS SENSITIVITY

Table F.1: Asset additions sensitivity (pre-allocation) [30]

Cost Driver	IMFT and Indirects	CAI	Business Support
Length	0.769***		
Density	0.381**		
CSV		0.762***	0.408**
Asset Additions	**0.086**	**-0.015**	**0.158**
Constant	-5.883***	-4.548***	-3.257***
RESET	0.278	0.779	0.132
Normality	0.328	0.288	**0.069**
Pooling	0.99	0.814	0.999
N	60	60	60
R^2	0.849	0.757	0.644

Source: CEPA analysis

Table F.2: Asset additions sensitivity (post-allocation) [31]

Cost Driver	IMFT and Indirects	CAI	Business Support
Length	0.824***		
Density	0.419**		
CSV		0.861***	0.421*
Asset Additions	**0.071**	**-0.06**	**0.162**
Constant	-6.548***	-5.353***	-3.598***
RESET	0.333	0.347	0.181
Normality	0.69	0.939	0.168
Pooling	0.987	0.833	0.996
N	60	60	60
R^2	0.802	0.654	0.573

Source: CEPA analysis

[30] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

[31] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

ANNEX G ADDITIONAL SENSITIVITY ANALYSIS

G.1. NOCs

Table G.1: NOCs OLS sensitivities tested (pre- and post-allocation).[32]

Cost driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
Length	1.067***	1.037***	1.059***	1.067***	1.066***	1.059***	0.969***	1.048***
Density	0.737***	0.716***	0.644***	0.747***	0.742***	0.747***	0.696***	0.642**
Constant	-10.402***	-10.015***	-10.054***	-10.435***	-10.402***	-10.350***	-9.147***	-9.839***
RESET	0.395	0.152	0.402	0.403	0.406	0.395	0.256	0.557
Normality	0.134	**0.042**	0.445	0.139	0.148	0.118	0.11	**0.087**
Pooling	0.981	0.995	0.976	0.978	0.978	0.98	0.981	1
N	60	88	60	60	60	60	60	56
R^2	0.737	0.734	0.774	0.746	0.745	0.738	0.706	0.681

Source: CEPA analysis

[32] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

G.2. CAI

Table G.2: CAI OLS sensitivities tested (pre-allocation) [33]

Cost driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks	Excluding Wayleave Payments
CSV	0.744***	0.787***	0.745***	0.775***	0.755***	0.745***	0.654***	0.785***	0.791***
Constant	-4.535***	-5.047***	-4.536***	-4.894***	-4.661***	-4.544***	-3.454***	-5.010***	-5.031***
RESET	0.862	0.914	0.848	0.688	0.775	0.846	0.648	0.862	0.713
Normality	0.276	**0.051**	0.292	0.506	0.281	0.311	0.204	0.273	0.203
Pooling	0.669	0.501	0.676	0.569	0.601	0.641	0.709	0.978	0.717
N	60	88	60	60	60	60	60	56	60
R^2	0.757	0.734	0.755	0.798	0.782	0.766	0.694	0.756	0.772

Source: CEPA analysis

[33] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

Table G.3: CAI OLS sensitivities tested (post-allocation) [34]

Cost Driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks	Excluding Wayleave Payments
CSV	0.793***	0.789***	0.776***	0.824***	0.804***	0.794***	0.702***	0.806***	0.855***
Constant	-5.302***	-5.297***	-5.111***	-5.662***	-5.428***	-5.311***	-4.222***	-5.450***	-5.973***
RESET	0.760	0.891	0.754	0.628	0.742	0.785	0.829	0.760	0.626
Normality	0.994	0.642	0.981	0.949	0.978	0.989	0.520	0.996	0.833
Pooling	0.718	0.173	0.706	0.639	0.643	0.702	0.729	0.773	0.813
N	60	88	60	60	60	60	60	56	60
R^2	0.652	0.597	0.625	0.699	0.688	0.659	0.592	0.622	0.665

Source: CEPA analysis

[34] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

G.3. Business support

Table G.4: Business support costs OLS sensitivities (pre-allocation).[35]

Cost driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
CSV	0.586***	0.608***	0.586***	0.634***	0.603***	0.587***	0.502***	0.580***
Constant	-3.390***	-3.615***	-3.387***	-3.952***	-3.583***	-3.398***	-2.385**	-3.318**
RESET	**0.077**	0.116	**0.079**	**0.043**	**0.083**	**0.063**	**0.076**	**0.077**
Normality	**0.059**	0.169	**0.058**	0.119	0.212	**0.048**	0.089	**0.058**
Pooling	0.994	0.807	0.993	0.993	0.993	0.992	0.994	0.998
N	60	88	60	60	60	60	60	56
R^2	0.622	0.562	0.625	0.667	0.651	0.642	0.553	0.578

Source: CEPA analysis

[35] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

Table G.5: Business Support Costs OLS sensitivities (post-allocation) [36]

Cost Driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
CSV	0.604***	0.599***	0.590***	0.652***	1.066***	0.794***	0.519***	0.548***
Constant	-3.734***	-3.664***	-3.580**	0.518***	-3.928***	-3.742***	-2.730**	-3.085**
RESET	0.225	0.439	0.754	0.191	0.221	0.225	0.269	0.218
Normality	0.135	0.907	0.128	0.293	0.25	0.153	0.165	0.16
Pooling	0.993	0.997	0.997	0.991	0.989	0.991	0.992	1
N	60	88	60	60	60	60	60	56
R^2	0.554	0.487	0.537	0.606	0.603	0.569	0.494	0.477

Source: CEPA analysis

[36] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

G.4. Tree Cutting

Table G.6: Business Support Costs OLS sensitivities (pre- and post-allocation) [37]

Cost Driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
Spans Cut	0.550**	0.598***	0.547***	0.547**	0.549**	0.547**	0.539***	0.597***
Constant	-3.448*	-3.923**	-3.406*	-3.429*	-3.441*	-3.418*	-3.305*	-3.875*
RESET	0.425	0.434	0.44	0.437	0.44	0.444	0.346	0.425
Normality	**0.042**	**0.016**	**0.02**	**0.042**	**0.043**	**0.049**	**0.074**	**0.053**
Pooling	0.96	0.992	0.951	0.961	0.96	0.963	0.953	1
N	56	82	56	56	56	56	56	52
R^2	0.243	0.269	0.236	0.241	0.243	0.24	0.252	0.289

Source: CEPA analysis

[37] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

G.5. Faults

Table G.7: Faults OLS sensitivities (pre- and post-allocation) [38]

Cost Driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
LV HV OHL Faults	0.883***	0.853***	0.902***	0.886***	0.885***	0.885***	0.878***	0.876***
Constant	-5.434***	-5.232***	-5.617***	-5.456***	-5.452***	-5.445***	-5.354***	-5.357***
RESET	0.161	0.109	0.718	0.159	0.161	0.178	0.288	0.161
Normality	**0.029**	**0.005**	**0.01**	**0.027**	**0.026**	**0.026**	**0.016**	**0.027**
Pooling	**0.096**	**0.091**	0.179	**0.099**	**0.098**	**0.098**	**0.079**	0.257
N	56	82	56	56	56	56	56	52
R^2	0.493	0.47	0.5	0.492	0.493	0.492	0.506	0.503

