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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

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Abstract

The past literature on the structure of railway costs has emphasised that estimates of economies of density should be derived from fixed effects estimation (within-variation); see e.g. Caves et. al. (1985). This paper proposes instead that exploitation of between-variation is required to estimate economies of density in railway datasets because of the need to capture the step-function impact of traffic on preventative maintenance regimes. Our empirical case is based on a panel dataset of 1149 track sections (2013–2018) for the French rail network. The work is important in the policy context in terms of setting rail track access charges in line with marginal cost principles and also meeting EU legislative requirements; and has implications for the wider rail cost function estimation literature.

Keywords: economies of density; preventative maintenance; rail infrastructure; marginal cost; fixed effects; between effects

1.0 Introduction

There exists a long and established literature studying the cost structure of vertically-integrated railways, inter alia to produce estimates of economies of scale and density, comparative efficiency analysis, and assessment of the impact of rail reforms internationally (especially with respect to Europe and the US; see e.g. Caves et al., 1985; Gathon and Perelman, 1992, Sanchez and Villarroya, 2000; Mizutani and Uranishi, 2013; Cantos et. al., 2010; Smith et. al., 2018; Bougna and Crozet, 2016; Fitzova, 2020). European rail reforms, starting in the mid-1990s saw vertical separation of infrastructure from operations (of various forms), combined with competition on the common infrastructure, thus creating the need for the setting of a price for access to the rail infrastructure (or track access charge). EU legislation requires track access charges to be based on marginal cost principles, with the short run marginal wear and tear cost of vehicles running on the network (referred to in the legislation as "direct costs") forming the starting point (Single European Railway Area Directive (2012/34/EU)).

This requirement has prompted increased academic interest in the cost structure of railway infrastructure, focusing in particular on using cost function estimation to estimate economies of density (the reciprocal of the elasticity of rail infrastructure costs with respect to traffic) in order to obtain an estimate short run marginal cost. In a seminal paper by Johansson and Nilsson (2004), estimates of marginal maintenance costs for the Swedish and Finnish railway networks were produced using econometric techniques. This work has been followed by a number of studies, such as Wheat and Smith (2008), Andersson (2008), Gaudry and Quinet (2009), Link (2009), Wheat et. al. (2019), Marti et al. (2009), Odolinski and Nilsson (2017), adding multiple case studies, methodological developments and generalisation of results. Further, SNCF Réseau and several other infrastructure managers in Europe have used such econometric cost function studies to set track access charges (see. e.g. Walker et. al., 2020)[1]. Whilst the econometric research in this area has focused on the EU, there exists a broader literature on rail competition and the importance of non-discriminatory access to (and pricing of) rail infrastructure in a broader range of countries, including the US, China and Russia (see e.g. Pittman, 2004 and 2010; Kang et. al., 2021).

It is important to note that the charging principles of the European Commission focus on short-run marginal cost – that is, the incremental cost of running an extra train service on a fixed network. Likewise, in the general rail cost function literature, the concept of economies of density is defined as the reciprocal of the elasticity of costs with respect to traffic levels, holding the network fixed (see e.g. Caves et. al., 1985). A key principle in the academic literature – as set out in the seminal paper of Caves et. al. (1985) – is that economies of density (a short-run concept) should be estimated using the fixed effects estimator (utilising within-variation in the data). This point reflects the fact that traffic may be correlated with unobserved network characteristics that vary across the cross-section, such that utilisation of between-variation in the data runs the risk of introducing bias, since the network does not remain fixed in the cross-sectional dimension (for example, if higher traffic levels require track enhancements to accommodate demand and minimize costs in the long run).

In this paper we challenge the notion that between-variation in datasets should be ignored when computing economies of density and in turn short-run marginal costs for rail infrastructure usage – and indeed to argue that between-variation is necessary for estimation of these quantities. The reason is that rail infrastructure costs comprise both preventative (inspections, grinding, tamping etc.) and corrective (or reactive) maintenance elements and both aspects should form part of short-run marginal cost. Rail infrastructure managers typically determine their preventative maintenance strategies based on assigning parts of the network a

[1] The legislation permits use of econometric, engineering or accounting methods to determine marginal costs (European Commission (2012): Directive 2012/34/EC Recast of the First Railway Package.

different "line category" based on whether the traffic level falls within certain traffic bands or ranges. Observed rail infrastructure maintenance costs can therefore be seen to comprise a mix between a continuous function (corrective maintenance) and a step function (preventative maintenance) as track sections move from one line category to another.

However, in panel datasets, changes in line category would rarely be observed for a given track section over time (within-variation) since preventative maintenance activities are not typically adjusted with respect to small (and perhaps temporary) changes in traffic. Therefore fixed effect estimates can only pick up changes in corrective maintenance as traffic increases; and in turn use of the between-variation in the data is needed in order to capture the preventative maintenance element of marginal cost, because it is only through the between variation that we observe changes in preventative maintenance regimes.

Thus we argue that in fact the danger in rail infrastructure cost applications is that fixed effects estimation under-estimates the traffic elasticity (over-states economies of density) and short-run marginal cost because it ignores the cross-sectional variation in preventative maintenance regimes. There is thus a motivation for the use of between-variation in rail infrastructure cost applications – this argument running counter to the argument of the key Caves et. al. (1985) study, which emphasised the importance of fixed effects for obtaining measures of economies of density in railways.

