CEPA

economics matters

Study on using econometrics to calculate variable charges

Office of Rail and Road

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FINAL REPORT

Important notice

Contents

EXECUTIVE SUMMARY

CEPA was commissioned by the Office of Rail and Road (ORR) to study the potential application of econometric methods to calculate Network Rail's marginal costs (or 'variable costs') for maintaining and renewing the rail network. These marginal costs form the basis of individual Variable Usage Charges (VUCs) which are paid by users of the network (passenger and freight train operators) depending on the number, type and weight of trains that they run. Currently, VUCs are based on an 'engineering approach', using the Vehicle Track Interaction Strategic Model (VTISM) operated by Network Rail to estimate the variable costs associated with additional traffic.

The results of this feasibility study demonstrate that an econometric approach can be both feasible and a valuable complement to the engineering approach for determining variable charges. It is the preferred method for setting variable charges in a range of other relevant European jurisdictions, including France, Spain and Sweden. However, we find that the available data on renewals expenditure in Great Britain is of insufficient granularity – limited to just 5 geographic regions – to control for differences in infrastructure characteristics that would influence the need for renewals activity, and then to identify a robust relationship between passenger and freight traffic and renewals expenditure. This is a significant limitation of the VUC rates reported in this paper and therefore we recommend caution when comparing our estimated VUC rates with the uncapped CP7 VUC rates which result from Network Rail's current methodology.

In the near term we would recommend using the econometric approach alongside the engineering approach to provide 'check and challenge' of the VTISM results. This combined framework would leverage the strengths of both methods. In addition, we recommend that ORR should encourage Network Rail to record renewals expenditure at a more granular level that would enable further econometric analysis to more accurately estimate marginal costs for all relevant cost categories.

MAIN RESULTS

The primary output of this study is a regression analysis of maintenance and renewals costs. We construct panel datasets to estimate marginal costs of traffic at the Maintenance Delivery Unit (MDU) level and regional level respectively, using data provided by Network Rail and ORR. Our regression estimates are then converted into a price list which facilitates an approximate comparison to Network Rail's current uncapped price list for CP7, noting that Network Rail's actual CP7 price list includes some VUC rates (such as for freight) which are capped due to decisions taken by ORR in the PR23 final determination.[1] We compare our estimates to the uncapped rates as this represents a more 'like-for-like' comparison of cost reflective rates. We estimate two different functional forms for our maintenance regressions: (1) a translog model which allows for non-linearities in the data; and (2) a simpler log-log model which assumes constant elasticities between traffic and maintenance costs.

Our results show that the implied elasticity of maintenance costs to passenger traffic are lower than the current engineering cost models would suggest. The elasticity to freight traffic produced by the log-log model is greater than the current models suggest but it is broadly similar between the translog model and the current models. This is based on maintenance cost regressions that produce robust results – particularly for passenger traffic – with positive and statistically significant coefficients that have plausible signs and magnitudes. Although the translog model does not yield statistically significant estimates for freight traffic, the coefficients remain stable across various model specifications. This stability suggests that we are estimating a robust result but that the statistical power of our models are reduced because there is relatively low residual variation in maintenance costs after accounting for changes in passenger traffic and controlling for other differences in variables across MDUs.

We are confident in the validity of our estimated marginal maintenance costs of traffic, as they closely align with previous findings in the literature, including Wheat and Smith (2008). Using our translog model, we estimate

[1] The approach to capping VUC rates for freight operators is summarised in Network Rail (December 2023) "Final determination consistent price lists: key assumptions" p.8., available at networkrail.co.uk.

marginal costs of 9.81 pence per vehicle-mile for passenger traffic (compared to 8.39 pence in Wheat and Smith[2]) and £2.00 per kgtm for freight traffic (compared to £1.99 in the same study).

Table E-1: Maintenance marginal cost comparison, 2023-24 prices

Maintenance – marginal cost	Metric	CEPA (Log-log)	CEPA (Translog)	Wheat & Smith (2008) (Inflation adjusted)
Passenger Traffic	pence/vehicle-mile	17.31	9.81	8.39
Freight Traffic	£/kgtm	3.68	2.00	1.99

Source: CEPA analysis

However, we cannot be confident in the robustness of our renewals regressions. Statistical constraints which arise from having only 5 regions of observation and 10 years of data (i.e., 50 observations) limit the number of control variables that we can include in the regression models without impairing its statistical power – in other words, the models' ability to identify significant relationships between the dependent and independent variables. Given these constraints, we estimated an elasticity with total traffic rather than separating passenger and freight traffic. The results are not robust to model specification, and as such, we do not consider them to be a reliable estimate of marginal costs or a robust basis for setting access charges. Nevertheless, these findings are presented in the report for completeness.

Due to the lack of robustness of our results for renewals, we are only able to make an approximate, illustrative comparison with Network Rail's CP7 uncapped price list. We adopt the same methodology as used in Network Rail's existing VUC calculation file[3] to convert our marginal cost estimates into a price list. We do not replicate the full price list, which is thousands of vehicles long, but instead present a simplified list. We also of necessity apply a series of assumptions and scaling factors in order to convert our marginal cost estimates into the relevant units (specifically, to convert our marginal costs from pence per train mile to £ per kgtm). We compare against uncapped CP7 rates to ensure a fair comparison, because following ORR's PR23 final determination, freight VUC rates are capped below fully cost-reflective rates on the trajectory set at PR18.[4]

As shown in the tables below, our estimates for passenger variable usage charges are lower than those in the current uncapped price list, while freight variable usage charges are higher under the log-log model and broadly similar under the translog model.

However, given the limitations which affect the robustness of our renewals estimates, policymakers should exercise caution and avoid interpreting our estimated VUC rates as 'accurate' at the passenger and freight level. In particular, we do not think it is possible to conclude – on the basis of this analysis alone – that freight charges would be higher under an econometric approach, given that the translog model produces freight charges which are broadly similar to the current 'uncapped' rates. Further analysis on a more granular renewals expenditure dataset would produce different results which might be more robust and support a different conclusion.

Moreover, this feasibility study is not intended to produce a perfectly like-for-like comparison of the econometrics approach to the engineering approach on which current rates are calculated. Specifically, the current engineering method excludes costs associated with certain assets which are not considered to be impacted by marginal changes in traffic, but which are included in our econometrics approach that looks at total maintenance and renewals costs. Therefore, the econometric approach might capture relationships between expenditure and traffic which are omitted under the engineering approach.

[2] We adjusted the figures reported in the Wheat & Smith (2008) study for inflation to ensure they are comparable to our marginal cost estimates.

[3] NR PR23 FD VUC model v2.2.xlsx provided by ORR on 10/10/2024.

[4] ORR (October 2023) "PR23 final determination: policy position – access charges" p.10., available at orr.gov.uk.

Therefore, we do not advocate for adopting the econometric method at present. Rather, the primary contribution of this paper is to demonstrate that, with more granular renewals expenditure data, an econometric approach is feasible in Great Britain.

Table E-2: Average passenger variable usage charges, 2023-24 prices

Average rate Vehicle Classification	CEPA Log-log (Pence Per Vehicle Mile)	CEPA Translog (Pence Per Vehicle Mile)	Network Rail CP7 (Pence Per Vehicle Mile)
Locomotive	57.66	54.47	99.19
Multiple unit (motor)	7.75	7.32	15.19
Multiple unit (trailer)	9.67	9.13	11.70
Coach	9.23	8.72	15.06

Table E-3: Average freight variable usage charges, 2023-24 prices (uncapped CP7 rates)

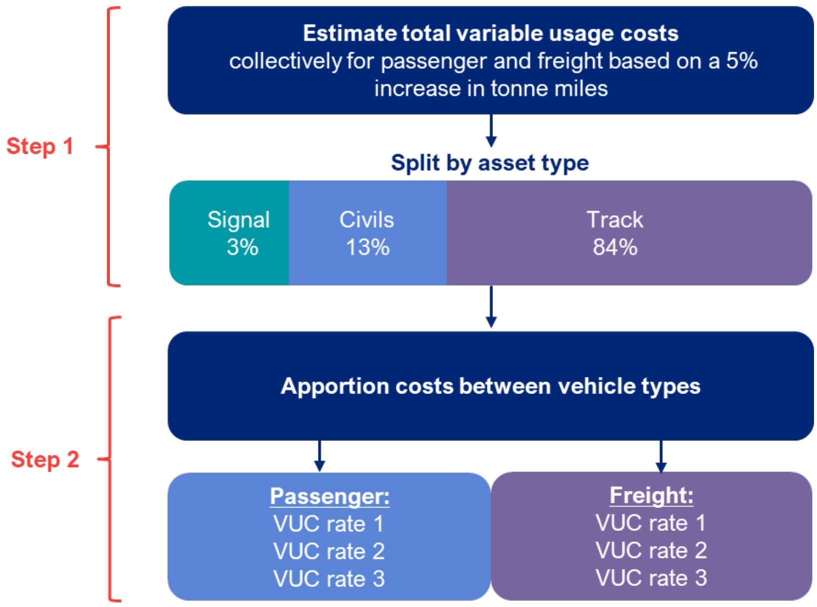
Average rate Vehicle Classification	CEPA Log-log (£/kgtm)	CEPA Translog (£/kgtm)	Network Rail CP7 (£/kgtm)
Locomotive	12.29	8.56	7.53
Wagon (laden)	6.73	4.69	4.55
Wagon (tare)	2.79	1.94	1.76

Source: CEPA analysis

Context to this study

The results of our feasibility study add to the discussion around the appropriate methodology for setting VUCs in Great Britain. The current 'engineering approach' is summarised in Figure E-1 below. Step 1 uses the VTISM to calculate total variable costs to be recovered from passenger and freight operators. Step 2 allocates these costs to vehicle types based on damage characteristics (for example axle load and speed), creating a detailed price list with charges per gross tonne-km that vary by vehicle type and freight commodity.

Figure E-1: Current approach to estimating VUC



Source: Network Rail, CEPA analysis

This application of VTISM in Step 1 is not its original purpose. VTISM is described as "*a whole life cost model for the vehicle–track system* […] *which links track and vehicle characteristics and maintenance regimes to track asset lives, replacement and maintenance costs*" (Serco, 2012). In the context of setting VUCs, Network Rail uses VTISM to estimate the outputs and cost required to address the wear and tear imposed on the track and maintain whole life track performance given forecast traffic growth for the next control period, which informs its SBP planning assumptions. It then calculates the additional maintenance and renewals costs (above those embedded in its SBP) that would be incurred in the next control period in a scenario where traffic is 5% higher by the end of the next control period relative to traffic at the end of the previous control period, to maintain the same level of residual asset lives and network performance. These additional costs represent the 'variable' costs that are used to set the basis of individual vehicle VUC rates in a separate calculation model.

Whilst the approach to setting VUCs for CP7 is broadly similar to that adopted at CP6, the significant reduction in passenger train-km (and by extension passenger tonne-km) in 2021-22 means that the variable costs estimated in Step 1 are divided by a denominator that is smaller than the one used in the calculation of the CP6 charges. This increases the VUC rates relative to those calculated for CP6. Although mechanically this is a predictable result, it is worth noting that:

- it implies that short-run marginal costs have increased with the lower traffic denominator; and
- it produces a higher VUC for freight customers, despite freight traffic being largely unchanged since pre-Covid-19 and therefore causing roughly the same amount of damage to the track infrastructure.

Freight stakeholders have expressed concern with the method and in the PR23 final determination ORR committed to review the issue in advance of CP8. In contrast to Network Rail's engineering cost modelling, most comparable European jurisdictions estimate variable access charges using an econometric approach. This alternative method addresses the shortcomings of the current approach by estimating marginal costs separately for passenger and freight traffic.

Rather than advocating for immediate adoption as the sole basis for setting VUCs, in the near term we would recommend using the econometric approach alongside the engineering approach to provide 'check and challenge' of the VTISM results. This combined framework would leverage the strengths of both methods, providing a more comprehensive and reliable basis for future applications.

Next steps

The results of this study provide encouraging insights into the potential for econometric analysis to contribute meaningfully to the assessment of VUCs. While our findings suggest that maintenance models derived from econometric methods may be as effective as those used by other regulators, this does not imply an immediate readiness to adopt these models as the sole basis for VUC determinations. Instead, we recommend the following next steps to improve the available data and help interpret the results:

- **Developing a train-tonnage dataset for comparative analysis:** Network Rail should establish a consistent tonne-km traffic dataset over at least the last 10 years. This is essential for a like-for-like comparison between current VUCs and the alternative "shadow VUCs" derived from econometric models. This will facilitate a clearer assessment of the model's accuracy and practical relevance (since 'wear and tear' is a function of both train movements and weight).
- **Capturing renewals expenditure at a sub-regional level:** The key to identifying a robust econometric relationship between traffic and renewals depends on obtaining a more geographically granular renewals dataset. ORR should encourage Network Rail to adopt a larger number of smaller 'sub-regional' units for reporting renewals expenditure.

  To illustrate what this would mean if Network Rail were to adopt best practice from other European jurisdictions, SNCF Reseau records renewals expenditure at the track-section level[5], encompassing over 2,000 units of observation across the network (a similar level of disaggregation to the 'route sections' geography used in GBRTT's 'Industry Financial Model'). As we explain in Section 3.2, this enables a two-stage approach to the modelling of renewals expenditure which facilitates an analysis with more variation in

[5] The track-section level in France is defined differently from the track-section level in Great Britain. However, the number of observations provides an indication of the volume of data Network Rail should aim to collect to effectively support the econometrics approach.

terms of the key infrastructure characteristics which drive differences in costs between those units, and therefore helps to isolate the variations in cost which are driven by changes in traffic.

However, noting that 2,000 track/route sections would be a substantial change from Network Rail’s approach to recording renewals expenditure today, we expect that ORR might find an improvement in the robustness of the analysis if Network Rail were able to disaggregate costs across 25–50 sub-regional units (i.e., similar to the number of MDU units).

- **Understanding the differences between the engineering and econometric results:** ORR and Network Rail should work together to better understand the differences in results between the econometric and engineering approaches, and the appropriateness of key assumptions from an asset management perspective. For example, the engineering approach relies on a narrower definition of 'direct costs' than that which is adopted in the econometric literature (and applied in this study) and also incorporates a ‘constrained funding’ assumption which informs the mix of maintenance and renewals activities to take into account the practical limits in funding available to Network Rail over future control periods, which we cannot replicate in the econometric approach. Although operators should share in the benefit of these assumptions (in the form of lower variable charges) where they are robust, the relative advantage of the econometric approach is that, subject to the availability of sufficient and high quality data points for estimation, it can establish a statistically robust relationship between traffic and costs without relying on such assumptions.

If the industry works together to address these issues over the coming years, we suggest that there is scope for econometric methods to play a more important role in setting variable charges directly in future periodic reviews.

1. INTRODUCTION

CEPA was commissioned by the Office of Rail and Road (ORR) to study the potential application of econometric methods to calculate Network Rail's marginal costs for maintaining and renewing the rail network as a potential basis for setting future Variable Usage Charges (VUCs). VUCs are paid by users of the network depending on the number, type and weight of trains that they run.

Network Rail currently uses an 'engineering approach' to set the VUC. The engineering approach uses the Vehicle Track Interaction Strategic Model (VTISM) to estimate the 35-year cost of remedying the direct impact of increased traffic on the infrastructure asset ("wear and tear"). Against a baseline which is calibrated to the track performance outputs and used life percentages assumed in Network Rail's CP7 Strategic Business Plan (SBP), Network Rail then calculates the increase in maintenance and renewals costs estimated by the model with a 5% increase in projected traffic (relative to the end of CP6). These 'variable costs' are then allocated to specific vehicle types based on their track wear characteristics in a separate VUC calculation model. However, following the PR23 recalibration, several stakeholders have raised concerns about this approach. Freight stakeholders, for instance, were concerned that the proposed charges would increase despite no significant change in freight traffic over the CP6 period – noting that ORR ultimately decided to continue capping freight VUCs below fully cost-reflective rates on the trajectory set at PR18.[6]. ORR also noted at PR23 that the large number of input variables to the VTISM model and the complex mechanism through which they interact with one another during and between control periods works against apportioning the drivers of the increase between freight and passenger in a precise manner. The proposed econometric approach aims to address these issues by offering a more data-driven and replicable approach.

The application of an econometric approach to estimating VUC is relatively underexplored in Great Britain, although it is common practice in Europe. Our study seeks to address the limitations of past studies and explore whether an econometrics approach in Great Britain is feasible. Rather than directly comparing the econometric and current engineering approaches, we view them as complementary methods that could be used in parallel to enhance the robustness of the overall charging methodology. This project also identifies valuable opportunities for Network Rail to enhance data collection practices, improving transparency and supporting a more robust econometric methodology in the future.

Following this introduction, the structure of this report is as follows:

- Section 2 sets out the background to the project, covering the current VUC methodology in Great Britain and its current issues.
- Section 3 summarises our literature review, focusing on econometric approaches to variable charges for rail networks in other European jurisdictions, which guides our methodology and highlights best practices.
- Section 4 details the data requirements for the econometric approach and presents an analysis of our constructed dataset.
- Section 5 describes our econometric methodology and its limitations.
- Section 6 presents the main results, including estimated elasticities, marginal costs, and price lists.
- Section 7 details our conclusions and discusses the implications of our findings for setting variable rail infrastructure charges in Great Britain going forwards.

[6] ORR (October 2023) "PR23 final determination: policy position – access charges" p.10., available at orr.gov.uk.

2. BACKGROUND

2.1. VARIABLE USAGE CHARGES

The variable usage charge (VUC) is a charge designed to recover the costs of operating, maintaining, and renewing the rail network that vary with marginal changes in traffic. In practice, this charge is set to recover a portion of maintenance and renewal costs ('wear and tear'), as operating costs are generally assumed to remain mostly unaffected by traffic variations. The VUC applies to all operators using the network, including passenger, freight, open access, and charter services. The VUC is disaggregated by vehicle class and, in the case of freight services, also by commodity. Typically, heavier and faster vehicles incur a higher VUC, reflecting the relatively higher levels of wear and tear (damage) that they cause to the network.

Under current legislation, the VUC should be calculated on the basis of the direct costs that Network Rail would incur as a result of a small change in traffic levels, assuming network capacity remains fixed. From an economic perspective, charging based on marginal costs ensures the most efficient use of infrastructure capacity, as the price reflects the true cost of providing the service.

The VUC is designed to encourage operators to:

(1) Use vehicles that cause less wear on the tracks

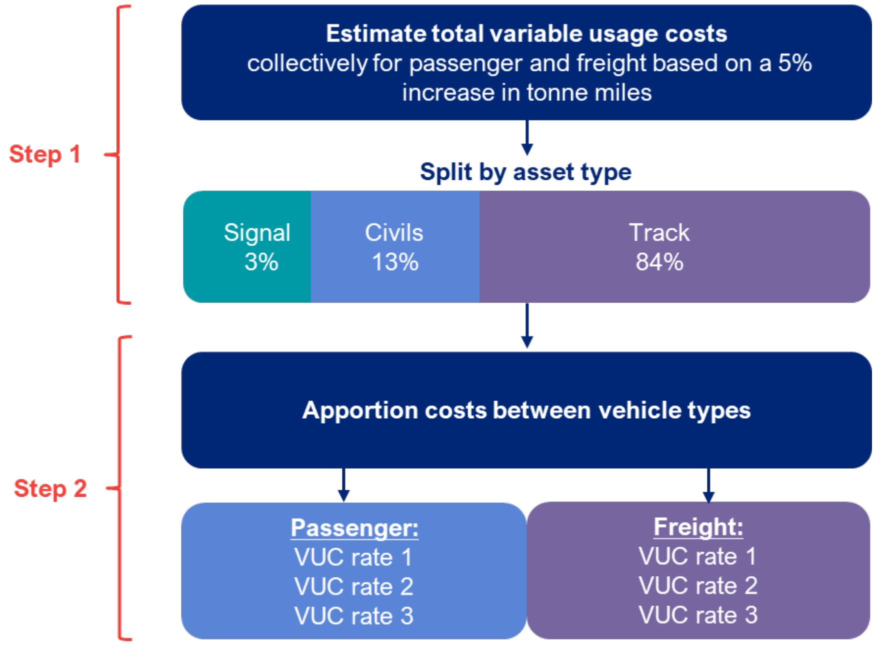
(2) Only run services where the additional benefits outweigh the marginal wear and tear costs on the infrastructure.