Source: CEPA analysis

[38] All explanatory and dependent variables are in natural logarithm.* indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

G.6. Capex

Table G.8: Capex OLS sensitivities (pre-allocation) [39]

Cost driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
MEAV	0.767***	0.793***	0.788***	0.771***	0.768***	0.766***	0.693***	0.846***
Constant	-7.782**	-8.212***	-8.090**	-7.846**	-7.798**	-7.759**	-6.573*	-9.055**
RESET	0.31	0.418	0.308	0.311	0.316	0.315	0.419	0.31
Normality	0.69	0.891	0.832	0.702	0.703	0.709	0.701	0.622
Pooling	0.201	0.213	0.108	0.188	0.19	0.192	0.233	0.529
N	60	88	60	60	60	60	60	56
R^2	0.359	0.425	0.362	0.366	0.364	0.362	0.303	0.384

Source: CEPA analysis

[39] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

Table G.9: Capex OLS sensitivities (post-allocation) [40]

Cost Driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
MEAV	0.739***	0.792***	0.768***	0.743***	0.740***	0.738***	0.666***	0.828***
Constant	-7.183**	-8.027***	-7.599**	-7.246**	-7.198**	-7.159**	-5.987*	-8.618***
RESET	0.438	0.446	0.419	0.438	0.445	0.447	0.559	0.437
Normality	0.732	0.979	0.938	0.764	0.759	0.733	0.622	0.849
Pooling	0.286	0.254	0.089	0.27	0.273	0.273	0.332	0.911
N	60	88	60	60	60	60	60	56
R^2	0.423	0.503	0.44	0.432	0.429	0.427	0.359	0.466

Source: CEPA analysis

[40] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

G.7. Load-related Capex

Table G.10: Load-related capex OLS sensitivities (pre-allocation) [41]

Cost driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
MEAV	1.088**	1.172***	1.103**	1.092**	1.089**	1.086**	1.014**	1.471***
Constant	-14.333*	-15.580***	-14.596*	-14.396*	-14.349*	-14.307*	-13.132*	-20.536***
RESET	0.893	0.971	0.885	0.899	0.9	0.893	0.922	0.893
Normality	0.38	0.762	0.53	0.401	0.39	0.41	0.458	0.188
Pooling	0.267	**0.014**	0.317	0.264	0.267	0.264	0.288	1.000
N	60	88	60	60	60	60	60	56
R^2	0.269	0.3	0.268	0.271	0.269	0.269	0.236	0.451

Source: CEPA analysis

[41] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

Table G.11: Load-related capex OLS sensitivities (post-allocation) [42]

Cost Driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
MEAV	0.884**	1.003***	0.904**	0.887**	0.884**	0.882**	0.813**	1.177***
Constant	-10.541*	-12.361**	-10.831*	-10.602*	-10.556*	-10.518*	**-9.381**	-15.289***
RESET	0.995	0.957	0.982	0.994	0.993	0.993	0.974	0.995
Normality	0.138	0.483	0.268	0.156	0.147	0.157	0.171	**0.047**
Pooling	0.499	**0.005**	0.491	0.497	0.501	0.495	0.524	1.000
N	60	88	60	60	60	60	60	56
R^2	0.322	0.364	0.332	0.325	0.322	0.323	0.278	0.525

Source: CEPA analysis

[42] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level.

G.8. Non-load-related Capex

Table G.12: Non-Load-related capex OLS sensitivities (pre- and post-allocation) [43]

Cost driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
MEAV	0.702***	0.679***	0.739***	0.706***	0.702***	0.700***	0.627***	0.645**
Constant	-7.056**	-6.763**	-7.622**	-7.122**	-7.072**	-7.035**	-5.836*	**-6.134**
RESET	0.178	0.264	0.151	0.177	0.179	0.182	0.246	0.182
Normality	0.24	0.236	0.471	0.255	0.259	0.241	0.346	0.203
Pooling	0.457	**0.061**	0.24	0.441	0.44	0.447	0.483	0.708
N	60	88	60	60	60	60	60	56
R^2	0.295	0.31	0.307	0.301	0.3	0.297	0.245	0.239

Source: CEPA analysis

[43] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

G.9. Totex

Table G.13: Totex OLS sensitivities (pre-allocation) [44]

Cost driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
MACRO CSV	0.822***	0.807***	0.823***	0.817***	0.813***	0.811***	0.738***	0.846***
Constant	-7.714***	-7.359***	-7.760***	-7.532***	-7.515***	-7.497***	-6.330***	-8.105***
RESET	0.325	0.46	0.34	0.358	0.372	0.388	0.504	0.324
Normality	0.576	0.492	0.569	0.783	0.765	0.595	0.509	0.551
Pooling	0.325	0.463	0.345	0.229	0.236	0.304	0.383	0.544
N	60	88	60	60	60	60	60	56
R^2	0.694	0.726	0.692	0.732	0.725	0.701	0.63	0.682

Source: CEPA analysis

[44] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

Table G.14: Totex OLS sensitivities (post-allocation) [45]

Cost Driver	Baseline	Full Ofgem RIIO-ED1 Sample	Using DPCR5 Rigs for GB DNOs	Local Labour Adjustment	Local Labour Adjustment - GB DNOs only	RWA using three-digit SOC codes	RWA using four-digit SOC codes	Excluding NIE Networks
MACRO CSV	0.821***	0.806***	0.815***	0.818***	1.066***	0.794***	0.739***	0.844***
Constant	-7.722***	-7.352***	-7.607***	0.518***	-7.572***	-7.508***	-6.359***	-8.090***
RESET	0.315	0.449	0.754	0.347	0.354	0.375	0.48	0.313
Normality	0.608	0.48	0.67	0.789	0.777	0.624	0.528	0.591
Pooling	0.319	0.462	0.303	0.234	0.24	0.298	0.375	0.53
N	60	88	60	60	60	60	60	56
R^2	0.698	0.728	0.696	0.73	0.724	0.704	0.635	0.685

Source: CEPA analysis

[45] All explanatory and dependent variables are in natural logarithm. * indicates statistical significance at a 10% level; ** indicates statistical significance at a 5% level; *** indicates statistical significance at a 1% level. Estimated coefficients in bold are statistically insignificant. Statistical diagnostic test results in bold indicate the test has failed.