Indeed, our argument that the between estimator should be preferred is analogous to the argument put forward by Caves et. al. (1985) for preferring the between estimator for estimating economies of scale in rail datasets. As Caves et. al. (1985) argued, when network size changes across the cross-section (between variation), there will likewise be associated changes in unobserved network effects that are correlated with network size. In this sense then, in the Caves et. al. (1985) work, the between estimator is a "biased" estimate of the pure cost effect of scale because it includes the cost effects of the associated unobserved network effects.

However, its use allows the variation in unobserved network characteristics to be correctly conflated with the pure network size effect. Thus the "biased" estimator is good because it gives the most accurate assessment of what really happens to costs when network size changes in practice.

In our case we have controlled for network characteristics through the inclusion of an extensive set of control factors, so such bias is not of concern. However, when traffic increases across the cross-section (between variation) we argue that there are associated, and in most datasets, unobserved effects relating to the cost impact of changes in preventative maintenance regimes, and that these are correlated with traffic. Thus the traffic elasticity is "biased", in the same sense as highlighted by Caves et. al. (1985) in respect of the estimation of economies of scale, but is useful because it allows the unobserved preventative maintenance effects to be correctly conflated with the estimate of a pure traffic effect (where the latter captures only reactive maintenance). So as with the Caves et. al. (1985) scale estimator, a "biased" estimator for economies of density in rail infrastructure maintenance turns out to be good, as we do not seek to estimate a pure traffic effect, but rather one that also captures the additional impact from changes in preventative maintenance across the cross-section.

We make use of a panel dataset from the French railway network during the years 2013–2018. Importantly, given our utilisation of the between-variation in the data, our dataset comprises an extensive set of control variables reflecting differences in the capability / characteristics of the different parts of the network, thus guarding against the danger of omitted variable bias in the traditional sense (that is avoiding capturing changes in costs related to changes in the fixed infrastructure). This means we can be confident that our estimates of economies of density and marginal cost are obtained whilst holding the infrastructure fixed and thus reflect short-run and not long-run estimates; whilst nevertheless capturing the steps in preventative maintenance that are a legitimate part of short-run cost effect of traffic that we want to estimate. We compare the estimates of economies of density and marginal costs using fixed effects, the between estimator, and random effects; also including variables to capture changes in preventative maintenance regimes to demonstrate their impact and support the argument in the paper.

In the remainder of the paper, Section 2 presents a brief literature review to position our work. Section 3 explains the important UIC line category variables used in the model and how they relate to traffic and preventative maintenance regimes, with the rest of the dataset presented in section 4. The translog cost function method is set out in section 5, while the results are shown in Section 6. Section 7 concludes.

2.0 Literature review

The estimation of the marginal costs of rail infrastructure has received a great deal of interest in the literature. This interest stems from the European Commission's policy of growing competition in rail, which requires some form of vertical separation of infrastructure from operations, in turn prompting the question of how to set track access charges. Following the seminal paper of rail maintenance marginal costs in Sweden and Finland (Johansson and Nilsson, 2004) a substantial academic literature has followed. Indeed, this academic work played a role in shaping EU legislation, which requires that access charges are based on direct costs (which can be interpreted as short-run marginal costs; Nash, 2005), and that econometric cost function or engineering methods may be used to estimate direct costs[2]. In addition to the references noted in the introduction, for a recent summary of this literature see Smith and Nash (2018). The rail infrastructure cost literature forms part of the wider literature on rail cost function analysis and cost structure and similar methods have been adopted across both literatures (see e.g. Caves et al., 1985; Wilson and Bitzan, 2003; Gathon and Perelman, 1992,

[2] European Commission (2012): Directive 2012/34/EC Recast of the First Railway Package.

Sanchez and Villarroya, 2000; Mizutani and Uranishi, 2013; Cantos et. al., 2010; Smith et. al., 2018; Bougna and Crozet, 2016; Fitzova, 2020).

Here we focus on the key issues relevant to this paper. The main methodological tool used to derive estimates of the elasticity of cost with respect to traffic / economies of density and in turn marginal cost has been either the translog cost function (also with testing of the Cobb-Douglas model; see section 5) or in some cases Box-Cox / Box-Tidwell models. Here it should be noted that the translog cost function is also the workhorse of the cost modelling literature more generally, not just in rail or transport (see e.g. Coelli at. al., 2005). The rail infrastructure cost literature has typically utilised high disaggregated track section data (see section 4), which means that the number of observations is plentiful, thus supporting the use of flexible functional forms.

Given the focus on economies of density and short-run marginal cost, a key issue is to obtain an estimate of the impact of additional traffic on rail infrastructure maintenance costs, holding the network fixed (in terms of its capability / characteristics). In a key study in the early, general rail cost function literature, Caves et. al. (1985) argued that in order to obtain unbiased estimates of economies of density, fixed effects estimation should be used. This point reflects the fact that traffic may be correlated with unobserved network characteristics that vary across the cross-section.