The two primary approaches to calculating VUCs are the engineering and econometric approaches. Network Rail currently uses an engineering approach, though some stakeholders have raised concerns about its methodology. A common alternative used in most other comparable European jurisdictions is the econometric approach, which could be adopted alongside reforms to the existing method. This feasibility study does not aim to directly compare the two approaches. Instead, we focus on the potential to use both the engineering and econometric approaches where appropriate, to enhance the overall robustness of the VUC methodology.

2.2. ENGINEERING APPROACH

Network Rail's current engineering approach follows a two-step process, as shown in Figure 2.1 below.

Figure 2.1: Current approach to estimating VUC



Source: Network Rail (2022); CEPA analysis

The first step involves estimating Network Rail's total variable costs using the Vehicle Track Interaction Strategic Model (VTISM). VTISM is a strategic long-term planning tool used by Network Rail to forecast maintenance and renewal work costs and volumes based on track characteristics, track condition and age, volume and type of traffic, and the assumed relationship between traffic and historically observed rates of track degradation. VTISM is informed by a combination of datasets, including an inventory of over 600,000 individual track sections across the GB network which documents a variety of track section characteristics which are directly relevant to Network Rail's maintenance and renewals planning.

Although not its original purpose, Network Rail also uses VTISM to estimate the additional maintenance and renewals activities and costs that would be required in the next control period (over and above its SBP) to address the wear and tear imposed on the track and maintain whole life track performance under a scenario where traffic increases by 5% compared to the end of CP6. These costs are expressed on a per thousand gross tonne-mile (£/kgtm) basis. The total variable costs are then split by asset type - track, signalling, and civils.

The traffic growth forecast used in the variable cost modelling is a matter of regulatory judgement. On the one hand, it is desirable to adopt a forecast which reflects the underlying growth in traffic – but this is challenging to forecast as demonstrated by the fall in passenger numbers and subsequent recovery in the aftermath of both the Global Financial Crises of 2008-09 and the Covid-19 restrictions of 2020-21. The +5% traffic growth assumption was first chosen for CP6 (and then again for CP7) because Network Rail considered that it should most closely represent the short run marginal cost increase. However, at CP5 Network Rail used a +20% traffic growth assumption because it was considered closest to the actual expected traffic increase over the medium term (Arup, 2018).

After determining the total variable costs, Network Rail allocates these costs to specific vehicle types based on characteristics that influence track wear. Key attributes considered in this allocation include axle load, speed, un-sprung mass, and primary yaw stiffness. By analysing these factors, Network Rail assigns costs proportionally, ensuring that vehicles imposing greater demands on infrastructure are charged accordingly. This process results in detailed price lists for both passenger and freight vehicles, encompassing thousands of individual vehicle specifications. This approach aims to reflect the marginal costs associated with different types of rail traffic on rail infrastructure.

However, freight stakeholders have expressed concern with the current methodology for CP7. There was a significant reduction in passenger train-km (and by extension passenger train tonnage) in 2021-22. This meant that the variable costs estimated are divided by a denominator that is smaller than the one used in the calculation of the CP6 charges, as total traffic (not disaggregated by passenger and freight) is used in VTISM. This produced a higher VUC for freight customers, despite freight traffic being largely unchanged since pre-Covid and therefore causing roughly the same amount of damage to the track infrastructure.

2.3. Econometric approach

Following best practice identified in our literature review, we use regression techniques to estimate the elasticity of maintenance and renewal costs with respect to traffic. This tells us, for example, that a 1% increase in passenger train-km increases maintenance costs by x%. We do this separately for passenger and freight, meaning that freight charges will not be significantly affected by changes in passenger traffic.

We benchmark our estimated elasticities against those from previous studies to evaluate the validity and reliability of our results. These elasticities are then converted into marginal costs and allocated to a price list, following the same framework as the existing engineering methodology.

Unlike an engineering model that relies on long-standing assumptions about the relationship between infrastructure characteristics and costs[7], the econometric approach derives insights directly from the data. However, it depends

[7] These engineering assumptions are derived from observed data. However, there is less external visibility of these assumptions, how they interact, and how they are updated over time to reflect new evidence.

on specific statistical assumptions for validity. Thus, neither approach is inherently superior; each has its own advantages and limitations. Below, in Table 2.1, we outline the key theoretical strengths and weaknesses of using an econometric approach to calculate the VUC.

Table 2.1: Evaluation of econometric approach

Advantages of econometric approach	Drawbacks of econometrics approach
Data-driven insights: provides empirical results based on actual data, allowing for quantifiable relationships.	**Data quality issues:** might limit usefulness. Requires: • Large sample size • Granular data.
Clear metrics for comparison: allows comparison of elasticity estimates with those from other studies.	**Potential for p-hacking:** risk of selectively reporting results to achieve statistically significant findings.
Flexibility: can model complex relationships between costs and traffic, informed by the data.	**Costly to switch approach:** requires econometrics expertise and high-quality data.
Allows for formal hypothesis testing: provides the tools to test specific assumptions which may change over time using statistical methods.	**Model dependent:** results can be dependent on model specification, choice of variables, and functional form.
Transparent calculation of VUC: VUC is set at marginal cost, which is the estimated elasticity multiplied by average total costs.	**Uncertainty over total cost recovery:** approach calculates marginal cost first and total cost recovery follows. Current approach calculates total marginal cost to recover and then average marginal cost.

Source: CEPA analysis

Finally, it is worth noting that the econometric approach is more of a 'backwards-looking' approach – in that the data used is by definition historical – and therefore it might be more susceptible to changes in the relationships between key variables going forwards. It relies on the assumption that if historic relationships are modelled robustly, it is reasonable to extrapolate them into the future. However, we do not consider this a clear disadvantage of the econometric approach relative to the engineering approach. Network Rail's current engineering approach allows for the overlay of more 'forward-looking' assumptions, such as how it responds to a constrained funding envelope and incorporating the ORR's view on efficiency gains over the upcoming control period. Although such factors are not typically applied to the econometric approach - and there is a strong argument that VUCs should reflect the future efficiency gains embedded in the SBP – these assumptions could also turn out to be speculative or inaccurate. In our view, this supports the view that both approaches are theoretically useful.

3. LITERATURE REVIEW

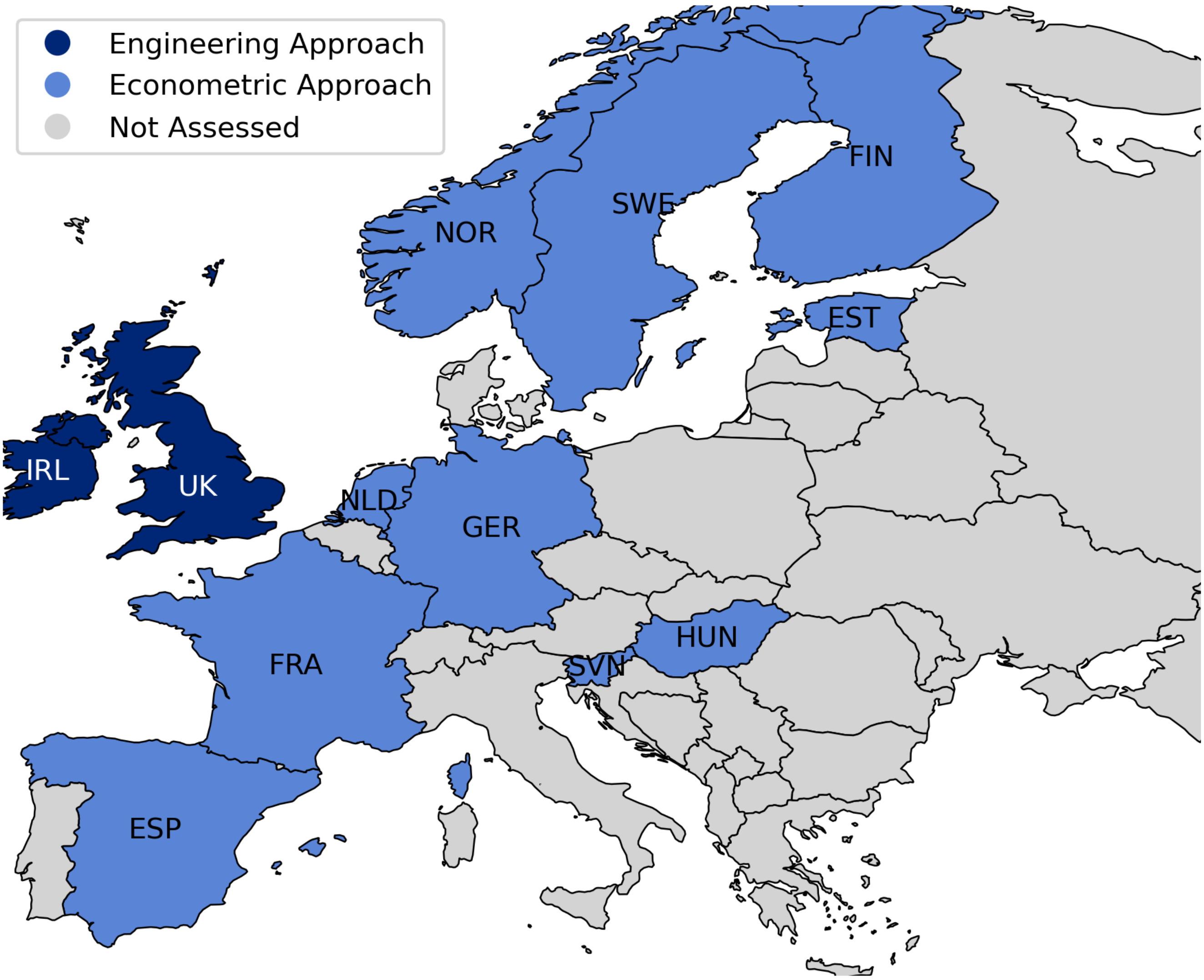
Our literature review provides an overview of existing research on the econometric approach to estimate marginal costs in the rail industry. We address key issues related to the econometric approach, focusing on the selection of variables, the choice of functional form, and the appropriate panel data model to use. This enables us to develop a robust methodology for our study on the feasibility of using econometrics for determining the VUC in Great Britain.

3.1. Current Approaches

According to the EU Commission Implementing Regulation 2015/909, infrastructure managers should base user charges on marginal costs to ensure the optimal use of available infrastructure capacity. Marginal cost pricing is known to lead to an efficient allocation of resources (Andersson et. al., 2012) because it ensures that the price charged for using a resource reflects the true cost of its provision. These marginal costs for setting VUC can be estimated using either engineering or econometric methods.

Figure 3.1 shows the current VUC charging practices in Europe and Great Britain. Most countries employ an econometric approach to estimate marginal costs of maintenance and renewals with respect to traffic levels.

Figure 3.1: VUC charging in Europe



Source: Independent Regulators' Group – Rail (2020); CEPA analysis

3.2. Econometric approach

The econometric approach seeks to estimate the statistical relationship between costs (such as maintenance and renewals) and traffic levels, while controlling for infrastructure characteristics. This method allows the data to determine the relationship, rather than depending on a fixed set of engineering assumptions. However, it is important to recognise that the parametric methods employed, such as Ordinary Least Squares (OLS), are based on several assumptions regarding the data's distribution. Therefore, neither approach is inherently superior from a theoretical standpoint.

The econometric approach to estimating VUC is most advanced in France and Sweden, where multiple studies over the past two decades have addressed several methodological and practical challenges, including the choice of functional form, panel data model, and variables to include. We extract key insights from this literature to inform our feasibility study and address the common challenges associated with the econometric method.

In contrast, the application of such methods in Great Britain remains relatively underexplored, with only a limited number of studies conducted to date. Wheat and Smith (2008) used a cross-section of maintenance costs at the Maintenance Delivery Unit (MDU) level to estimate the elasticity of maintenance costs with respect to traffic; however, their analysis was constrained by a small number of observations. Wheat, Smith, and Matthews (2015) employed a vector-autoregressive (VAR) model to estimate both short-run and long-run marginal costs of traffic on maintenance and renewals, but their approach did not account for the endogeneity arising from the use of lagged dependent variables. Our study seeks to address these limitations and explore whether an econometric approach in Great Britain is feasible.

Under an econometric approach, cross-country evidence on marginal costs is difficult to compare because marginal costs are influenced by scale effects and therefore vary between countries. Consequently, the literature typically focuses on estimating elasticities, which are scale-free and enable valid comparisons. European-wide studies provide useful insight into the range of maintenance and renewals elasticities with respect to rail traffic. We can use these estimated elasticities to validate our empirical findings from our econometric analysis.

The European-wide CATRIN study (Wheat et al., 2009) found that the mean elasticity for maintenance ranged from 20% to 35%, with a higher elasticity observed at greater traffic density. When maintenance and renewals costs were combined, the study reported an average elasticity of 35%. In Great Britain, Wheat and Smith (2008) estimated a marginal cost of 8.39 pence/vehicle-mile for passenger traffic and a marginal cost of 1.99 £/kgtm for freight traffic on maintenance costs based on an estimated mean elasticity of maintenance costs with respect to passenger and freight traffic of 25%.[8] We use these studies to validate our estimates of traffic elasticities and marginal costs in Section 6 of the report.

In the following sections, we examine the main challenges associated with using an econometric method and explore the potential solutions.

Costs Selected for VUC

There is debate on which costs should be included within the marginal cost estimation, particularly concerning:

- **Renewals costs**, which are irregular and substantial, with most track sections experiencing zero renewals in a given year.
- **Signalling maintenance**. It is not clear whether signalling maintenance should be included in the calculation of VUC because train traffic does not necessarily contribute to wear and tear on signals.

Odolinski et. al. (2023) argue that signalling maintenance should be included in the calculation of variable usage charges as an increase in traffic may increase signalling maintenance costs, not because of wear and tear but due to other economic factors. When traffic increases, the cost of possessions increases, and a given asset failure will cost more given higher traffic. As a result, inspections will be carried out with greater frequency to prevent these

[8] We adjusted the figures reported in the paper for inflation to ensure they are comparable to our marginal cost estimates. Average elasticity taken from Wheat and Smith (2008) Table 6, see Model 3 on p.206.

asset failures. This argument is supported by the authors finding a positive statistically significant relationship between traffic and signalling maintenance costs. SNCF Reseau (2023) used this analysis to update its methodology for calculating variable usage charges to include signalling maintenance costs in its most recent review of charges for French rail infrastructure. We include all maintenance costs in our maintenance regressions.

Renewals is a major cost category that is currently included in the calculation of variable usage costs in Great Britain using an engineering approach and is typically included in methods which featured in our literature review. However, as noted above, renewals pose a problem when adopting an econometric approach as they are lumpy and substantial in cost. For any given year, most track sections are likely to experience zero renewals.

In earlier studies, maintenance and renewals were simply added together to avoid the problem of zero cost for some sections of the track. This might be considered a second-best option because the estimated cost elasticity is no longer the elasticity of maintenance or renewals but some average of the two. However, Andersson et al (2012) and Odolinski et al (2020) explored two ways to more accurately estimate the elasticity of renewals with respect to traffic, where maintenance can be regressed separately.

The first approach is a form of 'survival' analysis, which estimates the probability of renewals occurring on a given track section as a function of the traffic occurring on this track section and the control variables. This requires assumptions on the distribution of renewals, from which the cost elasticity of renewals can be estimated. The second approach is a two-stage model, which estimates the probability of renewals occurring in the first stage and the cost of renewals given they occur in the second stage. This is a generalisation of the Tobit model, where the relationship between traffic, controls and costs are not forced to be the same in the first and second estimation stages.

The two approaches were compared by Odolinski et al (2020) using 16 years of track section data. The two-part model was preferred as it asks both how traffic affects the decision to renew and then how traffic affects the cost of renewals. This was the approach adopted by France in SNCF's most recent determination. We therefore run separate regressions for maintenance and renewals costs. Our preferred approach to renewals costs would have been to run a similar two-stage model. However, due to limited availability of geographically detailed renewals data (i.e., at track section or route section level), we were unable to implement this approach in this study.

Functional Form

The econometric approach requires an assumption about the functional form of the relationship between maintenance or renewals costs and traffic. Various data transformations assume different functional forms, which typically trade-off flexibility for transparency. The most used transformations to estimate marginal costs are the log-log, translog, and Box-Cox models. Smith et. al. (2016) find that elasticity estimates vary depending on the functional form used, estimating different maintenance elasticities using various models, including the translog and Box-Cox models.

The log-log model assumes that there is linear relationship between the log of cost and the log of traffic. This functional form is widely used in other sectors (e.g., by Ofgem in the energy sector for cost assessment), although is not widely considered in the transport literature due to its more restrictive assumptions on the shape of the cost-traffic relationship. The main advantage of the log-log model is that it is relatively transparent and easy to interpret (Goldberger, 1968), because the coefficients estimated are elasticities. In a regulatory context, the interpretability and transparency of results is important because this ensures that stakeholders can understand and trust the basis for decisions and results are more easily replicated. Another advantage of the log-log model is that it places fewer demands on the data compared to more complex models. When data limitations result in insufficient statistical power to accurately estimate all parameters in a more complex model, such as the translog model, the log-log model becomes a more suitable choice. Its simplicity makes it effective and reliable in situations where data constraints prevent the identification of every term in a more complex model.

A related functional form is the translog model, which incorporates non-linear log terms to allow for more flexible relationships. Interestingly, the translog model serves as a second-order approximation to any general functional form, making it a flexible tool for empirical analysis (Christensen et. al., 1973). The translog model is commonly used by regulators in Europe due to its flexibility. Unlike the log-log model, which assumes constant elasticity, the translog model does not impose restrictions on elasticities, allowing for a more accurate representation of how marginal costs change with varying traffic levels. This adaptability helps avoid the potential bias in elasticity estimates that can occur with the log-log model if the actual relationship between variables is not constant.

The transport literature often compares the translog model to the Box-Cox transformation. The Box-Cox transformation is a generalisation of the logarithmic transformation which aims to transform a variable so that it more closely represents a normal distribution. The Box-Cox transformation is the most general functional form, nesting the other functional forms including the linear, log-log and translog models. Gaudry and Quinet (2009) and Silavong, Guiraud and Brunel (2014) both use a generalised Box-Cox transformation to estimate the elasticity of cost as traffic changes using French data. They argue that a Box-Cox transformation offers more flexibility than the log-log model, which allows for a more representative estimate of the marginal costs.

However, there are some disadvantages to using the Box-Cox transformation, which are cited in the French regulator's decision to move from a Box-Cox transformation to a translog model (Frontier Economics, 2017). Models using a Box-Cox transformation are estimated using maximum likelihood, because the 'power parameter' which determines the specific shape of the data must be estimated at the same time as the parameters of interest. Maximum likelihood estimation (MLE) uses an optimisation routine which may not always converge. This means that results from the Box-Cox model are not always replicable. Using simpler models estimated using least squares rather than MLE also allows for more statistical tests to be conducted, such as tests for linearity, normality of residuals, homoscedasticity, and multicollinearity, thereby facilitating a more thorough evaluation of the model's validity and robustness. Additionally, the Box-Cox model has greater data requirements, and in contexts with limited data, it may not be possible to robustly estimate all parameters.

Given the data limitations outlined in Section 4, we consider the log-log and translog models to be the most suitable choices for this study.

Dealing with Zeros in the Dependent Variable

The main limitation of using a functional form based on the log transformation is that observations have to be strictly positive, since log(0) is undefined. This issue becomes increasingly relevant as data is more disaggregated. In our study, where data is aggregated at an MDU or regional level, this is not a concern. However, at a more granular level, this limitation can pose practical challenges, as certain track sections may have zero traffic for specific types, making log transformations problematic.

The methods for dealing with zeros is discussed by Gaudry and Quinet (2009), who offer three solutions. The most common solution is to add a positive constant to all observations (e.g., log(y+1)), making the log-transformation possible. However, the choice of constant is discretionary and may arbitrarily bias results. The size of the bias depends on the specific data, meaning there is no best choice of constant (Winkelmann, 2008).

Secondly, one could exclude track sections with no traffic. This approach may be suitable for models with coarse traffic definitions (i.e., passenger and freight) where most track sections have at least some traffic of both types. However, as the number of zeros increase, this approach becomes less appropriate because it introduces a selection bias and has context-dependent consequences (Bellego et al. 2022).

The third alternative proposed is to use dummy variables to exclude observations with zero traffic. The model could include a dummy variable that is equal to 1 if that track section has positive traffic of a certain traffic type. These dummy variables can be interacted with the parameters of interest to ensure that the parameter is estimated using only the data with positive traffic (i.e., the freight coefficient uses all track sections that have positive freight traffic). The authors consider that this is the best approach when traffic is more finely split.