ANNEX H OTHER EFFICIENCY RESULTS

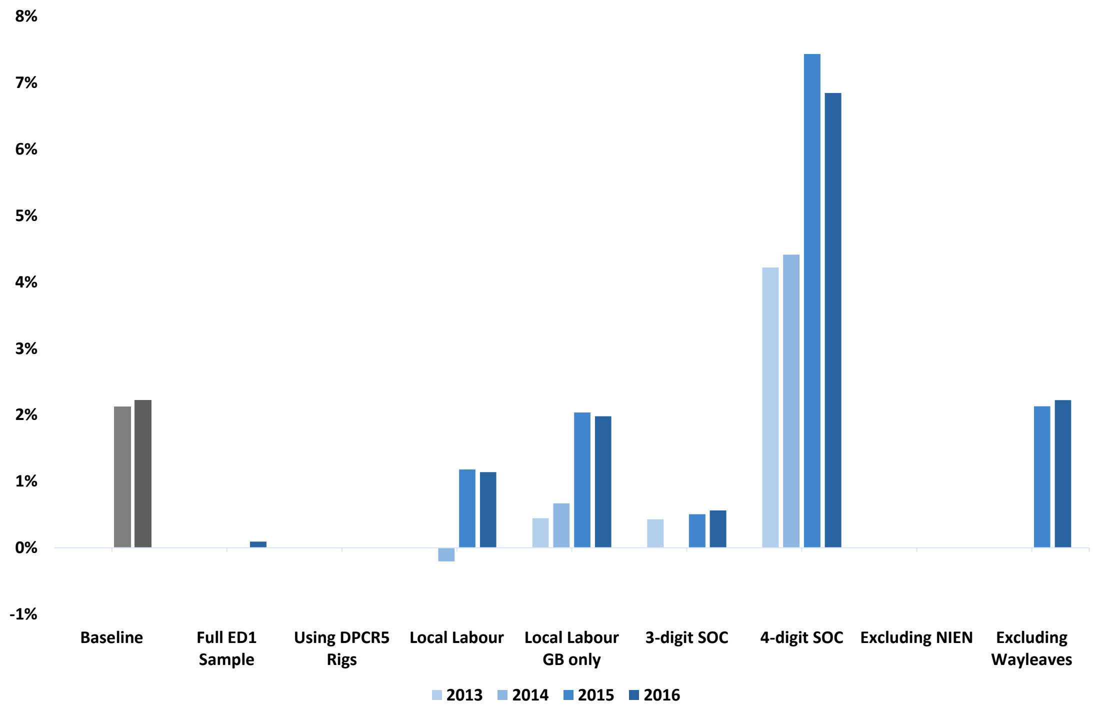
This section shows graphs of NIE Networks' efficiency gaps, compared to the upper quartile company, for each of the independently developed models (estimated using POLS). For ease, we have reproduced the description of the sensitivities below.

Table H.1: Independent developed models sensitivities tested

Sensitivity	Description
1	Using full historic Ofgem RIIO-ED1 panel
2	Using DPCR5 RIGs for GB DNOs
3	Including an adjustment for local labour
4	Only apply local labour adjustment to GB DNOs
5	RWA using three-digit SOC codes
6	RWA using four-digit SOC codes
7	Excluding NIE Networks from the sample
8	Excluding wayleaves costs

H.1. NOCs

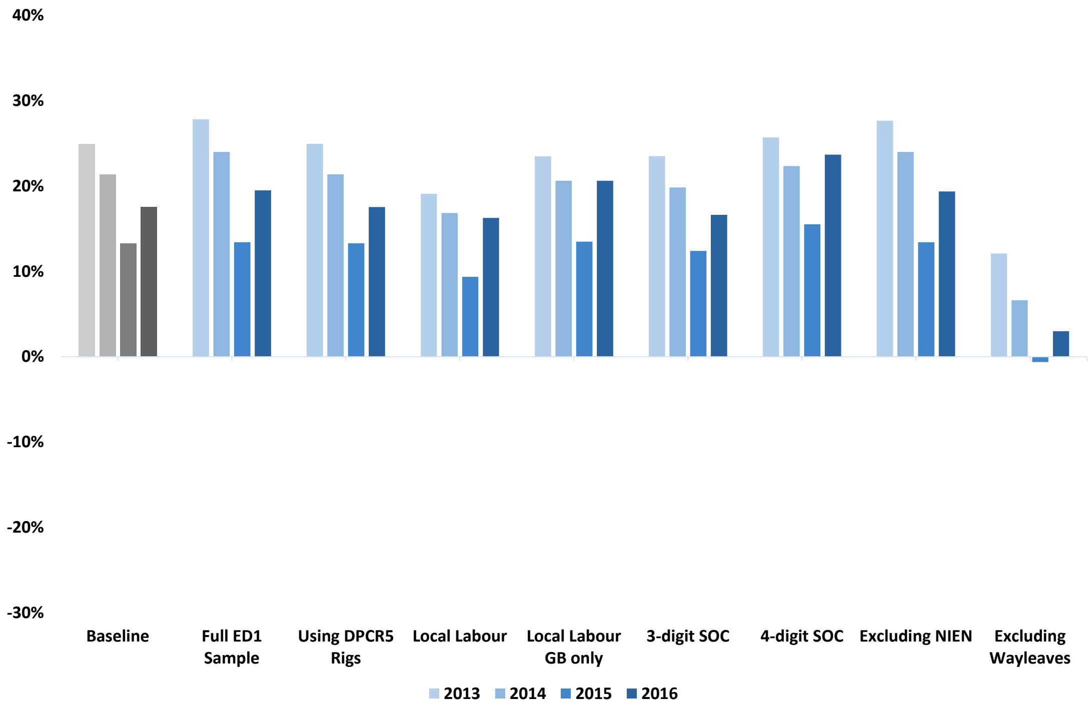
Figure H.1: NOCs ols efficiency gaps (pre- and post-allocation)



Source: CEPA analysis

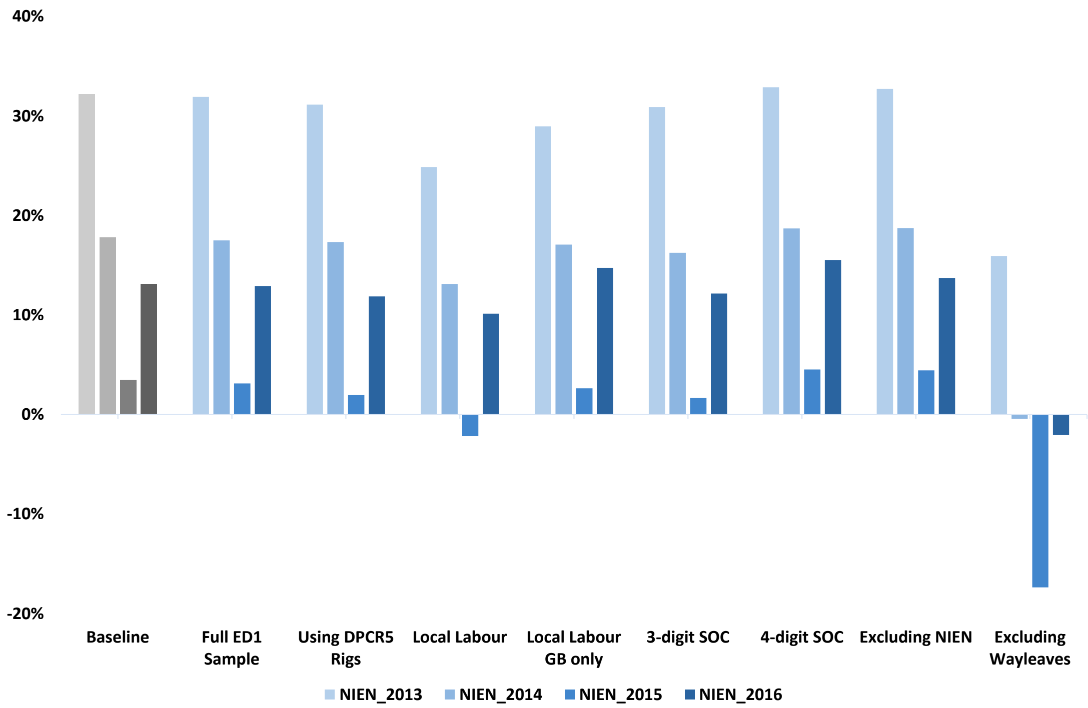
H.2. CAI

Figure H.2: CAI OLS efficiency gap (pre-allocation)