However, in the rail infrastructure cost literature, fixed effects models do not always produce sensible results and hence random effects is often used (see e.g. Wheat et. al., 2009; Walker et. al., 2020). This may occur, for example, if there is limited within-variation in traffic and other variables (e.g. linespeed capability) in the model. The same applies to wider vertically integrated railway systems applications where random effects (or pooled panel data methods[3]) are widely used (see e.g. Sanchez and Villarroya, 2000; Mizutani and Uranishi, 2013). More

[3] Pooled panel data methods such as pooled OLS makes the same assumption as random effects – namely that any unobserved firm effects are uncorrelated with the regressors.

widely, whilst use of fixed effects can ensure unbiased estimates when working with panel data, the general econometrics literature acknowledges that the choice of fixed versus random effects is not just a simple choice involving the computation of a Hausman statistic, but also reflects a trade-off between bias and precision (see e.g. Taylor, 1980). For this reason random effects may sometimes be preferred, even when there is a concern over potential bias.

The widespread use of random effects models in the rail infrastructure cost literature is mitigated by the extensive list of control variables available for such studies to guard against omitted variable bias (such as maximum linespeed; maximum axle load; rail weight; proportion of electrification; see e.g. Link, 2008). Nevertheless, there remains concern that reliance on random effects (and therefore the utilisation of between-variation as well as within-variation) may be biasing estimates of the traffic elasticity and marginal cost upwards, given that not all heterogeneity across track sections can be controlled for. This is particularly the case given that fixed effects estimation tends to produce either statistically insignificant results or much lower traffic elasticities (see for example, Wheat et. al., 2009; Wheat and Smith, 2008; Odolinski and Smith, 2016).

The above discussion then forms the entry point for our work which argues that whilst the choice of fixed or random effects is a complex balancing act between the dangers of omitted variable bias on the one hand and imprecision on the other (as with any panel data application), a strong argument in favour of utilising between-variation is the fact that it is able to capture variations in preventative maintenance regimes which fixed effects cannot. Rail infrastructure managers typically determine their preventative maintenance strategies based on assigning different parts of the network a different “line category”; and whilst these vary across the cross-section, changes in line category would rarely be observed for a given track section over time.

As described in more detail in section 3, variations in preventative maintenance strategies across the line categories can be seen as a valid part of short-run marginal cost, since the regime responds to changes in the level of traffic and not to any changes to the fixed infrastructure. Thus we argue that in fact the danger in rail infrastructure cost applications is that fixed effects estimation under-estimates the traffic elasticity (over-states economies of density) and short-run marginal cost because it is ignores the cross-sectional variation in preventative maintenance regimes. This point therefore provides a motivation for the use of between-variation in rail infrastructure cost applications – and runs counter to the argument of the key Caves et. al. (1985) study, which emphasised the importance of fixed effects for obtaining measures of economies of density in railways - as the remainder of the paper demonstrates. As noted in the introduction, however, our argument is analogous to the argument used by Caves et. al. (1985) for the use of the between estimator to capture estimates of economies of scale, but here applied to economies of density estimation.

3.0 Preventative maintenance and UIC[4] categories

Asset management typically involves preventative maintenance that detects and fixes defects before corrective maintenance is required. Examples of preventative maintenance activities on rail infrastructure are inspections, grinding, tamping, and minor replacements (major replacements are often termed renewals). The timing and volume of these activities are based on some type of prediction of the assets' condition and the consequences of a failure. Traffic volume and vehicle speed are important factors since they increase the deterioration of the infrastructure, *ceteris paribus*. These will also imply more train delay minutes if an infrastructure failure occurs.

These two predictors – volume and speed – are used in a UIC code developed to classify railway lines for the purpose of track maintenance (UIC, 2009), which are used by

[4] UIC refers to the International Union of Railways (https://uic.org/).

SNCF Réseau. Specifically, this code defines a set of UIC categories based on a traffic measure (T_{f2}) calculated as

$$T_{f2} = S(T_v + K_m \cdot T_m + 1.4 \cdot T_t) \quad (1)$$

where T_v is daily passenger tonnage, T_m is daily freight tonnage, and T_t is daily light engine tonnage (locomotive without wagons). S is a coefficient for line quality and is 1 for lines without passenger trains, 1.1 for lines with passenger trains running at speeds lower than 120 km/h, 1.2 for speeds at 120 to 140 km/h, and 1.25 for speeds above 140 km/h (see for example Duong et al., 2015). K_m is a coefficient for freight tonnage and is 1.15 if the axle load is lower than 20 tons and 1.3 otherwise. The UIC categories are then classified with respect to the different levels of T_{f2} as specified in Table 1 below. SNCF Réseau states that changes in UIC maintenance categories may not become effective unless tonnage variations are observed for three consecutive years[5].

Table 1. T_{f2} levels for UIC categories

UIC category	Tf2 level
1	Tf2 > 120 000
2	120 000 ≥ Tf2 > 85 000
3	85 000 ≥ Tf2 > 50 000
4	50 000 ≥ Tf2 > 28 000
5	28 000 ≥ Tf2 > 14 000
6	14 000 ≥ Tf2 > 7 000
7	7 000 ≥ Tf2 > 3 500
8	3 500 ≥ Tf2 > 1 500
9	1 500 ≥ Tf2

Source: Duong et al. (2015)

[5] Note that this delay does not make this a long-run concept – it is simply an (optimal or pragmatic) delay in re-classification. The key point is that the infrastructure is held fixed – as noted by Nash (2005), rail renewals form part of short-run marginal cost even if the cost response (e.g. a bringing forward of renewal) may not occur until many years hence.