Panel Data Model

The data we use to estimate marginal costs exhibits a panel structure, which means that there are observations over different units (e.g., MDUs) and over time. This enables us to write a simplified relationship between costs and traffic as:

$$\ln C_{it} = \beta_0 + \beta_1 \ln Q_{it} + \beta_2 \ln X_{it} + u_i + v_{it}$$

Where C_{it} is the maintenance or renewal cost on track section i at time t, Q_{it} is the measure of traffic and X_{it} is the vector of control variables. The error is broken into two parts, one specific to each unit of observation u_i and another idiosyncratic error. Ignoring the panel nature of the data will lead to biased estimates of the marginal cost if the unobserved unit-specific effect $v_i$is correlated with traffic. Smith et. al. (2023) provides a useful discussion of the relative merits of different panel data models used for estimating marginal costs, with the most relevant ones being fixed effects and random effects.

The fixed effects model removes the track section effect v_i, which allows for an unbiased estimate of marginal costs and requires less restrictive assumptions than the random effects model. However, including a fixed effects term removes variation in the time-invariant characteristics of track sections. By removing this 'within-group' variation, the fixed effects model is less efficient (has larger standard errors) than random effects, which means that a statistically significant relationship is less likely to be found.

The random effects model uses both the 'between' (cross-section) and 'within' (over time) variation, making it more efficient than fixed effects. It also allows the inclusion of time-invariant explanatory variables, which is not possible in a fixed effects model. The necessary assumption for random effects is that the individual-specific effect v_i is random and uncorrelated with the explanatory variables in the model (e.g., traffic). If this assumption does not hold, then the random effects model is biased. It is possible to test the assumption of the individual effect v_i being uncorrelated with traffic and other explanatory variables using the Hausman test (Hausman, 1978). In our analysis, we employ both fixed effects and random effects models to enhance robustness and to ensure the reliability of our results.

4. DATA REQUIREMENTS, COLLECTION AND PREPARATION

4.1. Data requirements

To reliably estimate marginal costs using an econometric approach, high-quality data is essential for drawing robust conclusions. This requires detailed data on maintenance and renewal costs, traffic volumes, and a broad array of infrastructure controls, captured at a granular level and over an extended timeframe. These data requirements are necessary to identify significant, non-spurious statistical relationships of traffic and costs.

For regression analysis, we require three types of variables:

- **Costs:** Network Rail's actual realised maintenance and renewals costs at an annual frequency. These costs are the dependent variable in our regression equations. These should be in real terms to account for inflation.
- **Traffic:** Traffic is our main explanatory variable. Traffic could be measured in train-km, vehicle-km or tonne-km and should be split by freight and passenger. Traffic should be measured at the same disaggregation as costs. It may be the case that different measures of traffic are better suited to explaining costs, depending on the category of cost being analysed. For example, it may be the main (variable) cost driver for signalling maintenance is the cost of the possession. If this were the case, train-km would be a more accurate cost driver than gross tonne-kms.
- **Controls:** Obtaining an unbiased estimate through linear regression depends on the Conditional Independence Assumption, which requires that all relevant variables are observable and adequately controlled for. The controls we include are designed to capture additional factors influencing maintenance and renewal costs that may correlate with traffic, enabling us to effectively isolate the impact of traffic on marginal costs. Ideally, the controls should vary over time and across observations and may include variables reflecting infrastructure differences between observations (such as track age, soil type, curvature, etc.), as well as other cost drivers, like regional wage indices. Failing to account for these variables could lead to omitted variable bias in our estimates.

Given the panel nature of our data, we need observations spanning multiple years. However, we aim to avoid including older years that may not reflect the current relationship between traffic and costs. A ten-year period strikes a balance between historical depth and relevance. To account for the impact of Covid-19 on traffic and cost relationships, we incorporate within-model controls, such as year fixed effects and time trends, rather than excluding the Covid-affected years. This approach allows us to address potential distortions without sacrificing valuable data, as discussed further in Section 5.1.2.

To identify meaningful statistical relationships, we need highly granular data. This is the main limitation of our study. Aggregated regional data may mask specific patterns found at the track section level, where renewal needs depend on factors like age, curvature, and traffic, which are often averaged out at the regional level. This aggregation limits insights into specific track characteristics that directly influence maintenance and renewal costs.

Finally, a large number of observations is needed to strengthen the reliability and validity of regression estimates. A large sample size increases statistical power, making it easier to detect real relationships among variables. Additionally, more data mitigates the influence of outliers and supports a robust, generalisable analysis. In econometric modelling, particularly when controlling for multiple variables, an extensive dataset allows for a more detailed examination of complex relationships, ensuring that nuanced dynamics among variables are effectively captured.

Ideally, we would observe data at the track section level.[9] There are approximately 600,000 track sections across Network Rail's footprint, and these are aggregated into approximately 2,000 route sections. Econometric analysis in France and Sweden occurs at a level similar to the route section. For example, Smith et al. (2023) utilized data

[9] A "track section" refers to a specific segment of a railway line that serves as a very disaggregated unit of analysis. Datasets at the track section level contain over 600,000 observations, which is well-suited for econometric analysis.

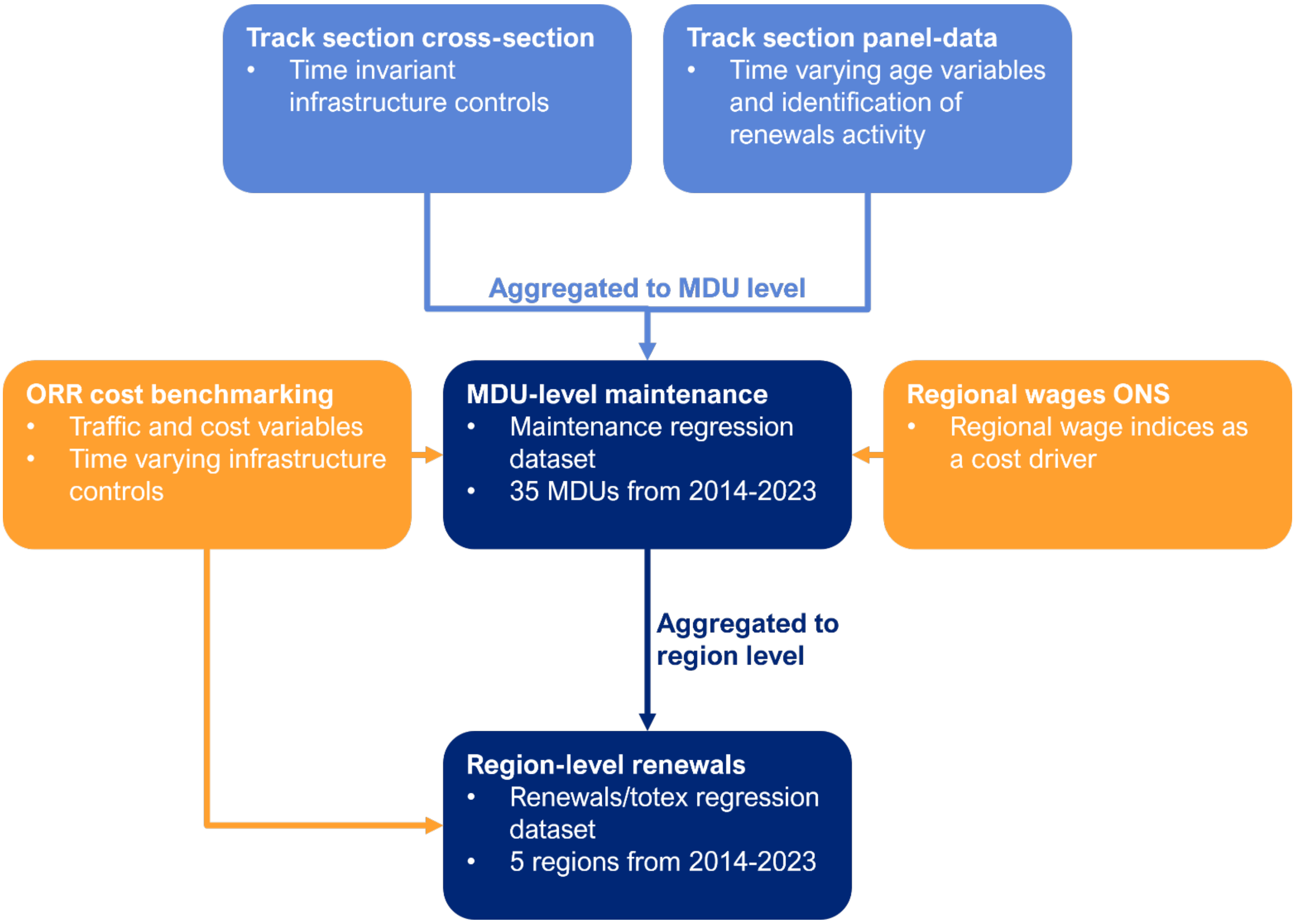
processed by SNCF Réseau, analysing 1,080 route sections per year, while Odolinski et al. (2023) used a more restricted sample of 633 route sections. In Sweden, Smith et al. (2021) used cross-sectional data with 244 route section observations, and Odolinski et al. (2020) used 260 route section observations.

At the outset of this project, we collaborated with Network Rail and ORR to identify the levels at which data on traffic, costs, and control variables are consistently collected and accessible. Network Rail currently provides annual data on traffic and maintenance costs to ORR at the MDU-level, along with traffic and renewals cost data at the regional level. However, with only 35 MDUs and 5 regions, the limited granularity of this data presents a significant constraint for detailed analysis. We requested further disaggregated data on actual costs and traffic. However, after discussions with Network Rail, it became clear that this data was either not collected or not readily accessible, and Network Rail was not able to produce it within the timescales of this project. Therefore, our maintenance dataset is at the MDU-level and our renewals dataset is at the region level.

4.2. Data collection and preparation

We combined several datasets provided by Network Rail and ORR to undertake our analysis. We produced an MDU-level dataset for maintenance regressions and a region level dataset for renewals regressions, as cost data at a more granular level was not available. Figure 4.1 below shows our process for creating the final datasets used in our analysis. We discuss each component in more detail below.

Figure 4.1: Constructing datasets for regression analysis



Source: CEPA analysis

Controls

Our regression models aim to approximate a cost function for maintenance and renewals costs. To estimate the impact of traffic on costs, we need to appropriately control for other variables in the cost function which also affect these costs. This includes infrastructure characteristics such as track age and input costs such as regional wages.

A detailed **cross-section of infrastructure data** for each track section was provided by Network Rail which we use for control variables in our regression. This dataset provides a snapshot of the state of the infrastructure across Network Rail's network in 2024, containing information on 646,000 track sections. We focused on running line track and aggregated these observations to MDU-level. Most variables were aggregated using a weighted average, with observations weighted by track length. Switches were counted for each MDU.

A limitation of this dataset is that we were only provided data for 2024. This means that we have a cross-section of infrastructure controls that do not vary over time. Another limitation is that three new MDUs were created in 2021/22. We removed these new MDUs created because they were missing expenditure data for all observations.

We complemented this cross-sectional dataset with a **panel of track age variables** at the track section level provided by Network Rail. This track summary panel data enabled us to calculate track, sleeper and ballast age on each track section for each year between 2014-2023. This is important because age is a useful predictor of maintenance and renewals activity.[10] This dataset also contained information on the rail and sleeper types, enabling us to calculate time-varying control variables relating to track, ballast and sleeper age, as well as rail weight and sleeper material. We merged this with the cross-sectional track section data and aggregated to the MDU-level.

ORR provided us with their **cost benchmarking dataset**, which contains some additional infrastructure controls at the MDU-level over time, such as the proportion of track electrified and the proportion of high-speed rail.

We combined these datasets with **regional wage data** constructed from ONS (2024) ASHE data. We only control for regional wages in our regression, because standard regulatory practice is to assume that there are national or international markets for other inputs (e.g., materials and machinery). Consequently, the prices of these inputs are unlikely to materially differ by region and so will be absorbed within the constant term (Wheat and Smith, 2008).

Costs and traffic

The source of historical maintenance and renewal costs and freight and passenger traffic data was ORR's cost benchmarking dataset. This contains maintenance costs and traffic data at an MDU-level, but renewals costs at the regional level. This dataset spans 2014-2023, providing us with 10 years of observations.

A summary of all variables used for our regression analysis are shown in Table 4.1 below.

Table 4.1: Summary of variables

Data source	Variable	Description
Track summary cross-section	ID	Unique ID for the section of track
	Switch ID	Asset ID for Switches and Crossings units
	Region	Network Rail Region
	IMDM	Maintenance delivery unit
	Track Priority	Track Priority (running lines, open sidings, closed lines, private lines)
	Earthworks – Embankment	1 = any embankment; 0 = no embankment

[10] Most track assets have an expected asset life and Network Rail will typically expect to replace those assets as they approach life expiry. However, expected life might vary by location and intensity of use – so track on a busy route section might typically be replaced every 25 years, whereas track on a remote rural route might deliver acceptable condition for 40 years or longer.

Data source	Variable	Description
	Earthworks – Soil Cutting	1 = any soil cutting; 0 = no soil cutting
	Earthworks – Rock Cutting	1 = any rock cutting; 0 = no rock cutting
	Curvature	Track curvature (1 / radius in meters)
	Cant	Track cant (mm)
	Switch Dummy	1 = is a switch or crossing; 0 = not a switch or crossing
Track summary panel data	ID	Unique ID for the section of track
	Year	Year variable from 2014 to 2023
	Rail Year	Year that the (left) rail was last renewed
	Rail Age	Rail Year – Year
	Sleeper Year	Year that the sleepers were last renewed
	Sleeper Age	Sleeper Year – Year
	Ballast Year	Year that the ballast was last renewed
	Ballast Age	Ballast Year – Year
	Rail Type	Description of rail type and weight (lbs)
	Sleeper Type	Description of sleeper type (metal/concrete/wood)
Cost benchmarking data	MDU	Maintenance delivery unit
	Region	Network Rail region
	Year	Year variable from 2014-2023
	Maintenance expenditure	Nominal maintenance expenditure (£m) at the MDU-level
	Renewals expenditure	Nominal renewals expenditure (£m) at the regional level
	Passenger traffic	Passenger train-km
	Freight traffic	Freight train-km
	Electrification	Proportion of MDU track that is electrified.
	Signals	Number of signals contained within each MDU
	Low Speed	Proportion of track classified as low speed (0-35mph)
	Mid Speed 1	Proportion of track classified as mid-speed 1 (40-75mph)
	Mid Speed 2	Proportion of track classified as mid-speed 2 (80-105mph)
	High Speed	Proportion of track classified as high speed (110-125mph)
ONS ASHE	Wages	Indices capturing differences in wages for each MDU

Source: CEPA analysis

We merged the datasets above to create a panel dataset for maintenance at the MDU-level and a dataset for renewals at the regional level (Eastern; North West and Central; Scotland; Southern; Wales and Western).

5. METHODOLOGY

In this section, we set out our methodology for estimating VUCs using an econometric approach. The first step involves using regression techniques to estimate the elasticity of costs with respect to traffic. The reality of empirical research is that data limitations will always inform several modelling decisions. We present the feasible regression approach employed in this study – given the available data – to estimate maintenance and renewals elasticities with respect to passenger and freight traffic. In our view, the approach adopted here is ‘second best’ and significantly limited by the unavailability of more granular data on renewals expenditure. To support ORR’s future exploration of these issues, we present our preferred ‘first best’ approach in Appendix A3.

Using the approach presented in the section, we then convert the estimated elasticities into marginal costs, which we discuss in Section 5.2. Finally, we discuss our approach to calculating a comparable price list using the estimated marginal costs.

5.1. REGRESSION APPROACH

In this section, we outline our actual approach, which differs from our preferred method due to data limitations. As noted in Section 4, our maintenance dataset includes observations across 35 MDUs, while the renewals data includes observations across 5 regions. The small number of regional units reduces the number of observations in the panel dataset and therefore the available statistical power, making it challenging to estimate more complex models and preventing robust statistical analysis for renewals.

Panel data model

Given that we are working with panel data, a key decision is how to model unobserved heterogeneity (u_i), which affects the consistency and efficiency of the regression results. Unobserved heterogeneity u_i can be modelled using either fixed effects or random effects, although we estimate both models for robustness. The RE estimator relies on the assumption that the unobserved effects are uncorrelated with the observed variables included in the regression. If this assumption holds, then RE is the most efficient estimator. This is because RE leverages both between and within variation to estimate coefficients, which means that the standard errors will be smaller and that the coefficients will be more accurately estimated. The FE estimator is always consistent but is less efficient as it only uses within variation, so should only be used if the RE assumptions do not hold. We can use the Hausman (1978) test to help choose between fixed effects and random effects. The Hausman statistic is distributed χ^2 and is computed as

$$H = (\beta_{FE} - \beta_{RE})^T (V_{FE} - V_{RE})^{-1} (\beta_{FE} - \beta_{RE})$$

Where β_{FE} is the FE estimator that is known to be consistent and β_{RE} is the RE estimator that is only consistent (and efficient) under the null. The null and alternative hypothesis are:

$$H_0: E[\,(\beta_{FE} - \beta_{RE}) \mid X\,] = 0$$

$$H_1: E[\,(\beta_{FE} - \beta_{RE}) \mid X\,] \neq 0$$

If the null hypothesis holds, and both FE and RE estimators are consistent, then there should be no systematic differences between the two estimators. Therefore, RE should be chosen. If there exists a systematic difference in the estimates, there is reason to doubt that the RE assumptions hold, and FE should be used.

Maintenance regression

For robustness, we estimate two different functional forms for our maintenance regressions. Consistent with our preferred approach (see Appendix A3), we employ a translog model, represented in the equation below, which allows for non-linearities in the data.

$$\ln C_{it} = \alpha + \beta_1 \ln Q_{it}^P + \beta_2 \ln Q_{it}^F + \beta_3 (\ln Q_{it}^P)^2 + \beta_4 (\ln Q_{it}^F)^2 + \beta_5 \ln Q_{it}^P \ln Q_{it}^F + \boldsymbol{X}_{it}\gamma + \delta_t + u_i + v_{it}$$

The elasticities of interest from the translog model are derived by differentiating the cost function with respect to passenger and freight traffic, as shown below.

$$\varepsilon_{it}^{P} = \frac{\Delta \ln C}{\Delta \ln Q_{it}^{P}} = \beta_1 + 2\beta_3 \ln Q_{it}^{P} + \beta_5 \ln Q_{it}^{F}$$

$$\varepsilon_{it}^{F} = \frac{\Delta \ln C}{\Delta \ln Q_{it}^{F}} = \beta_2 + 2\beta_4 \ln Q_{it}^{F} + \beta_5 \ln Q_{it}^{P}$$

However, even at the MDU-level, our dataset lacks sufficient statistical power to precisely estimate all parameters of the translog model. While we report the results of the translog model in Table 6.4 and discuss them in detail in the appendix, achieving statistically significant results is essential for drawing meaningful inferences and robustly estimating marginal costs.

Therefore, our primary model is the log-log model, which assumes constant elasticities between passenger traffic and maintenance costs, as well as between freight traffic and maintenance costs. This simpler model is more robust given our data limitations, as it requires estimating fewer parameters. However, the assumption of constant elasticity may not fully capture the complexities of the relationship between traffic types and maintenance costs. This limitation underscores the need for more disaggregated data collection to enable the application of more advanced modeling techniques in future analyses. The log-log model is shown below.

$$\ln C_{it} = \alpha + \beta_1 \ln Q_{it}^{P} + \beta_2 \ln Q_{it}^{F} + \boldsymbol{X}_{it}\gamma + \partial_t + u_i + \varepsilon_{it}$$

Year fixed effects (δ_t) are included in our regression models to capture economy-wide trends that are common to all units (i.e., track section). We model unobserved heterogeneity u_i using fixed effects (FE) and random effects (RE) specifications. Q_{it}^{P} is a measure of passenger traffic while Q_{it}^{F} is a measure of freight traffic. We use real maintenance costs to account for the effects of inflation and passenger and freight traffic is measured in train-km.

The coefficients β_1 and β_2 can be interpreted as elasticities of maintenance costs with respect to passenger and freight traffic respectively.