Source: CEPA analysis

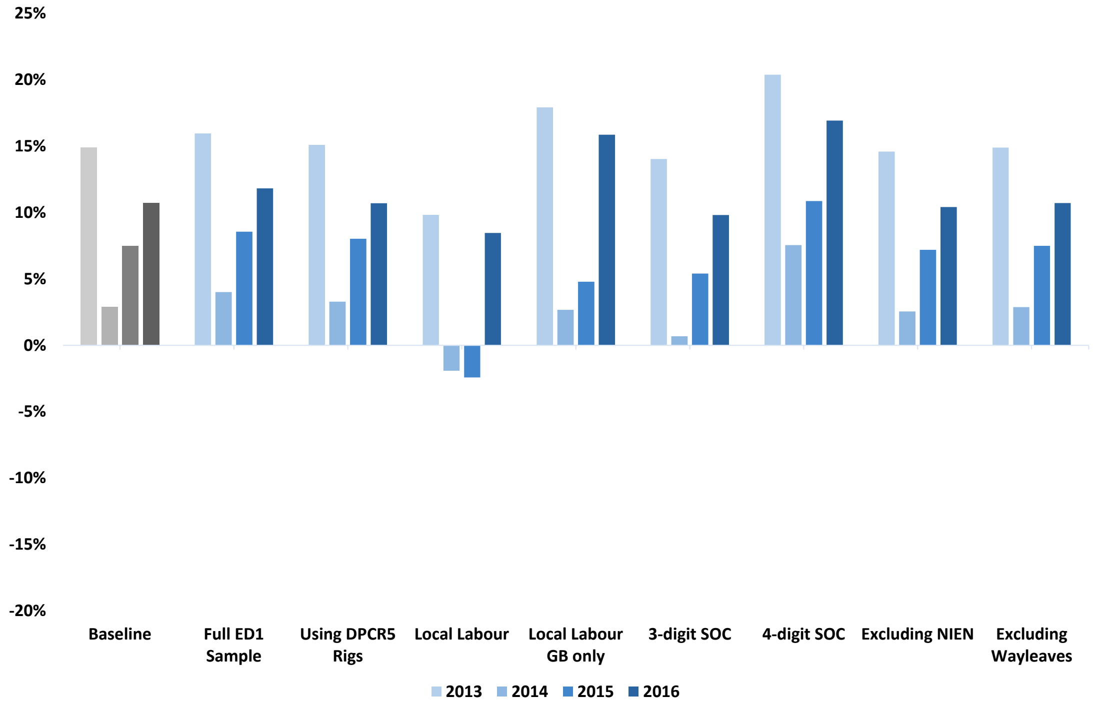
Figure H.3: CAI OLS efficiency gap (post-allocation)



Source: CEPA analysis

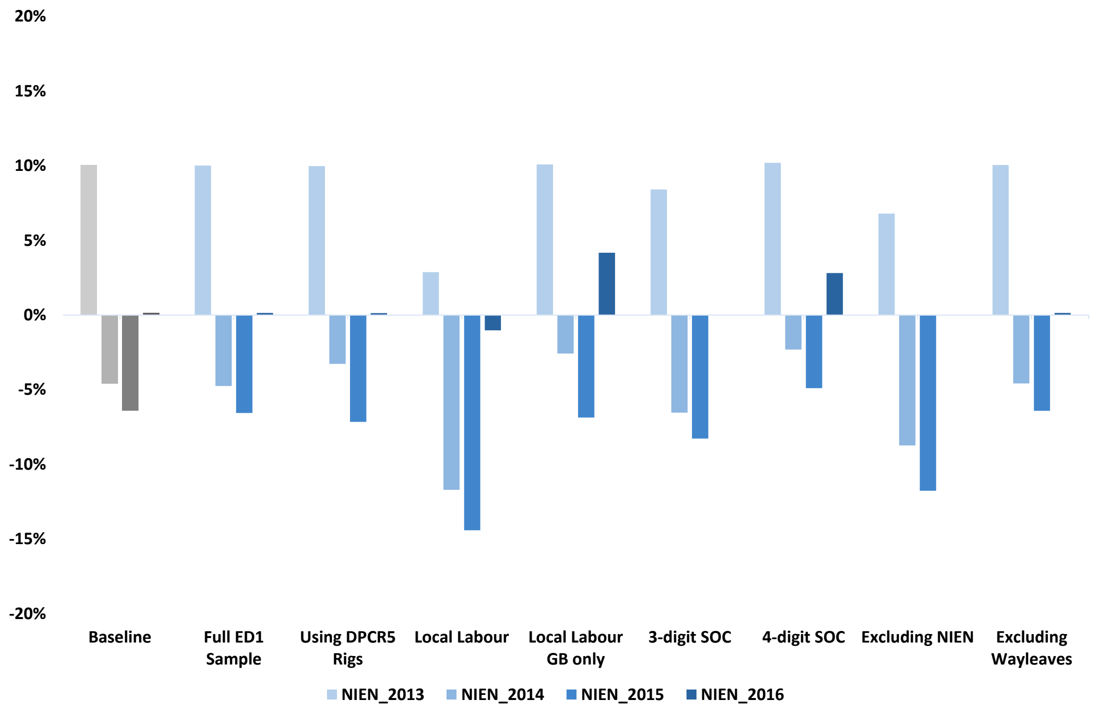
H.3. Business Support

Figure H.4: Business Support OLS efficiency gaps (pre-allocation)