These categories are used by SNCF Réseau to guide the preventative maintenance regime. For example, following a study by Meier-Hirmer and Pouligny (2008), SNCF Réseau decided to perform preventative grinding cycles that prioritizes lines belonging to UIC categories 1–4 and then category 5 and 6 (NeTIRail, 2015). Specifically, the grinding cycles with respect to UIC categories are 2 years for UIC categories 1 and 2, while UIC categories 3 and 4 have a cycle of 4 years and UIC categories 5 and 6 have a cycle of 6 years (INNOTRACK, 2009). Moreover, the inspection cycles also depend on the UIC categories (see Table 2).

The search for a minimum maintenance cost should lead the infrastructure manager (IM) to adjust as closely as possible preventative maintenance interventions according to the different levels and types of traffic running on the network. As shown by equation (1) the definition of these groups put a higher weight on the tonnage levels with higher line speeds and higher axle loads[6], both of which have an effect on deterioration. From a practical perspective the scale of expansion or reduction of preventative maintenance needs to be made in steps with respect to changes in traffic levels, hence the use of the traffic (T_{f2}) bandings. The UIC categories can therefore be seen as a useful proxy for how traffic impacts on preventative maintenance costs.

Table 2. Minimum inspection frequency for rail surface defects

UIC category	Minimum inspection frequency, months	
	Ultra-sound inspection	Walking inspection / visual inspection
1 and 2	6	12
3	9	12
4	12	12
5	30	12
6	Up to 36	12
7, 8 and 9	Up to 36	36

Source: IN2SMART, 2017

[6] The coefficient K_m increases when the axle load increases on freight trains, and passenger traffic (which generally have lower axle loads) are given a lower weight in the calculations than freight trains.

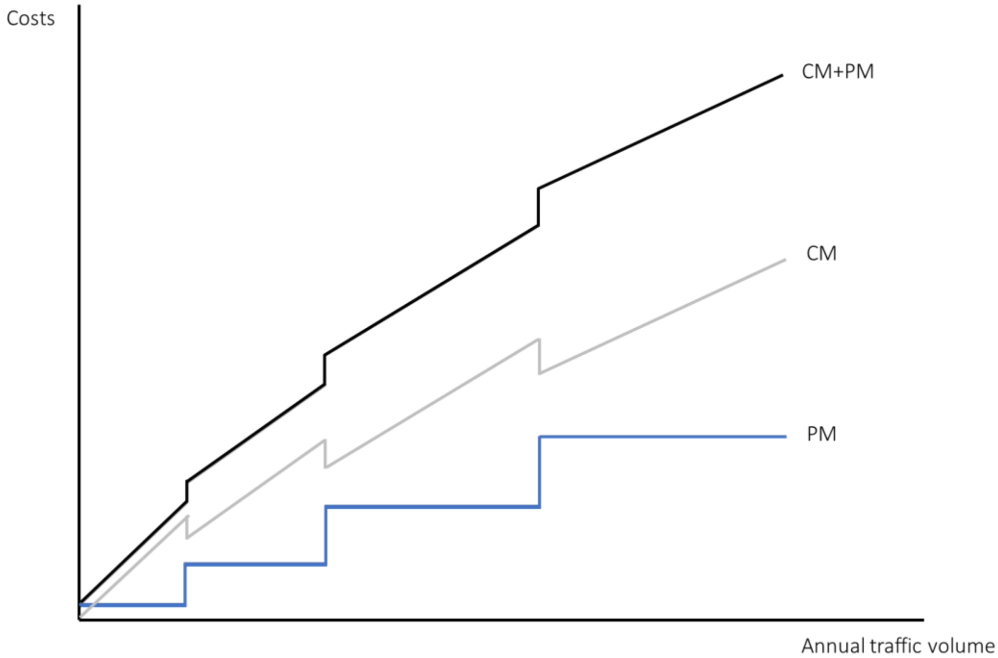

Fig. 1*. Assumed cost curves for preventative maintenance (PM) and corrective maintenance (CM).*

Source: own work

The assumed relationships between traffic and maintenance costs are illustrated in Figure 1, where it is considered that corrective maintenance (CM) is approximately a continuous function when aggregated over a large sample, whilst preventative maintenance (PM) is a step function for the same level of aggregation. Here we consider that the preventative maintenance steps are only partly offset by lower corrective maintenance, generating steps in the total maintenance cost function (CM+PM).

4.0 Data

The French state-owned railway company and infrastructure manager SNCF Réseau has provided data for the French railway network, comprising information about track maintenance costs, traffic, infrastructure characteristics, line categories, and regional structure of the network. The original dataset has been processed by SNCF Réseau and IMDM/ECOPLAN to resolve errors and data issues such as missing information (see IMDM/ECOPLAN, 2020).