Limitations

Our approach to estimating the marginal cost of traffic on maintenance involves several limitations that may impact the robustness and accuracy of our findings:

- **Use of Year Fixed Effects:** The inclusion of year fixed effects controls for time-related variation that is consistent across entities, capturing broad annual trends such as economic growth or policy changes. However, this approach also absorbs year-to-year variations in traffic and maintenance costs that could be relevant for estimating the marginal cost of traffic. By controlling all time-related factors in this manner, we risk excluding relevant annual fluctuations in the data that may offer insights into the relationship between traffic and maintenance costs. We tested alternative ways of accounting for time effects to mitigate this limitation in the appendix. Our findings suggest that year fixed effects provide the best fit for capturing year-by-year variation in maintenance expenditures, so we are satisfied that our approach is robust.
- **Lack of Granular Data:** Limited data granularity restricts our model's ability to capture detailed and nuanced relationships between variables. With maintenance data aggregated at the MDU-level, specific attributes of individual track sections—such as varying traffic intensities, track age, and local conditions—are not fully reflected. This limitation is more pronounced for the translog model, as it relies on more detailed data to estimate flexible elasticities and interaction effects. The lack of disaggregated data reduces the model’s statistical power, which is important for identifying statistically significant relationships.
- **Incomplete Control Variables:** There may still be unobserved factors that influence maintenance costs which we do not control for. These omitted variables, such as specific environmental conditions or regional maintenance practices, could bias our estimates if they are correlated with traffic levels. However, we include a comprehensive set of control variables to account for infrastructure characteristics and other cost drivers. The consistency of our results, even when excluding any particular variable, suggests that we have effectively captured a sufficient set of controls.

- **Limitations of the Log-Log Model:** Our main model, the log-log specification, assumes a constant elasticity between traffic and maintenance costs, which simplifies the relationship but may not fully capture its complexity. In reality, the elasticity may vary with traffic levels, especially when considering different types of traffic (e.g., passenger vs. freight). This assumption of constant elasticity may lead to overestimated marginal costs if elasticity decreases with increasing traffic. A more flexible model, such as the translog model, could address this issue but would require more granular data for accurate estimation.

These limitations highlight the need for more detailed, disaggregated data and a broader set of control variables to improve the reliability of marginal cost estimates in future analyses. Nonetheless, our maintenance results appear reasonable and remain robust across various modeling choices, including the consideration of time effects.

Renewals regression

Our renewals regression approach is limited by the structure of the dataset, which provides data only at the regional level, with observations for 5 regions over a 10-year period. This restricted dataset necessitates a substantial departure from our preferred approach, limiting our model selection and analytical scope. Given these constraints, we employ a log-log model to estimate the elasticity of traffic with respect to renewals costs. Due to the small sample size, we are unable to test more complex models, such as the translog model, which requires a higher degree of data granularity for reliable parameter estimation. Furthermore, when we attempt to separate traffic by passenger and freight types, we encounter negative or statistically insignificant coefficient estimates, as shown in Section 6. This outcome suggests that the models lack sufficient statistical power to produce robust results when disaggregating traffic types, underscoring the limitations imposed by the current level of data aggregation. Our renewals regression model is shown below.

$$\ln C_{it} = \alpha + \beta_1 \ln Q_{it} + \boldsymbol{X}_{it}\gamma + \partial_t + u_i + \varepsilon_{it}$$

We use real renewals costs to account for the effects of inflation and traffic is measured in train-km.

Limitations

Overall, we are not confident in the robustness of renewals regressions at the regional level. Better cost data availability at a more granular level is needed to develop a robust econometric model.

- **Limited Degrees of Freedom:** Due to the small sample size of our renewals dataset, we face restricted degrees of freedom, which limits the complexity of our model specifications. As a result:
    - **We can include only a limited number of control variables**, specifically track length and track age. This narrow set of controls is likely to result in omitted variable bias, as other potentially influential factors on renewals costs remain unaccounted for. Including additional control variables in renewals regressions very quickly removes useful variation in traffic. This is a multicollinearity issue. As evidence for this, when we regress traffic on electrification, track length, and track age (at the region level), we get an R-squared of 95%. This means that there is only 5% of the variation in traffic left to explain the variation in renewals costs, leading to inaccurate estimates.
    - **We are unable to differentiate between passenger and freight traffic** in the model. Instead, we rely on a combined traffic measure (passenger-km + freight-km) to identify a statistically significant relationship with renewals costs. This combined metric may not accurately capture the distinct effects of different traffic types on renewals.
    - **We are restricted to a simple functional form.** Due to data constraints, we cannot employ more flexible functional forms, such as the translog model, which might better estimate heterogeneous marginal costs by capturing non-linear relationships and interaction effects.
- **Inappropriate Level of Aggregation:** The aggregation of data at the regional level poses further challenges. Traffic likely affects renewals at a more granular level, such as the track-section level, where specific local conditions influence maintenance and renewal needs. By observing renewals costs and traffic data at an aggregated regional level, we risk obscuring localized effects, which could dilute or mask the

true impact of traffic on renewals costs. Additionally, the aggregated level may introduce spurious correlations, as it fails to capture the finer variations that drive renewals at the ground level.

- **Inappropriate Lag Structure:** Renewals costs are typically "lumpy" and planned in advance, meaning they do not respond immediately to traffic changes. Ideally, we would address this by including lagged traffic variables in our model, allowing us to isolate the short-run marginal cost of traffic on renewals. However, each lag we include removes 10% of our observations (5 out of 50 total), substantially limiting our already small sample and hindering our ability to incorporate lags without further reducing statistical power.

These limitations underscore the need for a more granular dataset and additional observations to improve the robustness and reliability of our renewals cost estimates. The sooner data collection efforts are initiated, the sooner the industry can benefit from more accurate insights. However, based on our discussions with Network Rail and staff at the GBR Transition Team (GBRTT), we understand that, (a) developing a retrospective sub-regional cost allocation method would be a time and resource intensive exercise, and (b) once Network Rail implements a new sub-regional accounting framework, several years of data collection will be required to achieve the critical mass needed for a robust econometric analysis.

5.2. Converting to VUCs

Marginal costs

Our econometric models enable us to estimate the elasticity of traffic with respect to costs, which is valuable for cross-country comparisons to validate our regression results. However, we need to convert these elasticities into marginal costs to calculate variable charges for rail infrastructure. As shown in the mathematical derivation below, the marginal cost of traffic can be decomposed into the elasticity of traffic with respect to cost and the average cost. Thus, to calculate the marginal cost, we multiply our regression-based elasticity estimates by the average cost per train-mile, which we obtain directly from the data. Note that we convert from kilometres to miles to enable a valid comparison with other studies and Network Rail's current price list, which report traffic in miles.

Converting from elasticity to marginal cost

We calculate marginal costs (MC_{it}) for each unit and time period by multiplying cost elasticities by average costs per train-mile. The marginal cost is defined as (without subscripts i and t):

$$MC = \frac{\partial C}{\partial q} = \frac{q \times \partial C}{C \times \partial q} \times \frac{C}{q} = \frac{\partial \ln C}{\partial \ln q} \times \frac{C}{q} = elasticity \times average\ cost$$

We then calculate a traffic weighted average marginal cost for passenger and freight as follows:

$$MC^W = \sum_{it} \left(\frac{MC_{it} \times q_{it}}{\sum_{it} q_{it}} \right)$$

Price list

Our analysis arrives at average marginal costs of maintenance for passenger and freight traffic, and an average marginal cost of renewals for total traffic. These are the required inputs to **Step 2** of the Network Rail's current VUC approach (see Figure 2.1). Hence, we used our inputs (in a slightly modified version of Network Rail's VUC calculation model used for the PR23 Final Determinations[11]) to arrive at the final price list. To calculate the price list, we followed these steps:

- **Convert marginal costs from pence per train-mile to £ per kgtm.** We calculate the marginal cost of passenger and freight traffic in terms of train-miles, because we only have sufficient data on train-miles and not on gross tonne-miles. We use mileage data available in the most recent Network Rail VUC model to convert

[11] NR PR23 FD VUC model v2.2.xlsx provided by ORR on 10/10/2024.

train-miles to thousands of gross tonne-miles (kgtm). For passenger traffic, we calculate that there are **3.6 train-miles per kgtm**; for freight traffic we calculate that there are **1.1 train-miles per kgtm**.

- **Apply Network Rail's efficiency adjustments to CEPA's marginal costs.** In calculating the efficient VUC rate, Network Rail assumes that they will experience 7.4% efficiency gains for maintenance costs and 12.6% efficiency gains for renewals costs over the CP7 period. Additionally, they apply a further 2% reduction to maintenance marginal costs and 5.7% reduction to renewals marginal costs. We apply the same efficiency adjustments to our marginal costs, which are estimated over the period 2014-2023.
- **Split step 2 of the VUC model into separate passenger and freight calculation sheets.** Step 2 of Network Rail's VUC methodology is outlined in their November 2022 consultation on regulated access charges.[12] We split this methodology into separate passenger and freight calculation sheets to reflect the fact that we input separate passenger and freight marginal costs, instead of a total marginal cost.
- **Calculate the full (uncapped) price list.** The final step of our analysis generates the full uncapped VUC price list. We present the uncapped price lists for both the current engineering approach (as given in the Network Rail VUC model) and our econometric approach to enable like-for-like comparison.[13] The capping (and phasing) of freight VUC charges was, and remains, a policy decision for ORR and is not reflected in our calculations.

[12] Network Rail (November 2022) "Consultation on regulated access charges in Control Period 7" available at networkrail.co.uk.
[13] Therefore, readers should note that the CP7 price list shown in Section 6.3 below does not match the one published on Network Rail's website – which presents capped VUC rates.

6. RESULTS

In this section, we present the results of our econometric analysis of the marginal costs of traffic for maintenance and renewals. Our findings shed light on the elasticity of costs with respect to traffic, enhancing our understanding of how traffic levels influence infrastructure expenditures. For both maintenance and renewals, we begin by summarising the data, exploring historical trends in traffic and costs, and describing the control variables used in our regressions. We then present the core results, including regression coefficients, elasticities, and marginal costs. To ensure robustness, we compare results across alternative models, including fixed effects and random effects estimations, and assess the effects of different control variables. We also discuss the limitations of each model, particularly concerning data granularity and aggregation, to contextualise the reliability of our findings. Finally, we compare our estimates with benchmarks from other studies, providing insights into the broader relevance of our results within infrastructure cost modelling.

6.1. Analysis of maintenance costs

Data summary

Our maintenance dataset consists of a balanced panel of 35 MDUs observed over a 10-year period (2014-2023), yielding a total of 350 observations. The dependent variable is the log of annual maintenance costs (measured in constant 2023-24 prices), while the main independent variables of interest are the log of passenger train traffic and the log of freight train traffic, both measured in train-km. A set of control variables are also included, which capture the physical characteristics of the track each MDU service, though these are not interacted with traffic variables. A summary of the dependent and main independent variables is presented in Table 6.1 below, while a summary of the control variables is presented in Appendix A.

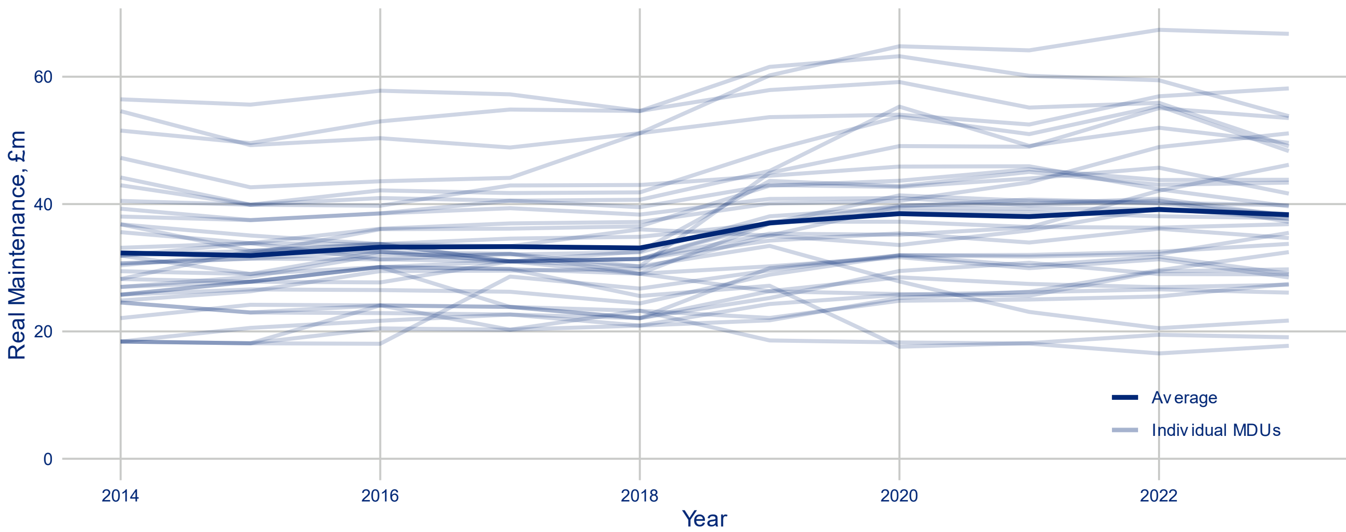
Table 6.1: MDU-level cost and traffic data, 2023-24 prices

Variable	Count	Mean	SD	Min	Max
Real maintenance expenditure (£m)	350	35.5	10.6	16.5	67.3
Passenger traffic (million train-km)	350	14.2	4.3	5.5	25.2
Freight traffic (million train-km)	350	1.3	0.8	0.1	4.2

Source: CEPA analysis

Figure 6.1 below illustrates the evolution of real maintenance expenditure over the last ten years. There is significant variation between MDUs (shown in the faint blue lines), with expenditure on maintenance ranging between £16.5m and £67.3m per year. There has been a slight increase in variation between MDUs over time, and this spread appears to have occurred from 2018-2020, which coincides with the start of CP6. There is less variation within MDUs, meaning that year-to-year maintenance expenditure does not shift by large amounts. Average maintenance expenditure (illustrated by the dark blue line) has increased slowly across the period, with the largest increase occurring between 2018-2020.

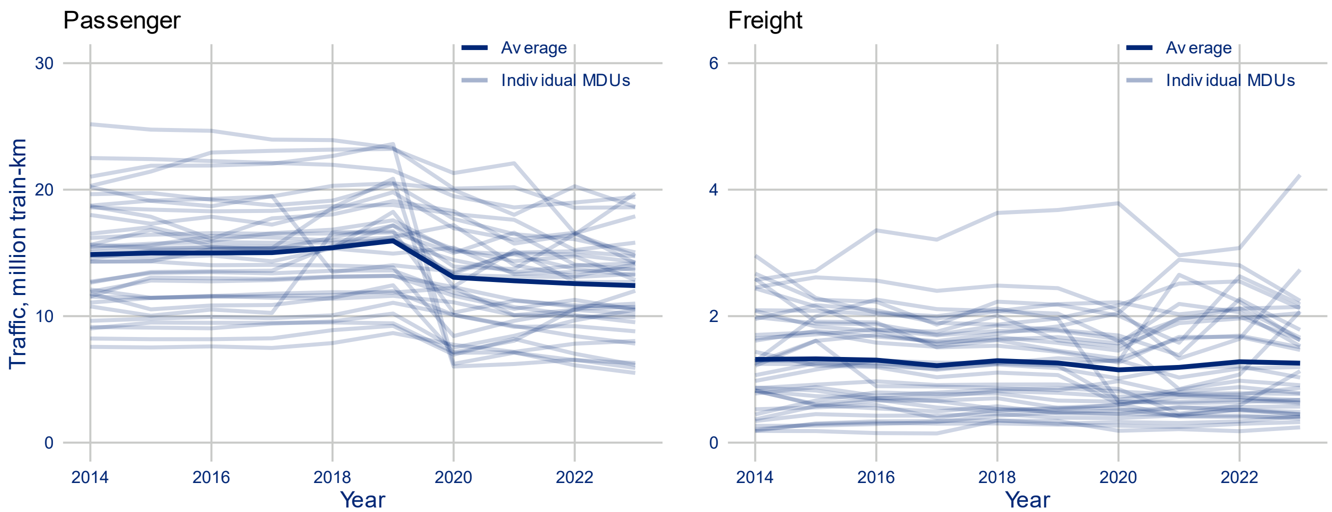
Figure 6.1: Real maintenance expenditure, MDU, £ millions, 2014-2023



Source: CEPA analysis

Passenger and freight traffic are illustrated in the figure below. Like maintenance expenditure, there is more variation between MDUs than within the same MDU over time. Passenger traffic is roughly 10 times higher than freight traffic. There is a significant decrease in passenger traffic for some MDUs from 2019-2020 and traffic remains at reduced levels post-2020, largely due to reduced demand stemming from Covid-19. Average freight traffic has remained fairly constant across the period, but there is some variation within MDUs, especially from 2019-2022 as freight traffic also reacts to Covid-19.

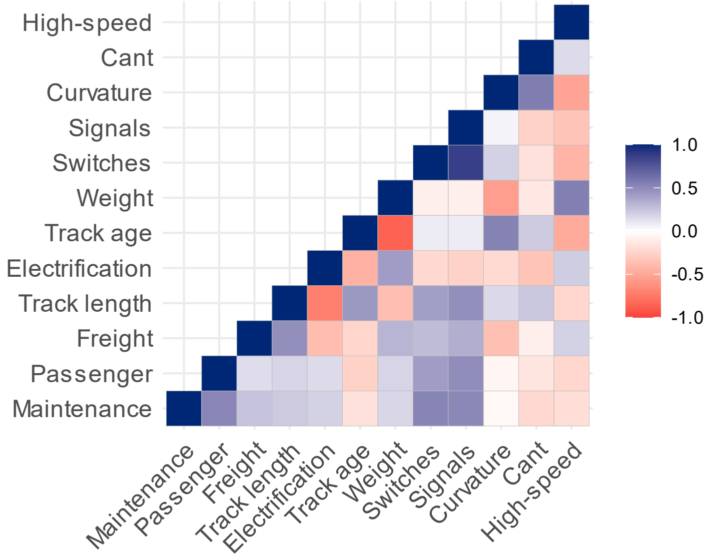
Figure 6.2: Traffic, measured in millions of train-km, for passenger and freight, MDU, 2014-2023



Source: CEPA analysis

The correlation plot in Figure 6.3 below shows that a range of variables are correlated with maintenance expenditure (the bottom row). Passenger and freight traffic are both positively correlated with expenditure, passenger more so than freight. Track length, electrification, track weight and the number of switches and signals are also positively correlated with maintenance expenditure. Electrification, average cant, and the proportion of high-speed track are negatively correlated with maintenance expenditure. Track age is negatively correlated with maintenance expenditure and traffic, which indicates that MDUs operating relatively old infrastructure, experience less traffic on average, and less maintenance expenditure.

Figure 6.3: Correlation plot of maintenance expenditure, traffic, and select controls



Source: CEPA analysis

The purpose of Figure 6.3. is to demonstrate the various relationships between the variables used in our study and note that whilst many of these correlations may appear intuitive (e.g., maintenance expenditure being positively correlated with passenger traffic and track length) other relationships may appear unintuitive (e.g., maintenance expenditure being negatively correlated with track age – likely because track age is negatively correlated with passenger traffic). In that context, it is important to remember that variables which one might ordinarily consider to be important drivers of maintenance expenditure – such as those typically associated with track age and complexity of infrastructure – may not turn out to be the dominant drivers in our regression results because those variables are the result of other factors (such as the ordinary level of traffic or the train speed that the track is designed for). As a result, the estimated parameters for some of the control variables may not align with our prior expectations (in terms of direction and/or magnitude) but we are confident that collectively our set of control variables perform well in controlling for variation in maintenance costs across MDUs which is not explained by differences in traffic.

Maintenance Results

Log-log model

The log-log regression results presented in Table 6.2 show the relationship between maintenance expenditure (log-transformed) and our two primary explanatory variables: passenger train-km and freight train-km (both also log-transformed), with models employing both fixed effects and random effects specifications. Four regressions are presented, allowing us to compare how the inclusion of controls affects the results.

Table 6.2: Log-log regression results, maintenance

Dependent variable	(1)	(2)	(3)	(4)
Log maintenance expenditure	FE	RE	FE	RE
Log passenger train-km	0.292***	0.340***	0.247***	0.264***
	(0.072)	(0.078)	(0.064)	(0.060)
Log freight train-km	0.115**	0.098***	0.093	0.095**
	(0.055)	(0.038)	(0.055)	(0.039)
Year fixed effects	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Constant	-2.975**	-3.535***	15.022	4.544
	(1.270)	(1.298)	(72.546)	(17.257)
Observations	350	350	350	350
Overall R-squared	0.509	0.472	0.572	0.771

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Our estimates of the parameters of interest (βs) are identified if, after accounting for unobserved MDU heterogeneity, time specific events, and our set of control variables, shocks to passenger and freight traffic are exogenous. We present results below that illustrate the inclusion of our set of control variables does not significantly change the estimated coefficients, which lends evidence to this being the case.