Source: CEPA analysis

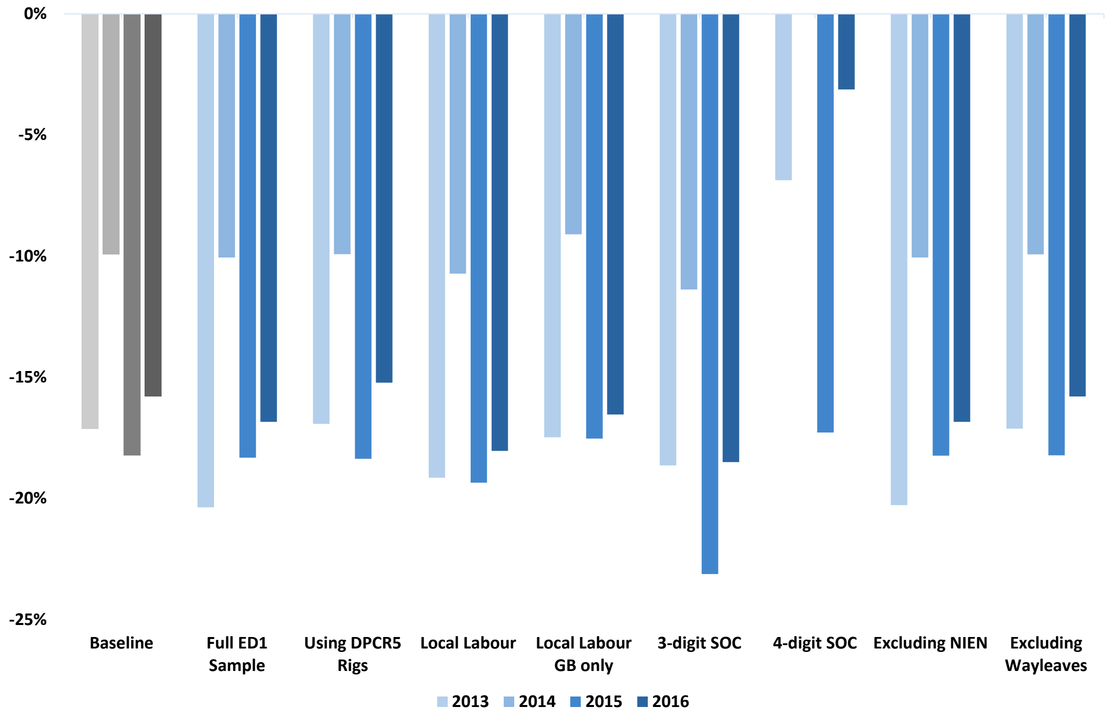
Figure H.5: Business Support OLS efficiency gaps (post-allocation)



Source: CEPA analysis

H.4. Tree Cutting

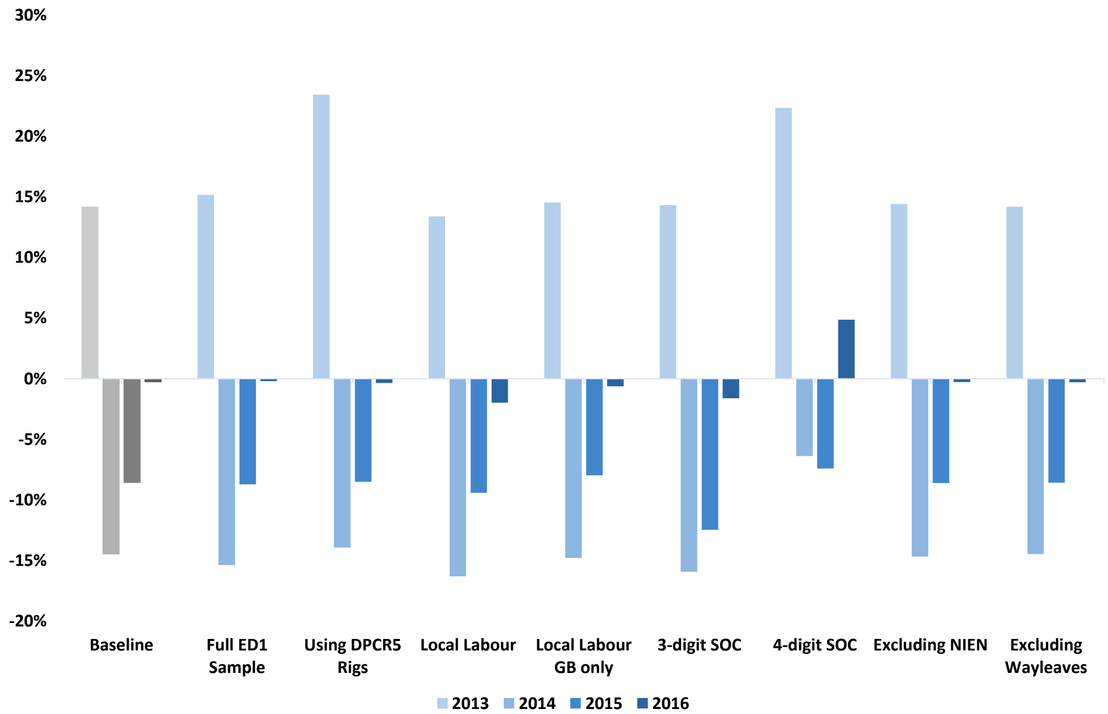
Figure H.6: Tree Cutting OLS efficiency gaps (pre- and post-allocation)



Source: CEPA analysis

H.5. Faults

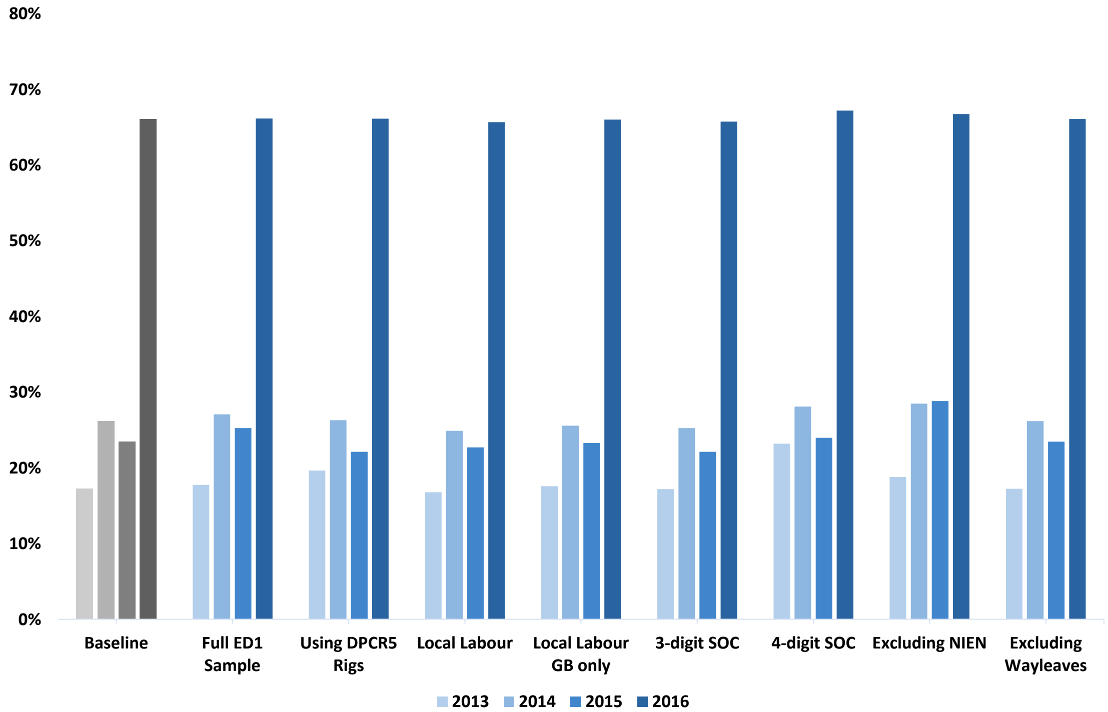
Figure H.7: Faults OLS efficiency gaps (pre- and post-allocation)