The dataset covers a rail network of around 26 000 km (route-km) and a total track length around 46 000 km, observed during years 2013 to 2018. The network in our dataset is divided into 1149 unique sections, which are the observation units for each variable in the dataset. We observe about 1080 track sections per year due to an unbalanced panel. In total, we have access to 6432 observations. Descriptive statistics of variables for costs, traffic, infrastructure characteristics/condition, track capability, and management, are presented in Table 3.

The traffic information distinguishes between freight and passenger traffic, and the variables are either ton-km or ton density (ton-km per route-km). Freight and passenger traffic may have different impacts on track deterioration. For example, passenger traffic usually operates at different speeds – and with more braking and acceleration – than freight traffic and their running gear will typically have different characteristics that may imply different damage mechanisms for the infrastructure.

To isolate the impact traffic has on maintenance costs, it is important to control for other cost drivers such as infrastructure characteristics and the condition of the assets. For example, the average age of the rail is a proxy for the condition of the tracks, where tracks with old rails typically require more (corrective) maintenance than track with recently renewed rails. The number of parallel tracks may capture the maintenance production environment with respect to available capacity, especially when controlling for track length and traffic. Specifically, this variable is an indication of line capacity, where a higher available capacity can allow more coherent track possessions and less maintenance during night-time (see for example Odolinski and Boysen, 2019).

Track capability is part of a long run cost concept and is thus important to control for when estimating short-run marginal cost (SRMC). The maximum speed allowed on the track sections is one capability variable and is closely connected to the LGV (high-speed) line dummy variable. Rail weight is also a capability variable since heavier rails (together with other associated characteristics of the substructure) can allow heavier trains/axle loads.

Table 3. Descriptive statistics 2013–2018 (6432 obs.)

Variable	Mean	Std. Dev.	Min	Max
Cost and traffic				
Maintenance cost, track, 000 euro	670.8	1,179.5	0.054	14,589.5
Freight ton-km, million	71.6	174.7	0	1,901.4
Passenger ton-km, million	149.6	517.7	0	9,421.9
Freight ton density (ton-km per route-km), million	3.2	5.3	0	34.2
Passenger ton density (ton-km per route-km), million	7.6	19.8	0	317.1
Infrastructure characteristics/condition				
Route length, km	24.01	26.02	0.37	268.17
Track length, km	42.75	50.98	1.03	559.42
Number of parallel tracks[7]	2.03	1.87	1.00	37.20
Average rail age	33.38	19.78	1.04	137.00
Switch density (switches and crossings per track-km)	0.84	1.04	0	9.30
Average switch age	29.62	15.93	0	116.00
Sleeper density (average number per track-km)	1,654.69	80.47	1,090.00	1,851.84
Continuously welded rail, proportion	0.69	0.37	0	1
Curved track, proportion	0.49	0.21	0	1
Track circuits per track-km	2.64	2.49	0	21.46
Capability				
Maximum speed, km/h	115.18	50.61	20.00	320.00
Rail weight, kg/m	51.57	5.06	32.72	65.98
LGV line, dummy	0.04	0.20	0	1
Electrified route, proportion	0.65	0.47	0	1
Management				
Région Alsace Lorraine Champagne-Ardenne, dummy	0.14	0.34	0	1

[7] For the number of parallel tracks the vast majority of the data values lie between 1 and 4 but there are a small number of instances of higher numbers, reflecting complex infrastructure at very busy and large stations. As an added sensitive we tested imposing a maximum number of tracks of 4 and found that this had little effect on the results.

Région Aquitaine Poitou-Charentes, dummy	0.08	0.26	0	1
Région Bourgogne Franche-Comté, dummy	0.07	0.26	0	1
Région Bretagne Pays-de la-Loire, dummy	0.06	0.23	0	1
Région Centre Limousin, dummy	0.07	0.26	0	1
Région Haute et Basse Normandie, dummy	0.05	0.21	0	1
Région Ile-de-France, dummy	0.16	0.37	0	1
Région Languedoc-Roussillon, dummy	0.03	0.18	0	1
Région Midi-Pyrénées, dummy	0.04	0.20	0	1
Région Nord-Pas-de-Calais Picardie, dummy	0.15	0.35	0	1
Région Provence-Alpes-Côte-d'Azur, dummy	0.04	0.20	0	1
Région Rhône-Alpes Auvergne, dummy	0.12	0.32	0	1

A set of management variables are available, comprising information about the different regions each track section belongs to. Further, a set of year dummy variables are included in the model estimations to control for year specific effects, such as overall changes in input prices or in budget constraints. However, in common with the literature in this area, input prices are typically excluded for within country (and within company) studies of this type because national pay scales and common procurement policies mean that most input prices can be considered constant across the organisation (further, there are no significant differences in staff qualifications and age across regions in France and equipment is rented for a price from the central functions within SNCF Réseau).

The distribution of the network to UIC sections is shown in Table 4 below. Categories 1 and 2 are combined due to only a small proportion of the network being allocated to UIC category 1. Most track sections belong to only one UIC category. In a small number of cases a section comprises sub-sections with different categories and in these cases we allocate the section to the UIC category which makes up the highest proportion of the section, which in most cases makes up the majority of the section length in any case (only one per cent of the observations have a maximum proportion in a single UIC category of less than 50%). A small share of the network has unknown UIC category classifications in the data – but these represent very small parts of individual track sections, so the sections of which they are part are then allocated fully to the dominant UIC category. As discussed earlier, there is some, though only limited, re-allocation of sections between categories over the relatively short period of our dataset; see the within section standard deviations in Table 4 (this amounts to roughly 450km of track having changed UIC category over the course of our sample).