Across all specifications, both passenger train-km and freight train-km are positively associated with maintenance expenditures. In the models without controls (Columns 1 and 2), a 1% increase in passenger train-km is associated with approximately a 0.292% increase in maintenance expenditures under the FE model and a 0.340% increase under the RE model. The significance of this relationship is consistent, with both coefficients statistically significant at the 1% level. The impact of freight train-km, while generally smaller than that of passenger train-km, remains statistically significant as well; a 1% increase in freight train-km is associated with a 0.115% increase in maintenance expenditures in the FE model and a 0.098% increase in the RE model, both significant at the 5% level.

When controls are added in Columns 3 and 4, the magnitude of the passenger train-km coefficients slightly decreases, suggesting that some of the variation in maintenance costs might be explained by these controls. However, the relationship remains positive and significant. Notably, freight train-km become statistically insignificant in the FE model with controls, though they retain significance at the 5% level in the RE model. The overall R-squared values indicate that the models with controls (especially the RE model in Column 4) explain a greater proportion of the variance in maintenance expenditures, with R-squared values rising from 0.509 in the initial FE model to 0.771 in the RE model with controls.

Overall, we consider the log-log model with controls using RE as our preferred model. The Hausman test, results of which are shown in the appendix, does not reject the null hypothesis, indicating no systematic difference between the RE and FE coefficients. This finding supports RE as a consistent estimator. Additionally, the RE model provides the best fit for the data, as evidenced by the highest R-squared value among the specifications.

We estimate that the elasticity of maintenance expenditure with respect to passenger traffic is 26.4%, while freight's elasticity is 9.5%. This is in-line with other econometrics studies, giving us confidence in our results. For example, the European-wide CATRIN study (Wheat et. al., 2009) found that the mean elasticity for rail maintenance generally ranged from 20% to 35%. These findings demonstrate a robust relationship between traffic and maintenance costs.

We present the estimated elasticities and marginal costs from Column 4 in Table 6.3 below. As outlined in Section 5.2, we later convert these marginal costs to consistent units to compare against the current Network Rail VUC price list. When adjusting for inflation, our marginal costs appear very similar to those estimated by Wheat and Smith (2008), increasing confidence in our results.

Table 6.3: Estimated maintenance elasticities and marginal costs, 2023-24 prices

Maintenance cost, log-log model	Elasticity	Marginal cost (pence per train-mile)
Passenger traffic	0.26	105
Freight traffic	0.09	426

Source: CEPA analysis

Translog model

We present the results of our translog model as an alternative to the log-log model. While data limitations mean that the coefficients of the translog model are not always statistically significant, this model provides a more flexible approach, enabling us to examine how elasticities vary with traffic levels. Results are presented in Table 6.4 below.

Table 6.4: Translog regression results, maintenance

Dependent variable	(1)	(2)	(3)	(4)
Log maintenance expenditure	FE	RE	FE	RE
Log passenger train-km	14.321***	12.725***	12.837***	10.555**
	(4.084)	(4.232)	(4.279)	(4.795)
Log passenger train-km squared	-0.426***	-0.378***	-0.389***	-0.311**
	(0.118)	(0.121)	(0.118)	(0.132)
Log freight train-km	0.979	0.780	0.528	0.784
	(1.154)	(1.110)	(1.358)	(1.310)
Log freight train-km squared	-0.026	-0.022	-0.022	-0.020
	(0.023)	(0.022)	(0.025)	(0.023)
Log passenger * log freight train-km	-0.012	-0.006	0.008	-0.011
	(0.068)	(0.066)	(0.082)	(0.075)
Year fixed effects	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Constant	-122.658***	-108.667***	-113.997	-90.979**
	(36.326)	(37.609)	(76.178)	(44.285)
Observations	350	350	350	350
Overall R-squared	0.557	0.444	0.606	0.722

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In this specification, the impact of passenger train-km on maintenance expenditures is positive and substantial across all four columns, with coefficients on the linear term ranging from 10.555 to 14.321. The coefficient on the squared term for passenger train-km is negative and statistically significant, with values between -0.311 and -0.426, indicating diminishing marginal effects. This suggests that as passenger train-km increase, the incremental increase in maintenance expenditures becomes smaller, pointing to possible economies of scale in maintenance costs associated with passenger trains. These diminishing returns are consistent across both the FE and RE models, underscoring the robust nature of this finding.

The freight train-km variables, however, show a slightly different pattern. While the coefficients on log freight train-km are positive, they are not statistically significant in any specification, and the squared terms are also statistically insignificant. This lack of significance for freight train-km terms suggests that maintenance costs related to freight traffic may not exhibit the same scale effects observed for passenger traffic. The interaction term between passenger and freight train-km is also statistically insignificant across all specifications, indicating that any interdependent effect on maintenance costs between passenger and freight activity is likely minimal in this model.

In terms of model fit, the translog model demonstrates good explanatory power, with R-squared values ranging from 0.444 to 0.722 across specifications. When controls are added (Columns 3 and 4), the RE model achieves the highest R-squared at 0.722, suggesting that the inclusion of additional variables enhances the model's ability to explain variation in maintenance expenditures. This model fit is very similar to the log-log specification, where R-squared values were slightly lower (0.472 to 0.771).

We plot the relationship between estimated marginal costs and traffic in Figure 6.4 and Figure 6.5 below. We do not see any observable difference in the relationship between marginal costs and traffic for pre-Covid (blue) and post-Covid (green) observations. The red line shows the fitted values of the relationship. It shows that the marginal costs are not constant with respect to passenger or freight traffic. Instead, the relationship is downwards sloping and non-linear, with higher traffic MDUs having lower marginal costs than lower traffic MDUs. This means that the log-log model may overestimate the marginal cost by assuming a constant elasticity as it underweights high traffic MDUs. It is important to note that these curves are based on imprecisely estimated coefficients. The standard errors of these coefficients are shown in Table 6.4. We present the weighted average elasticities and marginal costs from Column 4 in Table 6.5 below.

Table 6.5: Estimated maintenance elasticities and marginal costs, 2023-24 prices

Maintenance cost, translog model	Elasticity (weighted mean)	Marginal cost (pence per train-mile)
Passenger traffic	0.19	59
Freight traffic	0.05	231

Source: CEPA analysis

Estimates from the translog model are lower than those from the log-log model, indicating that non-linearities play an important role. Failing to account for these non-linearities may result in an overestimation of marginal costs.

In summary, the log-log model offers straightforward elasticity estimates with high consistency and ease of interpretation, making it a practical choice for estimating the direct elasticities of maintenance costs with respect to train-km. However, the translog model provides a more nuanced view of scale effects, particularly for passenger train-km, though this flexibility comes with increased complexity and some parameter imprecision, reflected in larger standard errors. This trade-off suggests that the choice of model should align with the research priority: if the goal is interpretive simplicity and stable elasticity estimates, the log-log model is preferable; if a more detailed representation of non-linear effects and scale economies is desired, the translog model may be more appropriate.

Figure 6.4: Passenger marginal costs by traffic

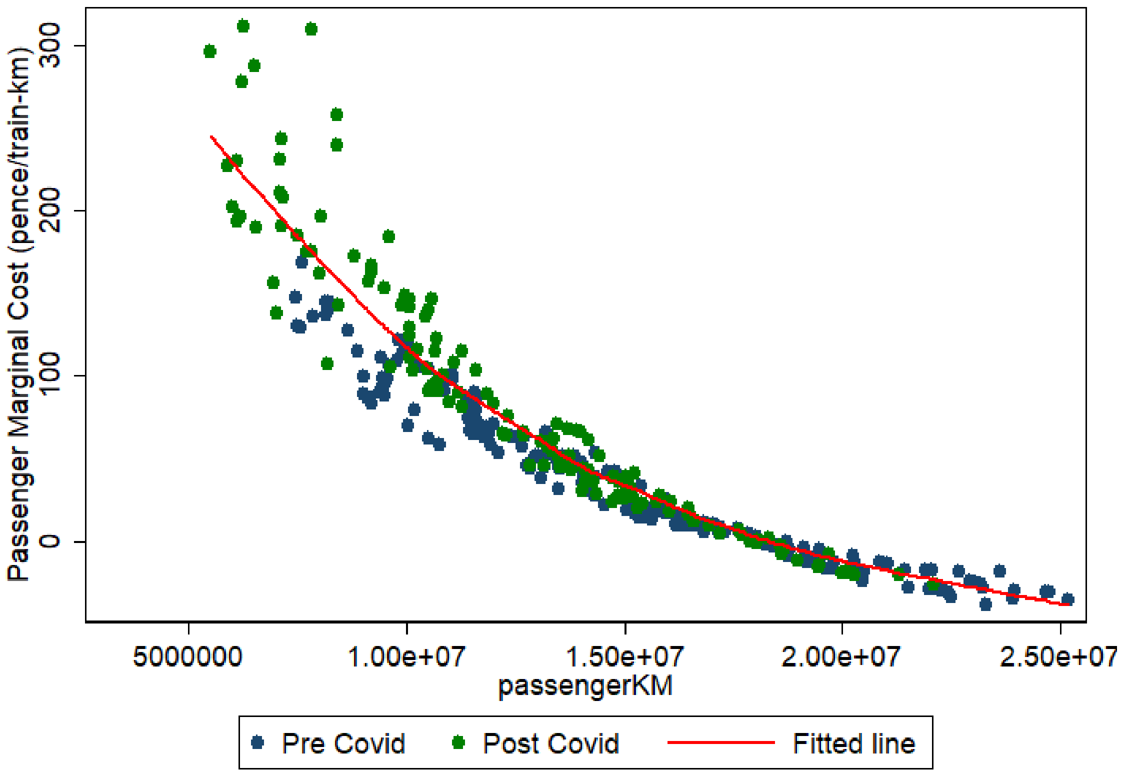
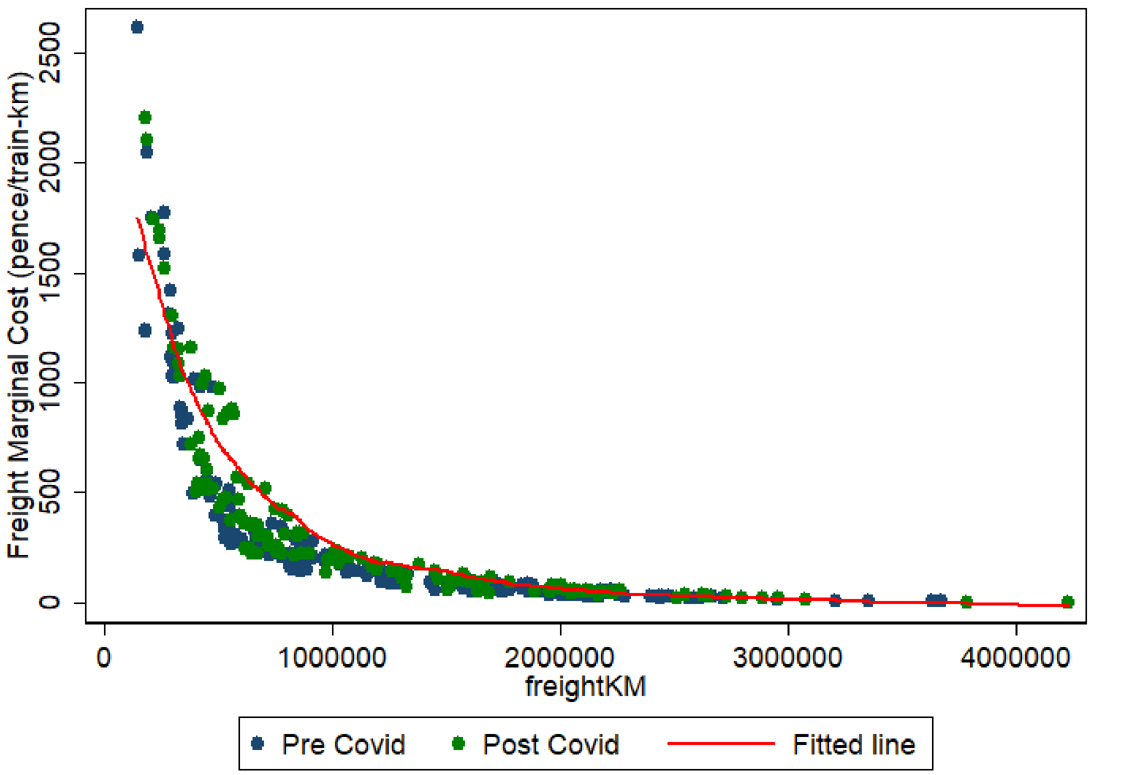


Figure 6.5: Freight marginal costs by traffic



Source: CEPA analysis

Sensitivities and limitations

Our primary concern when running the maintenance regression model was the inclusion of year fixed effects. Excluding these effects resulted in spurious relationships between traffic and maintenance expenditure, indicating that our results lack robustness without year fixed effects. This finding is expected, as including year fixed effects in panel regressions is a standard method to control for time-specific shocks that would uniformly affect maintenance costs across all MDUs, such as the Covid-19 pandemic.

However, applying year fixed effects without consideration has potential drawbacks: it can absorb meaningful variation that might otherwise highlight trends or effects specific to certain periods, and it may obscure the impact of critical events that uniquely influence only certain years or periods, such as a pandemic or regulatory adjustments. In this context, substituting year fixed effects with targeted temporal dummies (e.g., a Covid dummy, a regulatory cycle dummy, or a time trend) can more precisely capture relevant time-specific effects and potentially enhance the model's interpretability. The ORR also uses a Covid dummy in its cost benchmarking publications, which supports the need to address the altered relationship between costs and traffic caused by Covid.

The full results of our time effects sensitivity analysis are presented in Appendix A. We estimate three alternative models to compare with Column 4 from Table 6.2. The first model includes a Covid dummy for 2020-2023, the second includes a CP7 dummy for 2019-2023, and the final model incorporates a linear time trend. Across these specifications, key parameter estimates remain largely stable, while the R-squared decreases in each case. This suggests that year fixed effects provide the best fit for capturing annual variations in maintenance expenditures.

6.2. Analysis of renewals costs

Data summary

The dataset consists of a balance panel of 5 regions observed over a 10-year period (2014-2023), yielding a total of 50 observations. Given the high level of aggregation, we did not face the issue of observing many observations of zero renewals. Every region had conducted some level of renewals each year, so renewals costs were always positive. For this reason, we did not separately estimate the *probability* of renewals and the *cost* of renewals. Instead, we estimated a log-log model. The dependent variable is the log of annual renewal costs (measured in constant 2023-24 prices), while the main independent variables of interest are the log of passenger train traffic and the log of freight train traffic, both measured in train-km. As robustness checks, we included the first lags of these variables, and also considered a model where the main independent variable was the log of total train traffic. A small set of controls were also included, specifically the log of average track age and log track length. Average track age should capture the probability of renewals while track length should covary with the total amount of renewals occurring. Further controls were not included due to degrees of freedom concerns.[14] A summary of the variables used in this regression is presented in Table 6.6 below.

Table 6.6: Region-level summary statistics, 2023-24 prices

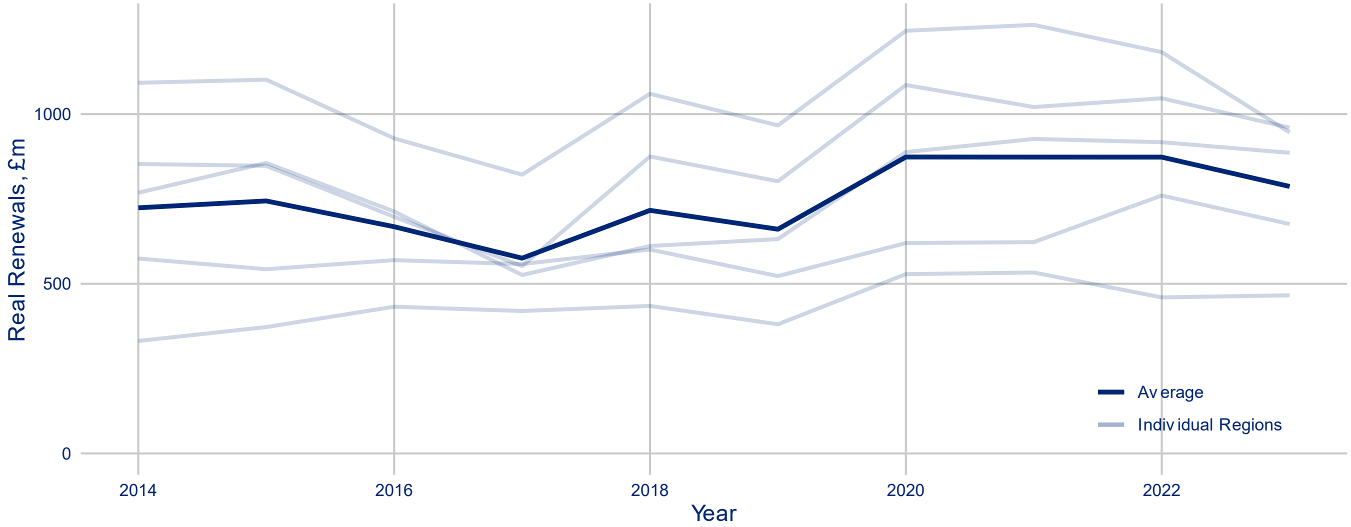
Variable	Count	Mean	SD	Min	Max
Real renewals expenditure (£m)	50	750	249	331	1,263
Passenger traffic (million train-km)	50	99.4	36.6	45.6	174.1
Freight traffic (million train-km)	50	8.8	5.2	2.5	18.1
Track length (km)	50	6151	1859	4240	9717
Average track age (years)	50	27.1	3.5	22.1	34.8

Source: CEPA analysis

[14] The slow changing nature (over time) of average track age and track length, and to a lesser extent traffic, meant that the variation between regions was almost perfectly explained if additional controls were included, which is suggestive of overfitting. More details are discussed in the methodology section of our report.

Figure 6.6 below illustrates the evolution of real renewals expenditure over the last ten years. There is significant variation between regions (shown in the faint blue lines), with expenditure on renewals ranging between £330m and £1,260m. The variation between regional expenditure on renewals has not changed significantly over time. There is less variation within regions, meaning that year-to-year renewals expenditure does not shift by large amounts. Average renewals expenditure (illustrated by the dark blue line) increased by £150m from 2014 to 2022, before falling almost back to 2014 levels in 2023.

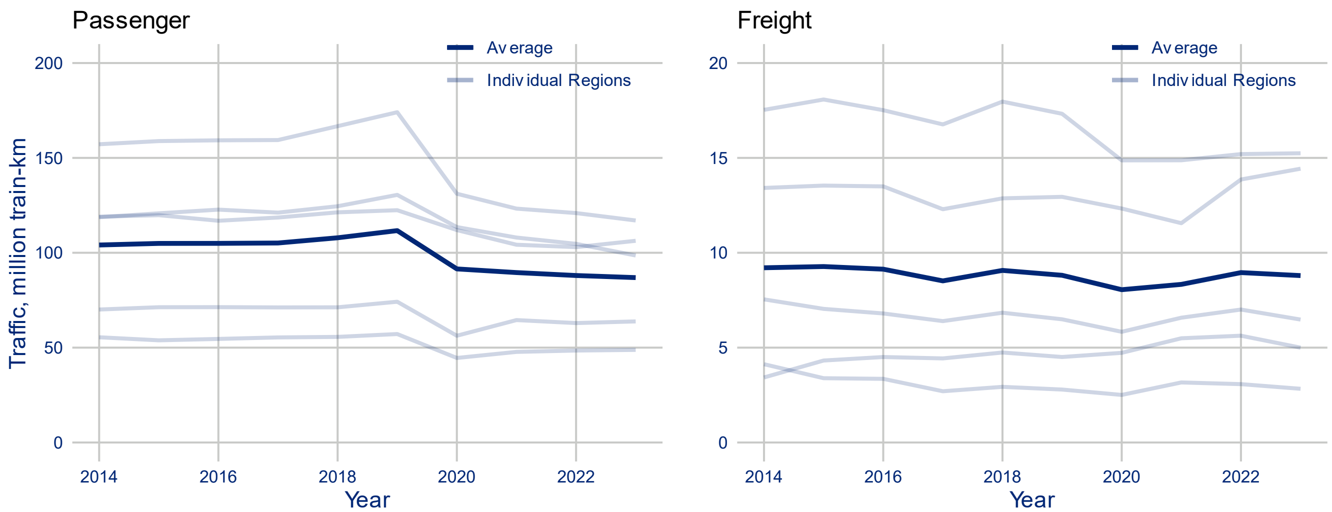
Figure 6.6: Real renewals expenditure, regions, £ millions, 2014-2023



Source: CEPA analysis

Figure 6.7 below illustrates variation in passenger and freight traffic between and within regions over the study period. Apart from the Covid-19 related traffic shock, occurring 2020, there is very little variation within regional passenger traffic. There is also very little variation with regional freight traffic. Variation does exist between regions but this is primarily driven by the size of the relevant networks.