Source: CEPA analysis

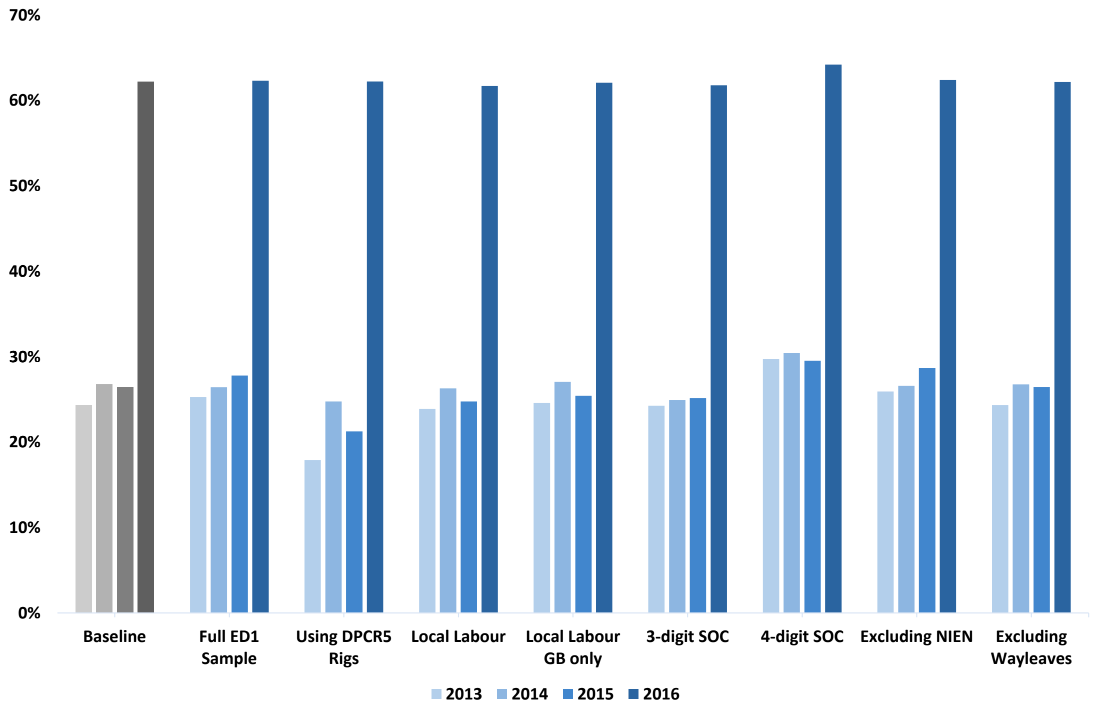
H.6. Capex

Figure H.8: Capex OLS efficiency gaps (pre-allocation)



Source: CEPA analysis

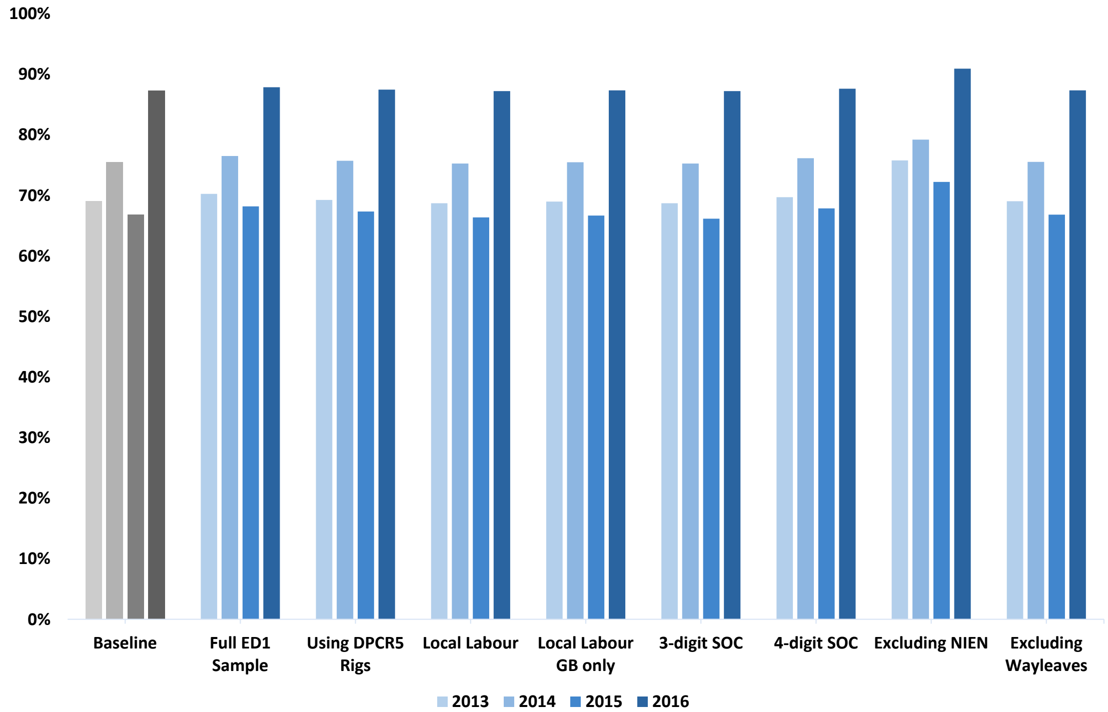
Figure H.9: Capex OLS efficiency gaps (post-allocation)



Source: CEPA analysis

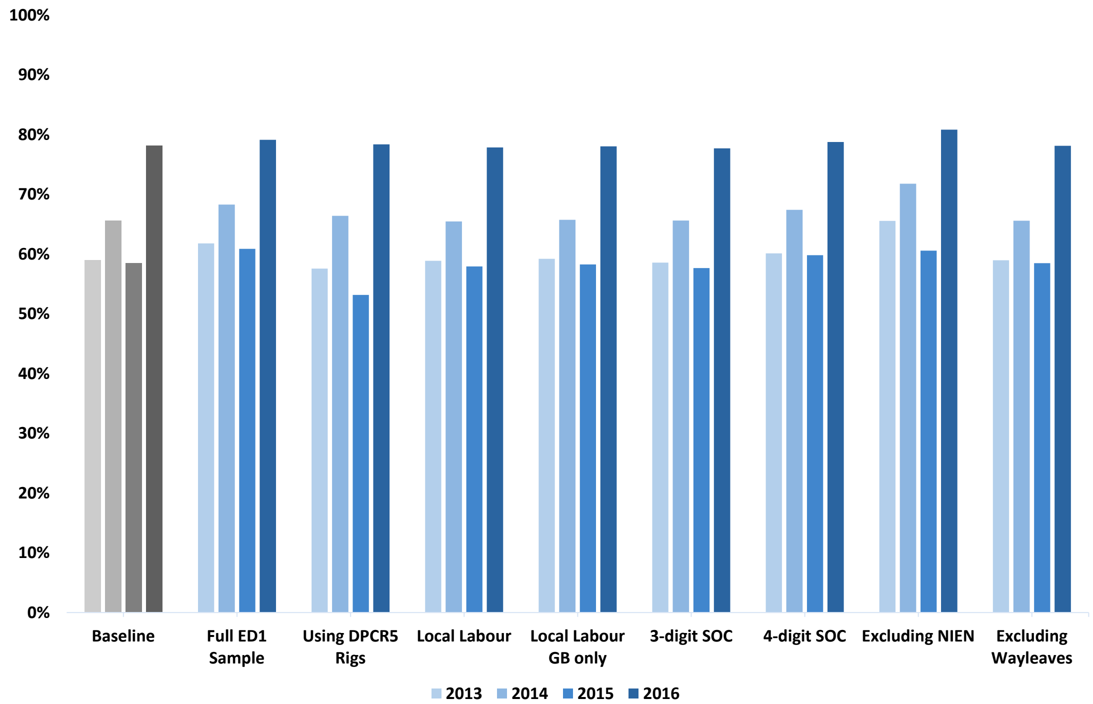
H.7. Load related capex

Figure H.10: Load related capex OLS efficiency gaps (pre-allocation)