All track sections are therefore allocated ultimately to one UIC category numbered from 2 to 9 (with category 1 and 2 combined as noted). It can be noted that the UIC variables are not highly correlated with the infrastructure variables – the highest correlation coefficient in our dataset is -0.52, which is between UIC 9 and proportion of continuously welded tracks; and variance inflation factors are low.

Table 4. Track length UIC categories, kilometres

	Year						Within section	Average share
UIC	2013	2014	2015	2016	2017	2018	std. dev., prop. of UIC	of track length 2013–2018
1 and 2	1,245	1,245	1,210	1,246	1,116	1,116	0.014	2.6%
3	8,106	8,117	8,019	8,117	8,018	7,811	0.024	17.5%
4	9,831	9,846	9,854	9,860	9,869	9,818	0.025	21.5%
5	6,555	6,555	6,555	6,571	6,693	6,582	0.021	14.4%
6	6,316	6,321	6,331	6,355	6,289	6,310	0.033	13.8%
7	3,512	3,545	3,577	3,539	3,512	3,412	0.029	7.7%
8	5,647	5,628	5,519	5,644	5,496	5,279	0.022	12.1%
9	4,962	4,858	4,676	4,555	4,476	3,904	0.023	10.0%
Unknown	216	219	219	231	234	244	0.008	0.5%
Total track length	46,390	46,333	45,960	46,118	45,704	44,476		

5.0 Method

We follow the rail infrastructure cost literature as set out in section 2 (starting with the work or Johansson and Nilsson, 2004) in specifying a cost function given by:

$$C_{it} = f(\boldsymbol{q}_{it}, \boldsymbol{x}_{it}, \boldsymbol{UIC}_{it}, \boldsymbol{z}_{it}) \tag{2}$$

where $i = 1, 2, \ldots, n$ track sections observed over $t =$ years 2013 to 2018. C_{it} is maintenance costs, $\boldsymbol{q}_{it}$ is a vector of traffic variables (freight and passenger ton density), $\boldsymbol{x}_{it}$ is a vector of variables for infrastructure capability and characteristics/condition, $\boldsymbol{UIC}_{it}$ is a vector of variables indicating sections belonging to a certain UIC category – from category 2 to category 9, where one dummy variable is dropped and thus used as the baseline. $\boldsymbol{z}_{it}$ is vector of dummy variables for years, and regions. As noted in Section 3, in common with the literature in this area, input prices are typically excluded for within country (and within company) studies of this type because they are considered to be constant (see section 3 for further discussion of this point).

We start with the translog specification as the functional form (see e.g. Coelli et. al., 2005) and typically used in the rail infrastructure cost and wider cost function literature:

$$lnC_{it} = \alpha + \sum_{k=1}^{m} \beta_k lnq_{kit} + \sum_{g=1}^{G-1} \gamma_g UIC_{git} + \sum_{r=1}^{n} \vartheta_r x_{rit} + \frac{1}{2}\sum_{k=1}^{m}\sum_{l=1}^{m} \beta_{kl} lnq_{kit} lnq_{lit} + \frac{1}{2}\sum_{r=1}^{n}\sum_{s=1}^{n} \vartheta_{rs} lnx_{rit} lnx_{sit} + \sum_{k=1}^{m}\sum_{r=1}^{n} \delta_{kr} lnq_{kit} lnx_{rit} + \sum_{d=1}^{D} \theta_d z_{dit} + u_i + v_{it} \tag{3}$$

where α is a scalar, u_i is the effect of unobserved track section specific effects, and v_{it} is the error term. β, γ, ϑ, δ, and θ are the parameters we estimate, where $\beta_{kl} = \vartheta_{rs} = \delta_{kr} = 0$ is the Cobb-Douglas constraint that we test using an F-test. As noted earlier in the paper, in estimating equation (3) we are seeking to make two important comparisons:

1. First whether fixed effects, which utilises just the within variation in the data produces substantially lower traffic elasticities (higher degree of economies of density) and lower marginal costs than models utilising the between variation (between estimator or

random effects). This is important because we argue that the between variation is important to capture changes in preventative maintenance that are mainly only observed through the between variation in the data.

2. Second, whether we can show empirically that preventative maintenance effects, modelled through the UIC dummy variables, are statistically significant. This would provide evidence of the additional cost effect of increased traffic, across the cross-section, beyond the pure traffic effect discussed earlier.

6.0 Results

Below we set out first our translog cost function estimation results (section 6.1), followed by the computation marginal costs for the different panel estimators (section 6.2).

6.1 Translog cost function estimation results

In Table 5, we present results from estimations using fixed effects (FE), between effects (BE), and random effects (RE); and for the latter two models we also estimate the models including the UIC dummy variables (BE_UIC and RE_UIC). As noted earlier in the paper, our focus here is firstly to compare fixed effects against the between and random effects estimators. This is important because we argue that the between variation is important to capture changes in preventative maintenance that are mainly only observed through the between variation in the data. Further, we want to understand whether we can identify the cost impact of moving between preventative maintenance regimes via the UIC dummy variables.