Figure 6.7: Traffic, measured in millions of train-km, for passenger and freight, regions, 2014-2023

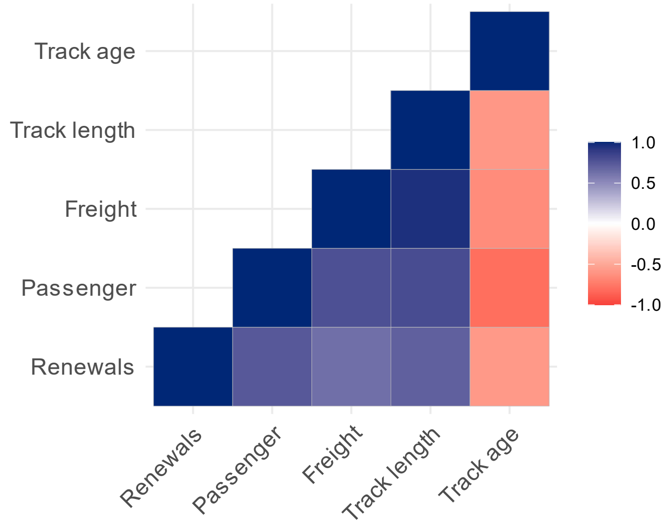


Source: CEPA analysis

The correlation plot (shown in Figure 6.8 below) shows very strong positive correlation between renewals, passenger traffic, freight traffic and track length. This will cause issues when running our regression, as in practice it is challenging to disentangle the effect of explanatory variables that are highly correlated. In this case, once the effect of track length is accounted for, there is very little residual variation in traffic and renewals expenditure to estimate the elasticity of renewals expenditure with respect to passenger and freight traffic.

The negative correlation between track age and renewals, traffic, and track length can be attributed to regions with lower traffic volumes, such as Scotland and Wales.

Figure 6.8: Correlation plot of renewals expenditure, traffic, and controls



Source: CEPA analysis

Renewals Results

Log-log model

Due to the small number of regional observations available, we only estimated a log-log model for renewals expenditure. The results presented in Table 6.7 below show the relationship between renewals expenditure (log transformed) and various traffic measures. Two specifications (Columns 1 and 2) separate passenger and freight train-km as individual predictors, while Columns 3 and 4 aggregate them into a single total train-km variable. Each specification is estimated using both FE and RE models to compare the robustness of the results.

Table 6-1: Log-log regression results, renewals

Dependent variables	(1)	(2)	(3)	(4)
Log renewals expenditure	FE	RE	FE	RE
Log passenger train-km	0.241	0.507*		
	(0.218)	(0.264)		
Log freight train-km	-0.259	-0.374**		
	(0.267)	(0.174)		
Log total train-km			0.091	0.592**
			(0.271)	(0.248)
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Constant	-4.055	-1.267	-3.942	-6.607***
	(5.703)	(5.938)	(5.381)	(1.831)
Observations	50	50	50	50
Overall R-squared	0.722	0.917	0.683	0.873

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Columns 1 and 2, passenger train-km show a positive relationship with renewals expenditure across both FE and RE models. While the effect is statistically insignificant in the FE model (coefficient: 0.241), it becomes marginally significant in the RE model (coefficient: 0.507, $p < 0.1$). For freight train-km, results indicate a negative relationship with renewals expenditure. In the FE model (Column 1), the coefficient is negative (-0.259) but not statistically significant. However, in the RE model (Column 2), the effect is both larger in magnitude (-0.374) and statistically significant at the 5% level. In terms of model fit, the random effects model demonstrates very good model fit with an R-squared of 0.917.

The difference between results for the FE and RE models (both in terms of magnitude and significance of estimates) suggests that there exists cross-sectional variation that influences renewals expenditure but is averaged out in the FE specification. For example, track length varies only slowly over time (as does traffic and track age), so once region fixed effects are included, there is very little meaningful variation left to estimate the effect of these variables on renewals.

One option to try and improve our model fit was to aggregate passenger and freight traffic, which is highly colinear at the region level. When aggregating passenger and freight train-km into a single variable (Columns 3 and 4), total train-km exhibit a significant positive effect on renewals expenditure in the RE model (coefficient: 0.592, $p < 0.05$), while the effect remains statistically insignificant in the FE model (coefficient: 0.091). This finding supports the interpretation that higher levels of overall traffic are associated with increased renewals expenditure, but the large difference between the RE and FE parameter estimates raises concerns about the robustness of these results. As expected, the R-squared values for these models are slightly lower than the models with traffic disaggregated by type. This is because the elasticity of renewals costs with respect to traffic is constrained to be the same for both freight and passenger traffic in these models. These findings highlight the importance of model selection and specification when assessing the drivers of infrastructure renewals expenditure.

Given the estimated parameters in Column 2 do not make sense economically, i.e., renewals expenditure should increase not decrease with freight traffic at the margin, we report an elasticity and marginal cost calculated for all traffic using the results in Column 4. It should be noted, and we emphasise, that there are serious limitations to this estimate, mainly generated by data limitations. However, we report it in Table 6.8 for completeness.

Table 6.8: Estimated renewals elasticities and marginal costs, 2023-24 prices

Maintenance cost, log-log model	Elasticity	Marginal cost (pence per train-mile)
Total traffic	0.59	659

Source: CEPA analysis

Sensitivities and limitations

A key limitation of our analysis was the relatively small sample size, as consistent data on renewals expenditure over the timeframe of our analysis is only available at the regional level (of which there are 5 regions). Given the low variation within each region for renewals expenditure, traffic, and control variables, this limited sample introduced significant collinearity between traffic measures and controls, which affected the accuracy of our parameter estimates. We explored various combinations of controls, including electrification, track length, and track age. Across these specifications, passenger traffic generally had a positive effect on renewals expenditure, while freight traffic had a negative effect. However, the magnitude and statistical significance of these estimates were sensitive to the specific controls included in the model, which is expected given the high collinearity between explanatory variables and controls. Key sensitivity tests are summarised in Appendix A.

Additionally, we investigated the inclusion of lagged traffic variables to account for the fact that renewals costs are often scheduled in advance and may be "lumpy". By incorporating lags, we aimed to isolate the contemporaneous impact of traffic on renewals, representing the short-run marginal cost. However, incorporating lags reduced our sample size by 10% (5 out of 50 observations per lag), limiting the ability to include multiple lags in the models. The models that incorporate lagged passenger and freight traffic are presented in Appendix A4. Lagged and current traffic are highly correlated and the inclusion of lags does not alter the sign of traffic elasticities but reduces their magnitude as the effect is distributed across two years. Notably, the estimated coefficients in these lagged models are statistically insignificant.

6.3. Resulting Variable Usage Charge price list

We converted the marginal costs estimated using the maintenance and renewals regressions into Network Rail's VUC price list using the procedure outlined in Section 5.2 above. The first step was converting our pence/train-mile marginal costs to a £/kgtm measure. As presented in Table 6.9 below, our resulting marginal costs are considerably lower for passenger traffic and higher for freight traffic (whilst noting that we cannot be confident in the robustness of our renewals regressions as described in Section 6.2 above). This makes sense as the Network Rail marginal costs are a weighted average of passenger and freight traffic.

Table 6.9: Summary of marginal costs used in VUC model, pre-efficiency and adjustments, 2023-24 prices

£/kgtm	Log-log	Log-log	Translog	Translog	Network Rail
Traffic	Passenger	Freight	Passenger	Freight	Total
Maintenance	0.29	3.89	0.16	2.11	1.45
Renewals	2.18	2.18	2.18	2.18	2.61
Total	2.48	6.08	2.35	4.30	4.06

Source: CEPA analysis

We then apply Network Rail's efficiency and cost adjustments to arrive at Table 6.10 below. These are the input marginal costs to Step 2 of the VUC model.

Table 6.10: Summary of marginal costs used in VUC model, post efficiency and adjustments, 2023-24 prices

£/kgtm	Log-log	Log-log	Translog	Translog	Network Rail
Traffic	Passenger	Freight	Passenger	Freight	Total
Maintenance	0.26	3.53	0.15	1.92	1.32
Renewals	1.80	1.80	1.80	1.80	2.15
Total	2.06	5.33	1.95	3.72	3.47

Source: CEPA analysis

Following Network Rail's calculation of total variable usage charge using traffic multiplied by the above marginal costs, and allocation of the total VUC based on vehicle damage characteristics, we derive a full VUC price list. We present the "default"[15] passenger and freight variable usage charges, as well as simple averages over the list of vehicles in Tables 6.11–6.14 below. For the freight comparisons in Tables 6.12 and 6.14 we use Network Rail's 'uncapped' CP7 VUC rates as these represent a more 'like for like' comparison, because following ORR's PR23 final determination, freight VUC rates are capped below fully cost-reflective rates on the trajectory set at PR18.[16]

[15] Default charges are the max variable usage charge for each broad vehicle type.

[16] ORR (October 2023) "PR23 final determination: policy position – access charges" p.10., available at orr.gov.uk.

Table 6.11: Default passenger variable usage charges, 2023-24 prices

Default rate Vehicle Classification	CEPA Log-log (Pence Per Vehicle Mile)	CEPA Translog (Pence Per Vehicle Mile)	Network Rail CP7 (Pence Per Vehicle Mile)
Locomotive	76.86	72.60	127.05
Multiple unit (motor)	35.34	33.38	60.44
Multiple unit (trailer)	16.54	15.62	28.23
Coach	14.08	13.30	23.45

Source: CEPA analysis and NR PR23 FD VUC Model v2.2

Table 6.12: Default freight variable usage charges, 2023-24 prices (uncapped CP7 rates)

Default rate Vehicle Classification	CEPA Log-log (£/kgtm)	CEPA Translog (£/kgtm)	Network Rail CP7 Uncapped (£/kgtm)
Locomotive	21.00	14.63	12.73
Wagon (laden)	13.71	9.55	8.37
Wagon (tare)	8.72	6.07	5.62

Source: CEPA analysis and NR PR23 FD VUC Model v2.2

Table 6.13: Average passenger variable usage charge, 2023-24 prices

Average rate Vehicle Classification	CEPA Log-log (Pence Per Vehicle Mile)	CEPA Translog (Pence Per Vehicle Mile)	Network Rail CP7 (Pence Per Vehicle Mile)
Locomotive	57.66	54.47	99.19
Multiple unit (motor)	7.75	7.32	15.19
Multiple unit (trailer)	9.67	9.13	11.70
Coach	9.23	8.72	15.06

Source: CEPA analysis and NR PR23 FD VUC Model v2.2

Table 6.14: Average freight variable usage charge, 2023-24 prices

Average rate Vehicle Classification	CEPA Log-log (£/kgtm)	CEPA Translog (£/kgtm)	Network Rail CP7 Uncapped (£/kgtm)
Locomotive	12.29	8.56	7.53
Wagon (laden)	6.73	4.69	4.55
Wagon (tare)	2.79	1.94	1.76

Source: CEPA analysis and NR PR23 FD VUC Model v2.2

In Table 6.11, we observe that default passenger rates are lower under the econometric approach developed in this study compared to the current engineering-based approach. For instance, under the log-log model, locomotives are charged at 76.86 pence per vehicle-mile, compared to 127.05 pence per vehicle-mile under the current methodology. A similar difference in magnitude is seen for the average passenger variable usage charges, as shown in Table 6.13. Passenger variable charges estimated from the translog model, which accounts for non-linear cost elasticities but is less robust, are slightly lower in magnitude than those from the log-log model.

On the other hand, in Table 6.12, we observe that default freight rates are higher under the econometric approach developed in this study compared to the current engineering-based approach. For instance, under the log-log model, wagons (laden) are charged 13.71 £/kgtm, compared to 8.37 £/kgtm under the current methodology using uncapped prices. A similar difference in magnitude is seen for the average freight variable usage charges, as shown in Table 6.14. Freight variable charges estimated from the translog model are far lower than those estimated from the log-log model and are marginally higher than the charges estimated under the current methodology. For example, the average charge for a tare wagon under the log-log model is more than 50% higher than Network Rail's current charge of 1.76 £/kgtm but is only marginally higher at 1.94 £/kgtm from the translog model.

The differences in variable charges between the two approaches should not be interpreted as an indicator of which method is superior, particularly as these charges incorporate results from our renewals regressions, which lack robustness. In particular, we do not think it is possible to conclude – on the basis of this analysis alone – that freight charges would be higher under an econometric approach, given that the translog model produces freight charges which are broadly similar to the current 'uncapped' rates. Further analysis on a more granular renewals expenditure dataset would produce different results which might be more robust and support a different conclusion.

We have greater confidence in the maintenance cost results, where data and model fit are stronger. Ensuring like-for-like comparisons is essential, and we validate our maintenance findings by referencing established estimates in the literature. Notably, our elasticity estimates align with the European-wide CATRIN study, falling within a similar range. As an additional validity check, in Table 6.15 below we compare our maintenance marginal cost estimates against those provided by Wheat and Smith (2008), which serve as a reliable benchmark. We scale our marginal cost estimates using publicly available data from ORR (2024), converting from pence/train-mile to pence/vehicle-mile for passenger traffic and to £/kgtm for freight traffic. We adjust Wheat and Smith's estimate to 2023-24 prices using the CPI index.

Table 6.15: Maintenance marginal cost comparison, 2023-24 prices

Maintenance – marginal cost	Metric	CEPA (Log-log)	CEPA (Translog)	Wheat & Smith (2008)
Passenger Traffic	pence/vehicle-mile	17.31	9.81	8.39
Freight Traffic	£/kgtm	3.68	2.00	1.99

Source: CEPA analysis

Our estimated marginal costs for maintenance using the translog model are closely aligned with those of Wheat and Smith (2008), after adjusting for inflation, suggesting that an econometric approach may be feasible once data limitations are addressed. Specifically, we estimate the marginal cost of passenger traffic at 9.81 pence per vehicle-mile, compared to 8.39 pence per vehicle-mile reported by Wheat and Smith (2008). For freight traffic, we estimate a marginal cost of £2.00 per kgtm, closely matching the £1.99 per kgtm from Wheat and Smith (2008). The log-log model, by contrast, produces higher marginal cost estimates for maintenance due to an overestimation of the elasticity. This overestimation occurs because the log-log model assumes a constant elasticity, which tends to underweight high-traffic observations, thereby inflating the marginal cost.

7. CONCLUSIONS AND RECOMMENDATIONS

In this section, we evaluate our study results to draw conclusions about the potential role of econometrics in setting VUCs at future periodic reviews. In particular, we ask the following questions:

- Do the econometric and engineering methods produce fundamentally different results?
- Would an econometric method fundamentally improve the practicability, robustness, and transparency of the methodology for setting VUCs; and
- Would the econometric method have implications for other desirable properties of track access charges, such as incentives for economic efficiency, predictability of charges, and recovery of Network Rail's sustainable revenue requirement.[17]

Based on the findings and conclusions reached in this study, we then set out our recommendations for ORR and Network Rail on how to further improve the econometric approach ahead of future periodic reviews.

7.1. DO THE ECONOMETRIC AND ENGINEERING METHODS PRODUCE FUNDAMENTALLY DIFFERENT RESULTS?

A 'like-for-like' comparison between the econometric and engineering methods is challenging as they are different in important respects. For example, one factor that may contribute to observed differences in rates is the definition of 'direct costs' used in the engineering cost model, which focuses on track, civils and signalling assets. By comparison, the econometric literature (and the approach we take in this study) typically focuses on total maintenance and renewals costs.

Table 6.13 (average passenger variable usage charge) and Table 6.14 (average freight variable usage charge) above show that there are differences in the reported charges for passenger and freight. But although they are two fundamentally different approaches to estimating variable costs, our results show that they can produce overall variable cost estimates of a similar scale. An indicative comparison of the overall variable cost estimate which VUCs are intended to recover shows that the econometric method would recover a similar (albeit lower) scale of costs:

- The uncapped passenger and freight VUCs as per the engineering cost models would recover £366m per year based on 2021-22 traffic; and
- The estimated VUCs as per our preferred econometric models would recover £161m per year from passenger charges and £132m per year from freight charges, or £293m per year in total.

We caveat these indicative estimates because we have much more confidence in the robustness of the maintenance elasticities compared to the renewals elasticities, and we have more confidence in the robustness of the passenger translog results compared to the freight translog results.

The robustness of our maintenance results might raise questions about whether the assets excluded from the engineering approach enhance or limit its ability to fully capture the costs of maintaining and renewing the network in response to marginal changes in traffic, and this is an issue that ORR and Network Rail may wish to explore in any follow-up work. The engineering approach is consistent with Network Rail's understanding of the relevant legislation, and it might (in theory) provide a better estimate of marginal costs if excluded asset categories are only minimally affected by changes in traffic. It might be that the econometric method is picking up some 'synergy' in maintenance work, in that Network Rail plans maintenance inspections and activities to deliver outputs efficiently

[17] Other desirable properties of access charges include fairness and non-discrimination. Since this primarily relates to *how* the method is applied with respect to particular operators / customers (rather than the method itself), we do not comment on these properties except to note it would seem fair to address the mechanistic link between passenger traffic volumes and freight variable charges which is a feature of the current method. It would not be 'fair' for freight customers to pay increased variable charges when they are causing similar levels of damage to the network, simply because passenger traffic has fallen.

rather than delineating maintenance schedules according to whether they are ‘wear and tear’ or cyclical jobs. On the other hand, where the econometric method considers all maintenance and renewals costs (irrespective of whether they are considered ‘direct’) it may be revealing elasticity factors which are incorrectly omitted under the engineering approach.

7.2. Practicability, robustness and transparency of method

The ORR asked us to assess the merits of the econometric approach in terms of the practicability, robustness and transparency of method relative to the current engineering cost model. Our assessment is set out in turn below.

Practicability

The engineering cost model – of which VTISM is a central component – is self-evidently practicable in that it has formed the basis of VUC setting in previous periodic reviews and the method is broadly accepted by both Network Rail and ORR. The appropriateness of the VTISM model has been reviewed previously on ORR’s behalf.[18] The only minor concern that we observe about the engineering cost model is that its operation is relatively limited to Network Rail given that VTISM is primarily concerned with forming an engineering assessment of the long-term maintenance and renewals requirement to maintain track condition, performance and safety standards.

By contrast, we find that there is potential for the econometric method to be a practicable means for setting VUCs in future. But the data – specifically the absence of consistent renewals expenditure over the timeframe of our study at a sub-regional or route section level – does not support a practicable method for setting VUCs at present, except as a ‘cross-check’ and challenge of the engineering model.

Once the necessary data is available, the econometric method would be more ‘accessible’ in that it could be practicably operated and improved by both ORR and Network Rail. It requires some expertise in econometrics and input from staff with an understanding of the potential infrastructure related factors which affect variable costs, but it requires less specialist knowledge and could therefore be operated by ORR if desired. Aside from a more geographically granular view of renewals expenditure, we note that much of the data required for this analysis is either already used by ORR or is already produced by Network Rail for its own internal purposes.

Robustness

Our scope did not include a review of the robustness of the engineering cost model. However, we observe that the robustness of the current engineering-based approach has been challenged by the impact of the Covid-19 pandemic on passenger traffic and the mechanistic way that VUCs are calculated in the current VUC model. It results in an increase in VUC rates for freight traffic in CP7 which does not reflect changes in the damage that those operators cause to the network. In other words, although the approach ensures ex-ante that Network Rail recovers its estimated variable costs over CP7, the VUC methodology is not entirely robust to outlier events.

Therefore, a key aim of our study was to explore whether the econometric method could robustly estimate variable costs for passenger and freight traffic separately.[19] Our analysis shows that econometric models can provide robust estimates for maintenance costs, particularly for passenger traffic, but there are more significant concerns for renewals costs.

Maintenance Costs. For passenger-related maintenance costs, the econometric models produce statistically significant coefficients that remain consistent across different model specifications. In particular, both the sign and magnitude of these coefficients are plausible when using a log-log model, aligning with intuition and comparable

[18] Arup (June 2018) “Review of Network Rail’s CP6 Variable Usage Charge assessment” available at orr.gov.uk.

[19] In finalising our report, Network Rail told us that the engineering approach could be adjusted to calculate separate variable costs for passenger and freight traffic, but the current approach to calculating VUC rates does not incorporate this step. We recommend that the feasibility of this change be explored.

econometric studies. Furthermore, the results from the translog model, which demonstrates statistically significant and robust results, help address potential non-linearity concerns in the data.