Source: CEPA analysis

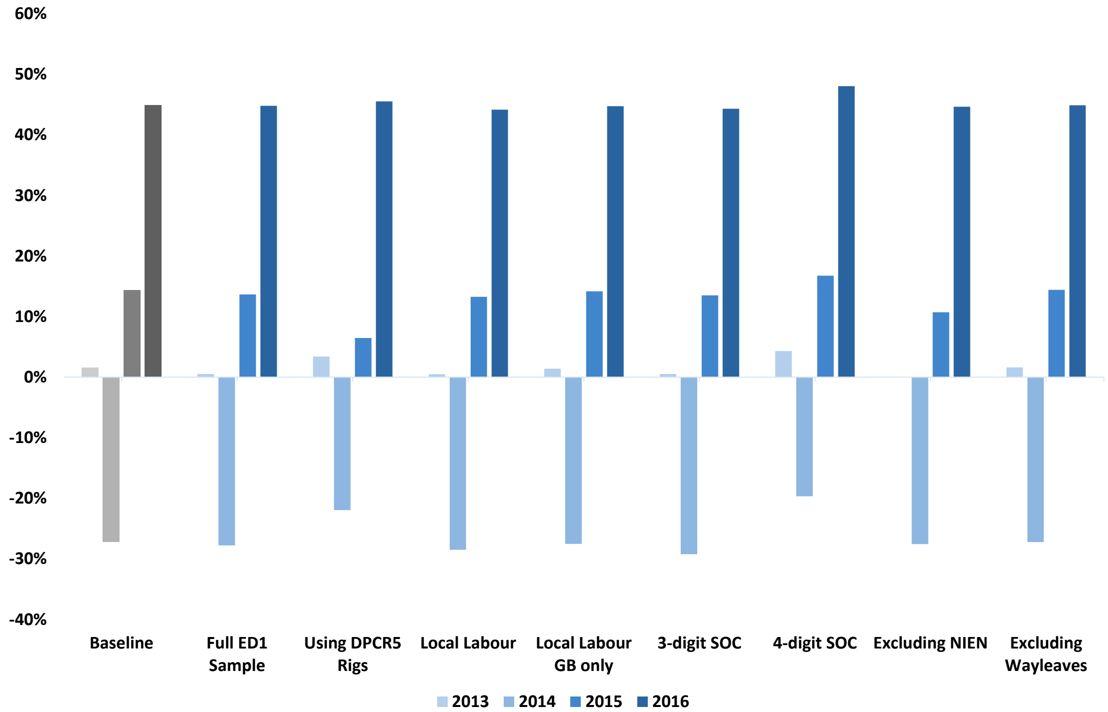
Figure H.11: Load related capex OLS efficiency gaps (post-allocation)



Source: CEPA analysis

H.8. Non-Load related capex

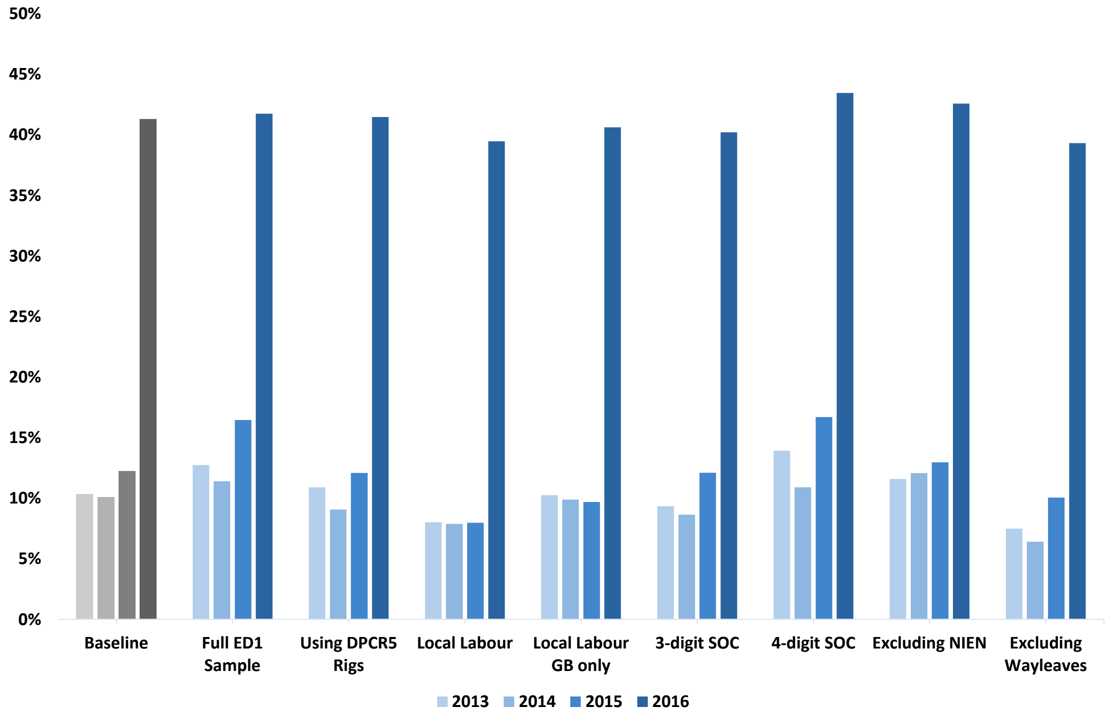
Figure H.12: Non-Load related capex OLS efficiency gaps (pre- and post-allocation)