Before turning to these core issues we first comment on the structure of the cost function model estimated. As noted in section 5 we start with the standard translog cost function that is commonly used in the rail and broader cost function estimation literature (see also section 2). Owing to the large number of explanatory variables we focus the translog expansion on the core output variables, but found that the freight squared variable was not statistically significant and that the passenger-freight interaction term produced counter-intuitive results. A similar finding was noted in the modelling work carried out by SNCF Réseau for the purpose of track access charges (and approved by the French regulatory body); see IMDM/ECOPLAN, 2020.

Returning to the choice of panel estimator, we first carry out a cluster-robust test between the fixed effects (FE) and random effects (RE) estimators in columns 2 and 5 of Table 5 by including group means of the time-varying variables when estimating the random effects models and test their joint significance with a Wald test (see e.g., Wooldridge, 2010, pp.290–291). As is standard in this literature, simple interpretation of this statistical test indicates that these group mean variables are statistically significant, indicating a preference for fixed effects.

However, as noted earlier, the rail infrastructure cost literature tends nevertheless to utilise random effects because of a lack of statistical significance on the key parameters of interest. In this case, we note that at the sample mean, the freight elasticity in the fixed effects model is close to zero and not statistically significant, which is hard to explain; whereas it is statistically significant in the BE and RE models. The general decision to utilise random effects in this literature also reflects the extensive list of control variables that tend to be included in the models (as is the case also in our models; see Table 5), which reduces the concern over omitted variable bias with respect to characteristics of the fixed infrastructure. In other cases in this literature it should be noted that fixed effects results are typically even more unpalatable, producing insignificant results for passenger traffic also (whereas in our case, FE does at least produce statistically significant results for passenger traffic).

Table 5. Estimation results

Dependent variable: ln(maintenance cost track)	**FE**[8] Coef.	**BE** Coef.	**BE_UIC** Coef.	**RE** Coef.	**RE_UIC** Coef.
Constant	18.337***	12.853***	12.507***	13.784***	13.366***
	(2.515)	(0.376)	(0.393)	(0.202)	(0.251)
ln(freight ton density)	0.018	0.062***	0.047***	0.034***	0.023*
	(0.019)	(0.013)	(0.015)	(0.013)	(0.014)
ln(passenger ton density)	0.180***	0.225***	0.209***	0.182***	0.175***
	(0.064)	(0.030)	(0.032)	(0.032)	(0.032)
0.5ln(passenger ton density)^2	0.018**	0.031***	0.029***	0.018***	0.017***
	(0.008)	(0.006)	(0.006)	(0.005)	(0.005)
ln(track length)	2.885**	1.100***	1.090***	1.080***	1.069***
	(1.179)	(0.033)	(0.033)	(0.033)	(0.033)
ln(no of tracks)	-0.744	-0.324***	-0.283***	-0.215**	-0.212**
	(0.764)	(0.093)	(0.093)	(0.099)	(0.100)
ln(rail age)	0.354***	0.237***	0.237***	0.267***	0.255***
	(0.061)	(0.059)	(0.059)	(0.047)	(0.046)
ln(switch density)	-0.006	0.163***	0.148***	0.122***	0.106***
	(0.071)	(0.045)	(0.045)	(0.040)	(0.041)
ln(sleeper density)	-2.773	-0.029	-0.290	0.225	-0.202
	(4.322)	(0.658)	(0.662)	(0.878)	(0.881)
Cont. weld. track prop	-0.724	-0.369*	-0.381*	-0.326	-0.351
	(0.798)	(0.213)	(0.217)	(0.225)	(0.230)
Curved track prop.	-3.859	0.680***	0.661***	0.615**	0.607**
	(3.281)	(0.220)	(0.220)	(0.287)	(0.286)
ln(track circ. per track-km)	3.507***	0.121***	0.108***	0.164***	0.139***
	(1.107)	(0.036)	(0.036)	(0.042)	(0.043)
ln(max speed)	0.837**	0.064	0.054	0.227*	0.182
	(0.389)	(0.112)	(0.112)	(0.127)	(0.126)
ln(rail w)	2.757**	-0.388	-0.937*	0.298	-0.252
	(1.291)	(0.414)	(0.482)	(0.448)	(0.542)
0.5ln(rail w)^2	-1.192	-12.078***	-14.211***	-9.745*	-11.721**
	(12.479)	(3.938)	(4.186)	(5.384)	(5.708)
D.LGV		-0.335**	-0.275	-0.655***	-0.569***
		(0.166)	(0.171)	(0.215)	(0.212)
D.UIC 2			0.637**		0.742*
			(0.254)		(0.381)

[8] Note that the FE can be estimated despite the inclusion of apparently time invariant variables such as track length because of small variations in those variables for some observations in the sample over the period.