However, achieving precise translog estimates for freight is challenging, which limits our confidence in the model's ability to represent non-linear relationships accurately. The coefficients' signs and magnitudes for freight suggest that relying solely on the log-log model could produce misleading results. Additionally, freight traffic appears less sensitive to recent variables, such as the Covid-19 dummy, likely due to a partial usage pattern on certain track sections. Although our primary goal is to evaluate variable costs rather than maximizing explanatory power, the relatively high R-squared gives us confidence that omitted variables do not introduce disproportionate bias. Notably, however, the robustness of the model for maintenance relies on including year-fixed effects or the Covid-19 dummy, which are variables not easily accounted for in all cases.

Renewals Costs. For renewals, the econometric approach is currently limited by sample size and the restricted degrees of freedom available to identify distinct impacts. Despite achieving high R-squared values, which could be misleading in this context, the lack of sufficient variation limits the model's ability to capture the nuances of renewals accurately. The current model only provides results for combined traffic, and although significant and plausible coefficients suggest further analysis could be worthwhile, the inability to separate passenger and freight effects is a notable drawback—especially given that the maintenance models and preliminary results indicate potentially important differences between these categories.

Although we are reasonably confident in the robustness of our results, we note that there are inherent data challenges with any econometric approach which might bias the results.

First, the dependent variable is based on "as-spent" costs rather than an exogenously determined renewals requirement. This could introduce bias if, historically, Network Rail had not spent sufficiently on renewals to maintain the required safety and performance standards. Given that Network Rail's business plans are assessed by ORR and the periodic reviews determine the efficient funding needed to operate, maintain and renew the network, we consider that it is reasonable to assume that this bias is not a material concern in our study. However, ORR should consider this factor in future updates to this analysis, as it paid particular attention to a planned reduction in renewals activity in Network Rail's CP7 SBP. Although it is expected that the average age of Network Rail's assets will increase as a result, ORR concluded that this increase was within acceptable bounds and that Network Rail would be able to maintain consistent network performance over CP7.[20]

Second, the analysis focuses on long-lived infrastructure assets across a relatively short time horizon (10 years). Whilst this ensures the relationships between costs, traffic and other infrastructure factors reflect recent conditions, it means the analysis may not fully capture the relevant trends and cycles in maintenance and renewals to the same extent as the assumptions in the VTISM model. This is one of the reasons why the econometrics would require a more sophisticated and geographically granular approach to regressing renewals expenditure against traffic.

Third, the econometrics demonstrates correlations between costs, traffic and other control variables (such as differences in infrastructure characteristics) but this does not necessarily imply causation, whereas causation is more evidentially demonstrated in the track deterioration evidence which informs the VTISM model. One potential risk with the econometric approach is that it is influenced by background growth in both traffic and expenditure variables, although the robustness of our maintenance results suggest that this risk is small.

Overall, we conclude that the econometric approach is robust with respect to maintenance costs and we take confidence from the fact that (including the renewals estimates) our study estimates a similar level of variable costs as that which is produced by the engineering cost models. But the renewals results are much less robust at present, particularly in relation to reporting separate elasticities for passenger and freight operators.

[20] ORR (October 2023) "PR23 final determination: sustainable and efficient costs", p.70., available at orr.gov.uk.

Transparency

A transparent method is one where it is reasonably straightforward to understand what drives changes in VUCs. One of the main criticisms levelled at the engineering cost model at present is that it lacks transparency given the many underlying engineering assumptions and the application of forward-looking overlays to fit with real world budget constraints. In discussions with us around the context to this study, ORR observed that at PR23 there were late-stage adjustments to the VTISM model which led to material changes in VUCs from CP6 to CP7. ORR noted in the PR23 final determinations that the large number of input variables to the VTISM model and the complex mechanism through which they interact with one another during and between control periods works against apportioning the drivers of the increase between freight and passenger in a precise manner and can lead to material changes in VUCs.[21]

Therefore, one of the key benefits of the econometric approach is that it would be a more transparent approach which is less subject to changes in the supporting assumptions. Unless these assumptions are well founded, there is a risk that they influence the resulting VUCs such that they are inconsistent with the empirical evidence on how maintenance and renewals expenditure react to marginal changes in traffic. For example, we envisage that ORR or Network Rail could publish the econometric models and the associated dataset, and external parties would be able to reproduce its results and subject them to critique and challenge. However, we also recognise that interpreting the results of econometric analysis brings its own challenges, in that there can be many relationships in the data and when the models produce unintuitive results, it can be challenging to isolate which relationships are likely responsible for those results and why. Moreover, the econometric approach also involves important decisions about methodology (many of which we have explored in this paper) which make certain assumptions about the underlying data.

7.3. Other considerations relevant to setting access charges

As part of any reform to the way that variable charges are determined, ORR will also need to consider whether changes to the methodology would impact on the other desirable properties of track access charges. For example:

- Access charges should **incentivise efficient use of a scarce resource**: access to the track infrastructure. Charges should ensure that operators run services only when the benefits of that service exceed the costs of providing it, and that each access slot is allocated to the most valuable use.
- Access charges should be reasonably **predictable**, to enable operators to plan services in advance and provide reasonable certainty on which they can invest in their rolling stock fleet and other key resources. This is particularly important for freight and open access operators.
- Access charges are a form of **Network Rail income** and should be sufficient (and sufficiently predictable given the nature of Network Rail's financial architecture) for the infrastructure manager to fund its efficient variable costs over a reasonable period.

We set out some considerations on each of these properties below.

Cost reflectivity and economic efficiency. At a high level, the engineering and the econometrics approach the same issue – the impact of additional traffic on the costs of maintaining and renewing the rail network – from different perspectives. As we explain in Section 2.3 above, both methods have their theoretical advantages and disadvantages. The main advantages of the econometric method are that it provides empirical evidence on the actual variability of Network Rail's costs with respect to traffic, and it allows the data to speak independently of any engineering assumptions or financial scenario constraints which might conceal the full costs.

[21] ORR (October 2023) "PR23 final determination: policy position – access charges" p.36., available at orr.gov.uk

In the context of the results reported in this study, we lack sufficient evidence to conclude that the econometric approach would improve the cost reflectivity of variable charges at present, although we see potential for further analysis which may produce more robust and valuable evidence on this issue.

Predictability of charges. Variable charges should be reasonably predictable in advance because they form a material component of the operating cost base for train operators. Most passenger operators now operate under a form of 'gross cost contract' (sometimes referred to as a "concession") structure with the Department for Transport (DfT), where they are not financially exposed to changes in access charging arrangements. But changes in variable charges are a concern for open access operators and freight operators who operate on a purely commercial basis, because they have a material impact on their operating cost base.

If variable charges became less predictable over time, open access and freight operators would have to manage their operating costs accordingly, even if demand for their services was relatively stable. Arguably, this would be a negative development, since industry and government share an ambition to decarbonise the transport sector by encouraging modal shift from road to rail, and because open access operators can play an important 'competitive' role in offering greater choice for passengers. In our view, the access charging framework needs to provide a fair and stable basis on which these more commercial operators can plan, manage and invest in their services.

Neither the engineering approach nor the econometric approach is clearly superior in this regard. Provided that the methodology remains relatively stable over time and the underlying evidence base evolves only gradually, both approaches ought to produce results which are reasonably predictable in advance. However, the issues encountered with the engineering approach at CP7 illustrate how extreme events such as the Covid-19 pandemic can impact the results in unpredictable ways. In our view, the main lessons from this experience is that there is an inherent risk of obtaining odd results when operating any model-based approach in a mechanistic fashion. One of the advantages of using the econometric evidence is that it could provide additional evidence for ORR to apply a reasonable amount of regulatory judgement in where to set VUCs when external circumstances undermine the stability of the engineering cost model.

Funding Network Rail's revenue requirements. Access charges are a form of income for Network Rail and VUCs are calibrated to enable Network Rail to recover its variable costs over a 5-year period. The variability of Network Rail's total income matters because it has a large and complex capital investment programme to deliver each control period. Efficient delivery of that programme requires it to plan that investment in advance and work closely with its supply chain partners to provide reasonable predictability of when that investment will occur. If Network Rail's in-year income falls, it may be required to cancel or defer certain works until later in the control period or the next control period, and this can be inefficient when done at short notice. Although Network Rail has some flexibilities within its financial architecture to 'smooth' variations in income from year to year, there are limits to its ability to manage fluctuations. It is possible that a material increase in the variability of Network Rail's income would increase its 'financial risk' requirement, which is effectively funded via the Network Grant (i.e., taxpayers).

Planned changes to the institutional structure of the rail industry will affect these financial flows. It is expected that, once fully established, Great British Railways (GBR) will specify the passenger train services currently directly contracted by the DfT as well as inheriting Network Rail's present role of infrastructure manager. Although longer-term access charging arrangements are still to be decided, it is expected that the future GBR infrastructure manager will be less exposed to changes in income from track access charges. It will still be exposed to income from freight and open access operators, but the scale of its overall exposure will be much reduced.

In that context, our study finds that the econometric method estimates variable costs of a similar scale to the engineering cost model, and therefore it may not have a material impact on the variability of Network Rail's income. However, this finding is subject to further improvement of the underlying renewals data. If further analysis suggests that an econometric approach would increase the variability of Network Rail's income, ORR will need to consider the trade-offs between any improvement in the economic efficiency and predictability of VUCs, against any increase in risk funding that Network Rail would require to mitigate the variability of income from access charges (noting that – over the longer term – the transition to GBR would remove much of this risk – albeit that GBR would then become exposed to the volatility of fares income – noting that fares income greatly exceeds that from VUCs today).

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7.4. Conclusions and recommendations

Overall, we conclude that the econometric results do not yet provide a sufficiently robust estimate of the relationships between passenger traffic, freight traffic and costs to support transitioning from an engineering-led approach to setting variable charges to an econometric-based approach. However, there is sufficient potential in the maintenance results to justify further exploration.

For renewals, the very small sample size (5 regions) is a severe limitation which limits our ability to control for differences in infrastructure features which determine the likelihood of need for renewals activity. Addressing this data availability limitation should be the focus of work going forward. The significant and plausible coefficients on the combined (passenger plus freight) traffic variable suggest that a more granular dataset should yield results which are more robust at a disaggregated passenger and freight level.

Although the econometric results do not yet provide a sufficiently complete picture of the causal relationships between traffic and costs, they do provide useful evidence which decision makers might take into consideration in respect of setting access charges. We take confidence in the statistically robust and plausible estimates of variable maintenance costs, the alignment of our maintenance results with results reported in the relevant literature, and the fact that our overall (maintenance + renewals) variable cost estimates are similar scale to those estimated by the engineering cost model at CP7.

We also understand – based on discussions with Network Rail – that the engineering approach could be evolved to separately estimate the impact of a given increase in passenger and freight traffic on required maintenance and renewals activities over the next 5-year control period, thereby addressing the main criticism of the current approach.

Therefore, rather than advocating for adopting an econometric method as the sole basis for setting VUCs in the near term, we would recommend using the econometric approach alongside the engineering approach to provide 'check and challenge' of the VTISM results. Whilst a like-for-like comparison between the two approaches is not possible, the combined framework would leverage the strengths of both methods, providing a more comprehensive and reliable evidence base for setting variable charges in future.

Recommendations

Building on the findings and conclusions from our study, we make a small number of recommendations which ORR and Network Rail should consider as part of any further work on reform of variable charges:

Recommendation 1: In the short-term, Network Rail should explore the feasibility of evolving 'Step 1' of the current engineering/VTISM-based approach to produce separate national passenger and freight usage charge rates, to address the issue that large changes in passenger traffic can drive material changes in freight charges.

Recommendation 2: Consider the evidence from the econometric models as a cross-check and challenge of the results of the engineering cost models. This will help to establish appropriate track access charges which are more transparent, predictable and robust without relying excessively on the mechanistic application of any one model.

Recommendation 3: To support the application of econometric methods to the analysis of Network Rail's costs, Network Rail should develop a tonne-km traffic dataset which covers at least the last 10 years. Whilst it might not be possible to develop a new dataset which is entirely consistent with how traffic weight was measured before CP6, a broadly comparable dataset will facilitate a more detailed econometric analysis of the impact of both train movements and weight, which is of practical relevance since 'wear and tear' is a function of both.

Recommendation 4: ORR may wish to encourage Network Rail to adopt a larger number of smaller 'sub-regional' units for reporting renewals expenditure and develop a more geographically granular renewals cost dataset. Although this would be a significant investment for Network Rail which will take time to develop, it is a necessary step in the application of econometric methods to robustly estimate the elasticity of Network Rail's costs to passenger and freight traffic.

To illustrate what this would mean if Network Rail were to adopt best practice from other European jurisdictions, SNCF Reseau records renewals expenditure at the track-section level, encompassing over 2,000 units of observation across the network (a similar level of disaggregation to the 'route sections' geography used in GBRTT's 'Industry Financial Model'). As we explain in Section 3.2, this enables a two-stage approach to the modelling of renewals expenditure which facilitates an analysis with more variation in terms of the key infrastructure characteristics which drive differences in costs between those units, and therefore helps to isolate the variations in cost which are driven by changes in traffic.

However, noting that 2,000 track/route sections would be a substantial change from Network Rail's approach to recording renewals expenditure today, we expect an improvement in the robustness of the analysis if Network Rail were able to disaggregate costs across 25–50 sub-regional units (i.e., similar to the number of MDU units).

Recommendation 5: ORR and Network Rail should work together to better understand the differences in results between the econometric and engineering approaches. They should also consider the appropriateness of key assumptions from the perspectives of setting economically efficient incentives for track access along with supporting Network Rail to manage the asset in an efficient way over the long-term.

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Appendix A DETAILED OUTPUTS

A.1. Variable Definition

Table A1 below summarises the variables included in the regression analysis for future replicability. These variables are calculated at both the MDU-level and the regional level for maintenance and renewals regressions respectively.

Table A-7-1: Description of Variables Used in Regression Analysis

Variable	Units	Description
Real Maintenance Expenditure	£ million, 2023-24 prices	Total expenditure on maintenance activities, adjusted for inflation to 2023-24 prices using the CPI index.
Real Renewals Expenditure	£ million, 2023-24 prices	Total expenditure on renewals activities, adjusted for inflation to 2023-24 prices using the CPI index.
Track length	km	Total length of railway track in kilometres. This is a scale variable, meaning units of observation with more track will likely incur higher costs.
Electrification	%	The percentage of track that is electrified. In isolation, we would expect electrification to increase maintenance costs due to the additional trackside infrastructure and increased complexity of maintenance work. However, there may be other interacting factors – including more intensive use, lower track age and lower curvature – which influence the magnitude and direction of the estimated parameters.
Embankments	%	The percentage of track that is constructed on raised ground (embankments). Track on embankments may incur higher costs due to the additional maintenance/renewal requirement of the earthworks, drainage, and engineering complexity.
Soil cutting	%	The percentage of track that involves cutting into soil to create the track bed, potentially increasing erosion-related costs.
Rock cutting	%	The percentage of track that involves cutting through rock, which may increase maintenance complexity and costs.
Low speed	%	The percentage of track classified as low-speed (<= 35 mph). The higher the speed on the track, the higher the wear and tear costs.
Mid-speed 1	%	The percentage of track classified as mid-speed (35-75 mph). The higher the speed on the track, the higher the wear and tear costs.
Mid-speed 2	%	The percentage of track classified as mid-speed (75-105 mph). The higher the speed on the track, the higher the wear and tear costs.
High speed	%	The percentage of track classified as high-speed (>= 105 mph). The higher the speed on the track, the higher the wear and tear costs and the lower the threshold for intervening to remedy alignment defects.
Avg. weight	lbs	The average weight of trains operating on the track, influencing track wear and maintenance needs.
Avg. track age	years	The average age of the railway track. In isolation, older track is more likely to need maintenance/renewals work. However, there is likely an interaction between the age of the track and the intensity of traffic, as Network Rail can leave track in situ longer in areas with lower traffic, before it needs to be replaced.
Avg. sleeper age	years	The average age of sleepers. Older sleepers are more likely to need maintenance/renewals work.

Variable	Units	Description
Avg. ballast age	years	The average age of ballast. Older ballast is more likely to need maintenance/renewals work.
Sleeper concrete	%	The percentage of sleepers made of concrete, known for durability and lower maintenance needs compared to other materials.
Sleeper wood	%	The percentage of sleepers made of wood, which may require more frequent maintenance due to wear and decay.
Sleeper metal	%	The percentage of sleepers made of metal. Metal sleepers are cheaper than concrete and have relatively low maintenance needs.
Wages	Median gross weekly pay (£)	Median gross weekly pay for full time workers. Higher wages will increase labour costs in the area.
Year	#	A set of dummy variables representing each individual year in the panel of observation. They capture external factors which are assumed to affect all units of observation (MDU or regions) equally in each year. In this case it captures the impact of Covid-19 which had a negative correlation with traffic. We would expect it to have a positive coefficient (with respect to maintenance and renewals) since the unpredictable nature of the disruption would have made it inefficient for Network Rail to reduce its maintenance and renewal expenditure entirely.

Source: CEPA analysis

A.2. Summary of control variables

Table A-2: MDU-level control variables

Variable	Count	Mean	SD	Min	Max
Track length (km)	350	841.0	347.0	349.0	1608.0
Electrification (%)	350	53.2	34.8	0.0	100.0
Embankments (%)	350	28.9	5.2	19.8	42.6
Soil cutting (%)	350	21.3	5.0	10.7	31.4
Rock cutting (%)	350	3.5	3.1	0.0	14.3
Low speed (%)	350	10.9	0.5	2.8	24.5
Mid-speed 1 (%)	350	51.1	17.6	19.7	76.7
Mid-speed 2 (%)	350	25.3	13.1	0.0	60.0
High speed (%)	350	12.7	17.1	0.0	54.1
Avg. weight (lbs)	350	112.7	2.1	105.4	117.7
Avg. track age (years)	350	25.5	5.5	14.0	41.6
Avg. sleeper age (years)	350	29.9	5.6	14.5	45.0
Avg. ballast age (years)	350	28.2	5.9	13.3	44.2
Sleeper concrete (%)	350	77.3	10.7	54.4	93.4
Sleeper wood (%)	350	14.0	6.8	4.2	33.3
Sleeper metal (%)	350	8.4	6.7	0.0	23.2
Median gross weekly pay	350	612.8	116.7	446.2	1137.7

Source: CEPA analysis

A.3. CEPA's Preferred Regression Approach

In this appendix sub-section we outline our preferred econometric approach in a first-best scenario without data availability constraints, outlining the forefront of econometric modelling in transport literature and the data required to achieve it. Data constraints mean that we are currently unable to adopt this approach, and instead adopt a feasible "second-best" approach (as described in Section 5).

Once the identified data limitations are addressed, the preferred approach can serve as a robust guide for estimating VUCs and applying econometrics more broadly within the rail industry.

Differences between the adopted approach and our preferred approach

To help illustrate how the 'second best' data constrained approach adopted in the study differs from our 'preferred approach' presented in Appendix A3, we use Table 5.1 below to summarise the key differences between the two.

Table 5.1: Differences in approach

	CEPA approach	Preferred approach	Reason for difference
Unit of observation	Annual MDU-level data for maintenance Annual region level data for renewals	Annual route section data	Data limitations. Neither traffic nor costs disaggregated further
Measure of traffic	Train-km	Tonne-km and train-km	Data limitations. Tonne-km traffic variables not available
Measure of costs	No disaggregation of maintenance but treat maintenance and renewals separately	Disaggregated maintenance (for robustness) and renewals	Data limitations. Maintenance and renewals not disaggregated further
Measure of controls	Control for both infrastructure and other cost drivers	Control for both infrastructure and other cost drivers	No difference
Maintenance regression model	Main results based off log-log, although still estimate translog for robustness	Translog to allow for non-linearities	Translog parameters cannot be accurately identified given data limitations
Unobserved heterogeneity	Estimate both fixed and random effects and use random effects if possible	Estimate both fixed and random effects and use random effects if possible	No difference
Renewals regression model	Linear regression model	Two-part approach to separately estimate probability and cost of renewals	Data limitations. Only observe renewals cost at region level so cannot observe route sections where renewals occurs.

Costs

Maintenance and renewals activities are fundamentally different. Maintenance involves routine tasks to keep existing assets in working order and prevent degradation, focusing on short-term, regular interventions. In contrast, renewals replace or significantly refurbish infrastructure components nearing the end of their useful life. This means that maintenance and renewals costs should be estimated using separate regressions, as they will have a different relationship with traffic.