Source: CEPA analysis

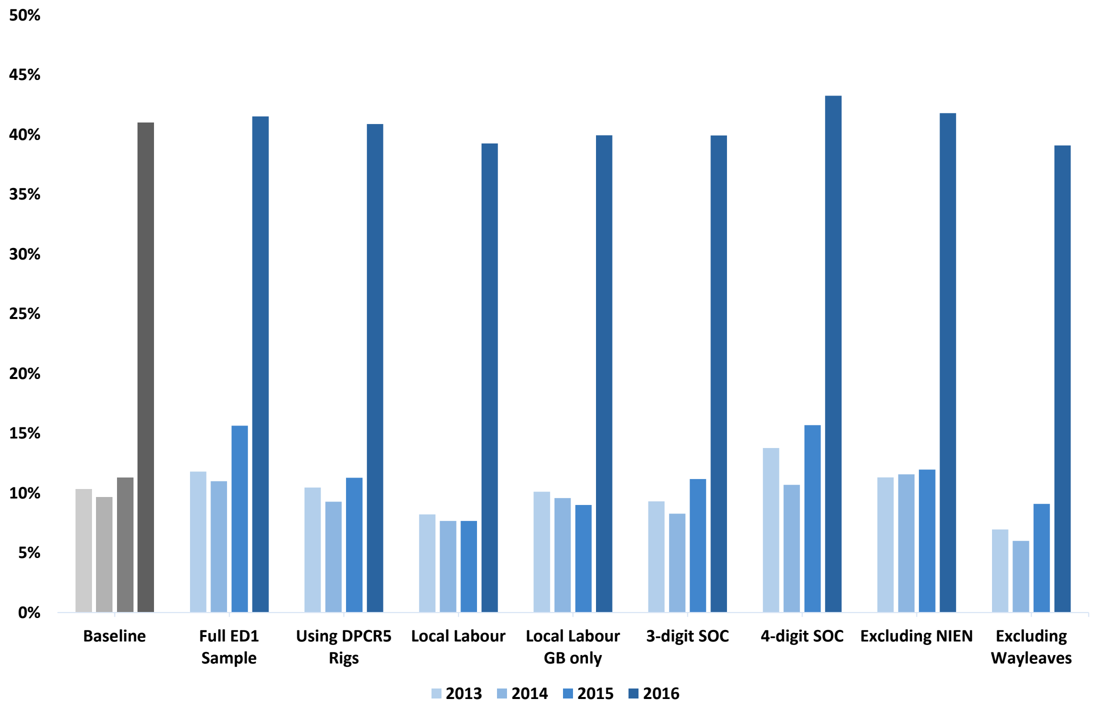
H.9. Totex

Figure H.13: Totex OLS efficiency gaps (pre-allocation)



Source: CEPA analysis

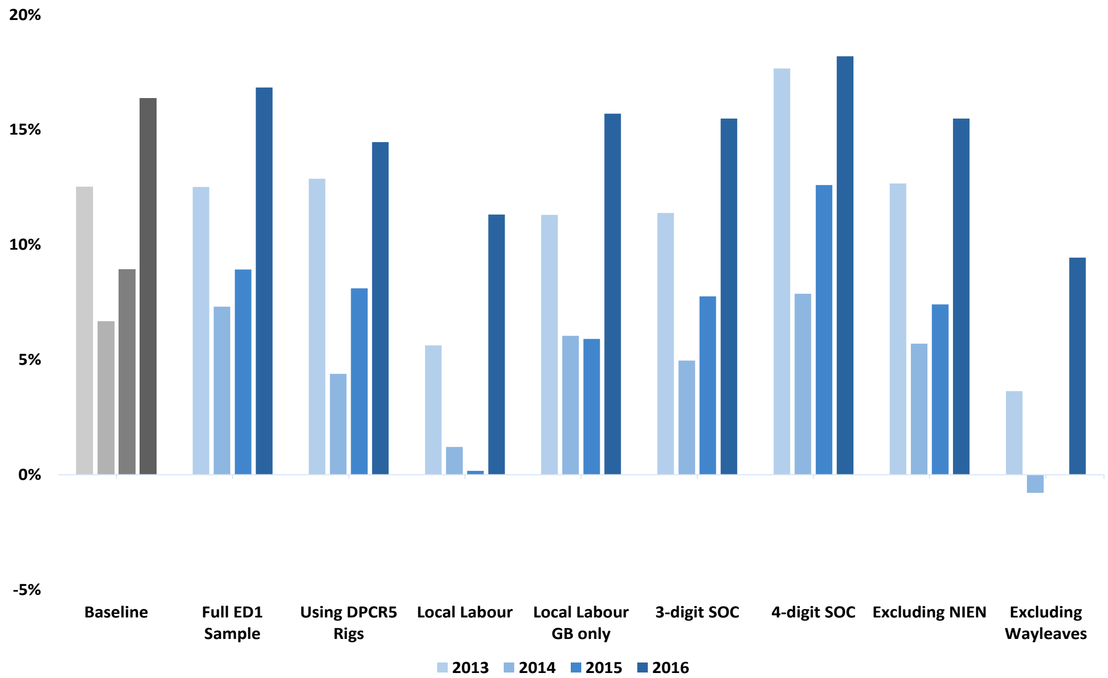
Figure H.14: Totex OLS efficiency gaps (post-allocation)



Source: CEPA analysis

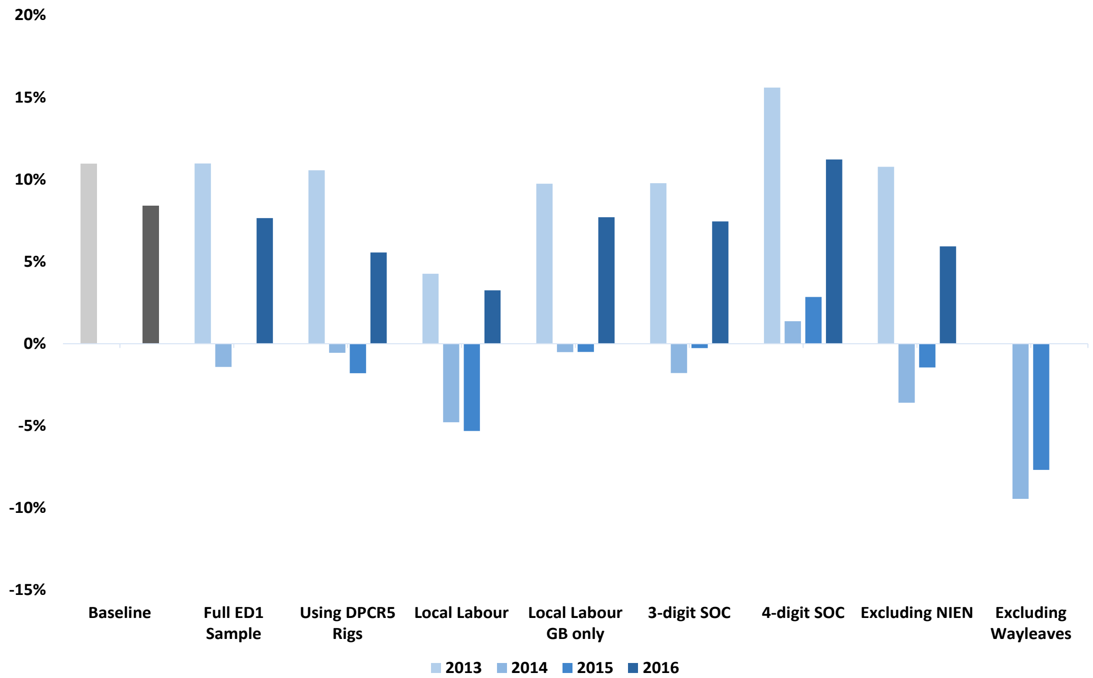
H.10. IMFT and Indirects (Middle-Up)

Figure H.15: IMFT and Indirects (Middle-up) OLS efficiency gaps (pre-allocation)



Source: CEPA analysis

Figure H.16: IMFT and Indirects (Middle-up) OLS efficiency gaps (post-allocation)



Source: CEPA analysis