Previous studies have further disaggregated maintenance costs into track maintenance, signalling, earthworks, and other maintenance costs (Odolinski et. al., 2023). This allows the researchers to estimate separate elasticities for different categories of maintenance costs, for example traffic and signalling. This is important because it can improve the precision of cost charging and supports more effective infrastructure planning. Our approach would run separate regressions for maintenance and renewals expenditure, and then a suite of models using disaggregated maintenance costs as a robustness check. However, this was not possible with the data available.

Maintenance regression

For maintenance expenditure, our preferred approach is to estimate the elasticity of maintenance costs with respect to traffic by estimating a translog model. A translog model is preferred to a simple log-log model because it allows the elasticity of maintenance costs with respect to traffic to depend on both passenger and freight traffic, which allows for economies of scale. While more complex, the translog model still provides interpretable results, and using OLS ensures replicability without the non-convergence issues associated with the Box-Cox model. Additionally, adopting the translog model aligns Great Britain with industry best practices, as countries like France use this approach for estimating marginal costs.

The translog model is represented in the equation below.

$$\ln C_{it} = \alpha + \beta_1 \ln Q_{it}^P + \beta_2 \ln Q_{it}^F + \beta_3 (\ln Q_{it}^P)^2 + \beta_4 (\ln Q_{it}^F)^2 + \beta_5 \ln Q_{it}^P \ln Q_{it}^F + \boldsymbol{X}_{it}\gamma + \delta_t + u_i + v_{it}$$

Year fixed effects (δ_t) are included to capture economy wide trends that are common to all units (i.e track section). We model unobserved heterogeneity u_i using fixed effects (FE) and random effects (RE). Q_{it}^P is a measure of passenger traffic while Q_{it}^F is a measure of freight traffic. Our preferred metric for measuring traffic is gross tonne-km, as train weight is a key factor in track wear and associated costs. This measure more accurately reflects the relative impact of passenger versus freight trains on track infrastructure, given that freight trains are generally much heavier and thus contribute more significantly to track damage than passenger trains. However, Network Rail told us that tonne-km traffic data was not available on a consistent basis over the window of our study.

The elasticities of interest from the translog model are derived by differentiating the cost function with respect to passenger and freight traffic, as shown below.

$$\varepsilon_{it}^P = \frac{\Delta \ln C}{\Delta \ln Q_{it}^P} = \beta_1 + 2\beta_3 \ln Q_{it}^P + \beta_5 \ln Q_{it}^F$$

$$\varepsilon_{it}^F = \frac{\Delta \ln C}{\Delta \ln Q_{it}^F} = \beta_2 + 2\beta_4 \ln Q_{it}^F + \beta_5 \ln Q_{it}^P$$

Renewals regression

The preferred approach to estimating the elasticity of renewals expenditure requires a two-part approach. This is due to the lumpy and infrequent nature of renewals on any track or route section. The two-part approach separately models the probability of any renewals occurring on a track or route section each year, and conditional on renewals occurring, the cost of those renewals. This approach is discussed in detail by Odolinski et al (2020).

The first stage models the probability of renewals occurring as a function of traffic and a relevant set of controls. This is presented in the equation below.

$$P(C_{it} > 0 | Q_{it}^P, Q_{it}^F, \boldsymbol{X_{it}}) = \Phi(\beta_0 + \beta_1 \ln Q_{it}^P + \beta_2 \ln Q_{it}^F + \boldsymbol{X_{it}}\gamma + \delta_t + v_{it})$$

Where Φ is the standard normal cumulative distribution function (CDF). This is a probit model and can be estimated using maximum likelihood.

The second stage models the cost of renewals conditional on it occurring as a function of traffic and a relevant set of controls.

$$\ln C_{it} | C_{it} > 0 = \alpha_0 + \alpha_1 \ln Q_{it}^P + \alpha_2 \ln Q_{it}^F + \boldsymbol{X}_{it}\pi + \psi_t + v_{it}$$

This part can be estimated by running OLS on the restricted sample that contains only observations with positive renewals. Notice that the parameters are different in both stages of regression, meaning that the relationship between traffic (or controls) and the probability of renewals is allowed to be different to the relationship between traffic (or controls) and the cost of renewals. For example, track age likely predicts the probability of renewals but may not predict the cost of renewals.

Note that the Tobit model is very similar to the model described above but restricts $\alpha = \beta$ so the effect of traffic on the probability of renewals and the cost of renewals is the same.

The marginal effects of traffic are

$$ME_{it}^{P} = \beta_1 P(C_{it} > 0) + \alpha_1$$

$$ME_{it}^{F} = \beta_2 P(C_{it} > 0) + \alpha_2$$

The elasticities of interest can then be calculated as

$$\varepsilon^{P} = \frac{\sum_{it} ME_{it}^{P} Q_{it}^{P}}{\sum_{it} C_{it}} \quad \text{and} \quad \varepsilon^{P} = \frac{\sum_{it} ME_{it}^{F} Q_{it}^{F}}{\sum_{it} C_{it}}$$

The appropriate measure of traffic for the renewals model is not immediately clear. It is unlikely that train weight directly drives renewals costs or renewal likelihood in the short run. However, current traffic weight is likely highly correlated with historical weight, which may influence the need for renewals. Conversely, measuring traffic in train-km may better capture the cost of a possession, which could represent the primary variable cost in renewals activities that typically require multi-year planning.

Totex modelling

Running separate regressions for maintenance and renewals aligns with the methodology used in other studies and provides flexibility to tailor the econometric approach according to differences in Network Rail's planning processes. For example, we can incorporate time ths in the renewals model to account for longer planning cycles typical of larger renewals projects. However, we recognise that there is also an asset management 'trade-off' between maintenance and renewals, in that a well-maintained asset may last longer (and vice versa, timely renewals will reduce maintenance costs) such that a responsible asset manager seeks to minimise whole life, whole system total costs. Therefore, we would also recommend conducting total expenditure (totex) regression modelling as a robustness check to capture potential interdependencies. Unfortunately, the inclusion of renewals in the totex model introduces the same data limitations encountered in the renewals regression, making the totex results less robust under current conditions. We recommend conducting totex modelling once the data limitations are addressed to achieve more reliable insights into the trade-offs between maintenance and renewals expenditure.

A.4. REGRESSION SENSITIVITIES

Table A-3: Maintenance sensitivity analysis

Dependent variable	Covid Dummy	CP7 Dummy	Time trend
Log maintenance expenditure	RE	RE	RE
Log passenger train-km	10.208**	12.200***	10.953**
	(4.858)	(4.496)	(4.764)
Log passenger train-km squared	-0.300**	-0.359***	-0.329**
	(0.133)	(0.122)	(0.130)
Log freight train-km	0.786	0.776	0.383
	(1.384)	(1.310)	(1.334)
Log freight train-km squared	-0.020	-0.013	-0.010
	(0.022)	(0.021)	(0.024)
Log passenger * log freight train-km	-0.011	-0.022	-0.003
	(0.080)	(0.071)	(0.077)
Time trend			0.028***
			(0.008)
Covid Dummy	YES	NO	NO
CP7 Dummy	NO	YES	NO
Constant	-93.497**	-111.055***	-93.742**
	(45.867)	(41.639)	(44.153)
Observations	350	350	350
Number of id	35	35	35
Controls	YES	YES	YES
R-squared	0.540	0.551	0.514

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Including year fixed effects in panel regressions can be a straightforward way to control for time-specific shocks affecting all units equally, such as macroeconomic conditions or broad policy changes. However, blindly applying year fixed effects has drawbacks: it can absorb meaningful variation that might otherwise reveal trends or effects specific to particular periods, and it may mask the influence of critical time-related events that affect only certain years or periods in a unique way, like a pandemic or regulatory shifts. In this context, replacing year fixed effects with targeted dummies (such as a Covid dummy, regulatory cycle dummy, or a time trend with a squared term) helps to capture relevant temporal effects more precisely, potentially improving the interpretability of the model.

In the sensitivity analysis, three alternative models replace year fixed effects with targeted time variables to account for specific temporal influences on maintenance expenditures. The first model includes a Covid dummy for 2020-2023. This alternative does not appear to significantly impact the coefficients on the primary variables (passenger and freight train-km), which remain comparable to those in the year fixed effects model, though the within R-squared decreases slightly from 0.583 (with year fixed effects) to 0.540. This suggests that while the Covid period captures some temporal effects, year fixed effects provide a slightly better model fit by capturing additional year-specific variation beyond just the pandemic period.

The second model includes a CP7 dummy for 2019-2023, which has a more noticeable impact on the passenger coefficient compared to the Covid dummy, though the overall results remain broadly similar. The choice between these two dummies depends on the assumed timing of a structural break in the relationship between maintenance costs and traffic. Again, the R-squared decreases slightly to 0.551, suggesting that year fixed effects provide a slightly better model fit.

The third model introduces a linear time trend term t, capturing a continuous time effect rather than discrete year or event-based controls. Here, the linear time trend is positive and significant at the 1% level, indicating an upward trend in maintenance expenditures over time. This model also shows a slight reduction in explanatory power (R-squared of 0.514) compared to the year fixed effects model, though it retains similar passenger-km coefficients.

Regulators often use time trends to estimate efficiency, as the time trend reflects the annual increase in costs after accounting for all other relevant cost drivers. However, in this context, interpreting a positive time trend as cost inefficiency requires caution. This is because the model may not capture potential uncontrollable factors that drive additional costs. For instance, if Network Rail faces an increased need for maintenance or renewals due to external demands, costs may rise each year even if operational efficiency improves. Therefore, a positive time trend could reflect rising maintenance demands rather than inefficiency.

Overall, the findings suggest that year fixed effects provide the best fit for capturing year-by-year variation in maintenance expenditures. However, when there is concern about over-fitting or losing interpretability with year fixed effects, the Covid dummy and time trend offer reasonable alternatives that capture key time effects without masking specific trends.

Table A-4: Renewals sensitivity analysis

Dependent variables	Log-Log	Log-Log
Log renewals expenditure	RE	RE
Log passenger train-km	0.507*	0.327
	(0.264)	(0.418)
Log passenger train-km (lag)		0.233
		(0.163)
Log freight train-km	-0.374**	-0.131
	(0.174)	(0.185)
Log freight train-km (lag)		-0.188
		(0.263)
Year FE	YES	YES
Constant	-1.267	-2.691
	(5.938)	(6.862)
Observations	50	45
Number of id	5	5
Controls	YES	YES
R-squared	0.917	0.912

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

We examined the use of lagged traffic variables to account for the fact that renewal costs are often scheduled in advance and can be irregular. By including lags, we aimed to isolate the short-run marginal cost of traffic on renewals. However, incorporating lags reduced our sample size by 10% (5 out of 50 observations per lag), limiting the number of lags we could include. The model with lagged passenger and freight traffic shows that while the inclusion of lags does not change the sign of traffic elasticities, it does reduce their magnitude by distributing the effect over two years. Notably, the coefficients in these lagged models are statistically insignificant.

A.5. Hausman test for FE vs RE

We conduct the Hausman test to identify the preferred panel data model, testing specifications without controls for simplicity. We note that our regression results remain consistent and exhibit greater precision when controls are included. The null hypothesis for the Hausman test is that there is no systematic difference between the coefficients of the fixed effects and random effects models. If we fail to reject the null hypothesis, the random effects model is preferred, as it is both efficient and consistent under this condition. Conversely, if we reject the null, it indicates a systematic difference between the coefficients, favouring the fixed effects model as it provides consistent estimates in this case. The hypotheses for the Hausman test are as follows:

$$H_0: E[\,(\beta_{FE} - \beta_{RE}) \mid X\,] = 0$$

$$H_1: E[\,(\beta_{FE} - \beta_{RE}) \mid X\,] \neq 0$$

The test statistic is calculated as shown below and is distributed chi squared.

$$H = (\beta_{FE} - \beta_{RE})^T (V_{FE} - V_{RE})^{-1} (\beta_{FE} - \beta_{RE})$$

β_{FE} is the FE estimator that is known to be consistent and β_{RE} is the RE estimator that is only consistent (and efficient) under the null.

The table below presents our Hausman test results. We find that we do not reject the null hypothesis for any of the models for maintenance, indicating that the RE model is preferred. In our main results, the RE model not only fits the data best, as shown by the highest R-squared values, but also identifies significant relationships, reflecting its greater efficiency compared to the FE estimator. This efficiency advantage allows the RE model to capture associations with higher precision, further supporting its selection as the preferred approach in our analysis. For our renewals regression, the model failed to meet the asymptotic assumptions required for the Hausman test. As a result, we are unable to comment on the preferred model based on this test.

Table A-5: Hausman test of FE vs RE

Model	Cost	Test statistic	Prob > test stat	Decision	Preferred model
Translog	Maintenance	13.46	0.413	Do not reject null	RE
Log-log	Maintenance	12.30	0.342	Do not reject null	RE
Log-log	Renewals	Failed to meet asymptotic assumptions	N/A	N/A	N/A

Source: CEPA analysis

A.6. Full Maintenance Regression Results

For completeness, we present the full regression results from our log-log and translog models with random effects. It is important not to overemphasize the significance of individual control variables, as these controls are included primarily to account for economically relevant cost drivers. Some controls may capture overlapping effects, reflecting shared influences on costs rather than distinct causal relationships.

Table A-6: Full maintenance regression results

Dependent variable	Log-log	Translog
Log maintenance expenditure	RE	RE
Log passenger train-km	0.264***	10.555**
	(0.060)	(4.795)
Log passenger train-km squared		-0.311**
		(0.132)
Log freight train-km	0.095**	0.784

	(0.039)	(1.310)
Log freight train-km squared		-0.020
		(0.023)
Log passenger * log freight train-km		-0.011
		(0.075)
2015 year	-0.014	-0.014
	(0.016)	(0.015)
2016 year	0.031	0.028
	(0.023)	(0.022)
2017 year	0.041	0.033
	(0.032)	(0.032)
2018 year	0.008	0.006
	(0.028)	(0.027)
2019 year	0.109***	0.110***
	(0.041)	(0.040)
2020 year	0.215***	0.207***
	(0.054)	(0.054)
2021 year	0.203***	0.191***
	(0.057)	(0.059)
2022 year	0.232***	0.220***
	(0.064)	(0.064)
2023 year	0.215***	0.208***
	(0.069)	(0.068)
Log track km	0.222**	0.212**
	(0.088)	(0.091)
Log wages	0.190**	0.137**
	(0.077)	(0.063)
Proportion electrified	0.158**	0.111
	(0.078)	(0.082)
Proportion embankment	-0.605	-0.160
	(0.579)	(0.706)
Proportion soil cutting	1.377**	1.221*
	(0.640)	(0.637)
Proportion rock cutting	-3.700***	-4.185***
	(1.022)	(1.122)
Log average track weight	-2.526	-0.963
	(3.706)	(3.592)
Log average track age	-0.050	-0.110
	(0.289)	(0.292)
Log average sleeper age	-0.130	0.155
	(0.666)	(0.630)
Log average ballast age	-0.071	-0.241
	(0.445)	(0.421)

Proportion sleepers concrete	2.863	2.930
	(2.564)	(2.877)
Proportion sleepers wood	2.342	2.440
	(2.759)	(3.032)
Proportion sleepers metal	2.489	2.718
	(2.683)	(3.035)
Proportion of low-speed track	1.422**	1.453**
	(0.602)	(0.634)
Proportion of high-speed track	0.172	0.011
	(0.279)	(0.324)
Proportion of mid-speed (1) track	0.564**	0.520
	(0.288)	(0.360)
Constant	4.544	-90.979**
	(17.257)	(44.285)
Observations	350	350
Number of id	35	35
Year FE	YES	YES
Controls	YES	YES
Overall R-squared	0.771	0.722

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix B SCOPE OF WORK

Table A-7: Scope of work

Scope of work	
01	Conduct a literature review outlining how European regulators/infrastructure managers calculate the charges to recover costs directly incurred.
02	Consider the level of granularity required to build a robust econometric model, liaising with Network Rail on the availability of the necessary data.
03	Assess the advantages and disadvantages of using these inputs compared with those used in other countries and how this is expected to affect the robustness of findings, including in comparison with the current engineering approach.
04	Collect data (preferably panel data on Network Rail's maintenance and renewals costs and cost drivers at an appropriate level of granularity) and build a robust econometric model that informs the calculation of variable usage charges for passenger and freight operators.
05	Based on the results, estimate (i) the expected direct (marginal) costs of running the Network Rail network; (ii) the marginal costs for passenger and for freight traffic; (iii) the individual VUCs in the format of a price list (covering passenger and freight vehicles); and (iv) compare this price list with the CP7 price list which was produced using the engineering models in PR23.
06	Analyse the econometric model's sensitivity to its key assumptions and input variables.
07	Assess the merits of the econometric approach in terms of practicability, robustness, and transparency relative to the current engineering cost-model.

Source: ORR

Appendix C BIBLIOGRAPHY

Andersson, M., Smith, A., Wikberg, A., and Wheat, P. (2012). “Estimating the marginal cost of railway track renewals using corner solution models.” *Transportation Research Part A: Policy and Practice,* 46(6): 954-964.

Arup (2018) “Review of Network Rail’s CP6 Variable Usage Charge Assessment”, p.25. Available at orr.gov.uk.

Bellego, C., Benatia, D. and Pape, L. D. (2022). “Dealing with Logs and Zeros in Regression Models.” *CREST - Série des Documents de Travail.*

Christensen, L., Jorgenson, D. and Lau, L. (1973). “Transcendental Logarithmic Production Frontiers.” *The Review of Economics and Statistics,* 55(1), 28-45.

Commission Implementing Regulation (EU) 2015/909. (2015) “On the modalities for the calculation of the cost that is directly incurred as a result of operating the train service” available at www.legislation.gov.uk

Frontier Economics (2017). “Estimation des Couts Marginaux d’Entretien du Reseau Ferre National », available at frontier-economics.com

Gaudry, M. and Quinet, E. (2009). “Track wear-and-tear cost by traffic class: Functional form, zero output levels and marginal cost pricing recovery on the French rail network.” PSE Working Papers, n2009-32.

Goldberger, A. (1968). "The Interpretation and Estimation of Cobb-Douglas Functions." *Econometrica*, 36(3), 464-472.

Hausman, J. (1978). “Specification tests in econometrics.” *Econometrica,* 46(6): 1251-1271.

Network Rail (2022). “Network Rail’s consultation on regulated access charges in Control Period 7 (CP7).” Available at: networkrail.co.uk

Odolinski, K., Nilsson, J., Yarmukhamedov, S., and Haraldsson, M. (2020). “The marginal cost of track renewals in the Swedish railway network: Using data to compare methods.” *Economics of Transportation,* 22, 100170.

Odolinski, K., Smith, A., Wheat, P., Nilsson, J., and Dheilly, C. (2023). “Damage or no damage from traffic: Re-examining marginal cost pricing for rail signalling maintenance.” Transport Policy, 131, 13-21.

Office for National Statistics. (2024). *Annual Survey of Hours and Earnings (ASHE) dataset*. Median weekly pay (gross) by local authority district.

ORR (2023). “PR23 Final Determination: Policy position – access charges”, p.35. Available at: orr.gov.uk.

ORR (2024) “Passenger rail usage – April to June 2024”, available at orr.gov.uk.

ORR (2024) “Freight rail usage and performance – April to June 2024”, available at orr.gov.uk.

Serco (2012). “Vehicle Track Interaction Strategic Model – VTISM overview” available at networkrail.co.uk.

Silavong, C., Guiraud, L. and Brunel, J. (2014). “Estimating the marginal cost of operation and maintenance for French railway network.” ITEA Conference Paper.

Smith, A., Odolinski, K., Wheat, P. and Dheilly, C. (2024). “Why the Fixed-Effects Estimator May Not Be the 'Gold Standard' for Estimation of Economies of Density in Rail Transport: An Application from Rail Infrastructure Maintenance Data in France.” *Journal of Transport Economics and Policy*, 58 (2), 207-226.

Smith, A., Wheat, P., Walker P. and Marti, M. (2016). “Modelling railway infrastructure maintenance cost in France: Overview of estimates.” Final Report for SNCF Réseau.

SNCF Reseau. (2023) “Charging Principles of Minimum Services.”

Wheat, P. and Smith, A. (2008). “Assessing the Marginal Infrastructure Maintenance Wear and Tear Costs for Britain's Railway Network.” *Journal of Transport Economics and Policy,* 42 (2): 189-224.

Wheat, P., Smith, A., Nash, C. (2009). “D8 – Rail Cost Allocation for Europe.” CATRIN.

Wheat, P., Smith, A., and Matthews, B. (2015). “D5.3: Access Charge Final Report.” SUSTRAIL.

Winkelmann, R. (2008). “Econometric Analysis of Count Data.” *Springer Science & Business Media.*

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