D.UIC 3			0.531***		0.627***
			(0.183)		(0.215)
D.UIC 4			0.394**		0.455**
			(0.163)		(0.194)
D.UIC 5			0.274*		0.402**
			(0.150)		(0.173)
D.UIC 6			0.229*		0.321**
			(0.136)		(0.156)
D.UIC 7			0.355***		0.389**
			(0.132)		(0.158)
D.UIC 8			0.310***		0.386***
			(0.107)		(0.125)
(Cont. Weld. tr.)(Curved tr.)	0.617	-0.615*	-0.607*	-0.463	-0.485
	(1.354)	(0.315)	(0.315)	(0.359)	(0.358)
Region dummies	N/A	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Dummies, zero pass. ton, freight ton, switch den., and track circuits[9]	Yes	Yes	Yes	Yes	Yes
R^2 overall	0.384	0.536	0.539	0.686	0.689

***, **, *: Significance at the 1%, 5%, and 10% level, respectively. Robust standard errors in parentheses.

Of course, we have a further motivation for abandoning fixed effects, since we want to capture the cost impact of changes in preventative maintenance through the between variation in the data. We first consider the models without the UIC category dummy variables. Here we find that for the BE and RE models the summation of the elasticities of cost with respect to passenger and freight traffic (at the sample mean) are indeed higher than in the FE model. Taken together, the overall cost elasticity (at the sample mean) with respect to traffic (passenger and freight) is 0.198, 0.288 and 0.216[10] for FE, BE and RE respectively. The individual passenger and freight traffic elasticities are also individually statistically significant at the sample mean in the RE and

[9] These dummies are used to handle zero observations (e.g. zero freight traffic on some sections), following Gaudry and Quinet, 2013.

[10] Computed as (0.018+0.180), (0.062+0.225) and (0.034+0.182) respectively.

BE model, though the freight elasticity is not significant in the FE model. Thus, we find that the utilisation of between variation either through the between estimator or random effects models, increases the overall elasticity of costs with respect to traffic, and therefore reduces our measures of economies of density compared to fixed effects.

Before discussing these results further, and also the implications for marginal cost, we consider the impact and statistical significance of the UIC dummy variables, which reflect the variation in preventative maintenance regimes across the network. Table 5 shows that the UIC coefficients in Model BE_UIC vary between 0.229 (UIC 6) and 0.637 (UIC 2), and in Model RE_UIC between 0.321 (UIC7) and 0.742 (UIC2). All of the UIC dummy variables are statistically significant for both the BE_UIC and RE_UIC models (see Table 5), which means that the cost impacts for UIC categories 2 to 8 are all statistically significantly different from UIC 9 (the excluded category). Table 6 shows a complete list of tests for the BE_UIC and RE_UIC model, showing that there are also statistically significant differences between other UIC categories (see Table 6).

Table 6. Tests of differences between UIC coefficients

Test: H0	BE_UIC F(1, 1105)	RE_UIC Chi2(1)	Test: H0	BE_UIC F(1, 1105)	RE_UIC Chi2(1)
UIC 2 = UIC 5	2.81*	1.05	*UIC 3 = UIC 9*	8.39***	8.53***
UIC 2 = UIC 6	3.41*	1.55	*UIC 4 = UIC 9*	5.86**	5.49**
UIC 2 = UIC 9	6.26**	3.79*	*UIC 5 = UIC 9*	3.34*	5.43**
UIC 3 = UIC 4	1.76	2.99*	*UIC 6 = UIC 9*	2.82*	4.25**
UIC 3 = UIC 5	4.41**	3.36*	*UIC 7 = UIC 9*	7.23***	6.05**
UIC 3 = UIC 6	5.27**	5.09**	*UIC 8 = UIC 9*	8.41***	9.61***

***, **, *: Significance at the 1%, 5%, and 10% level, respectively.

It is informative to observe what happens to the traffic elasticities when the UIC variables are included or excluded. For both the BE and RE models, excluding the UIC variables from the model (which would be the normal practice in the literature), increases both the passenger and freight elasticities, with the sum of the two elasticities at the sample mean increasing from 0.256 to 0.288 for the BE models and from 0.199 to 0.216 for the RE models compared to the versions that include the UIC dummies (BE_UIC and RE_UIC; see Table 5). This is intuitive since the UIC effects are correlated with traffic; therefore when they are excluded we would expect that the effects would partly end up within the traffic elasticities. This finding is in line with the thrust of this paper that the traffic effect can be thought of as a pure traffic effect plus an effect of changes in preventative maintenance regime that occurs across the cross-section. We further note that the inclusion / exclusion of the UIC dummy variables does not impact greatly on coefficients on the variables for infrastructure characteristics/condition or capability.

Table 7 summarises the resulting elasticities and measures of economies of density for the different models, this time computed in the usual way for this literature, as traffic weighted average elasticities. These results broadly mirror the findings from evaluating the elasticities at the sample mean reported above. We show the results from the models excluding the UIC dummies since in most real railway datasets data would not be readily available on preventative maintenance regimes, or the level of aggregation of the cost data – that is, at the firm or regional level - would make such variables difficult to construct even if available. Further we saw that when dropping the UIC dummies the effects shifted into the traffic elasticities, which increased as a result[11].

Table 7 emphasises the importance of accounting for between-variation in the data in the computation of economies of density, noting that the between estimator sees a much higher overall traffic elasticity than the fixed effects estimator (the random effects elasticity is also higher, though to a lesser extent). Table 9 shows that, if we rely simply on fixed effects estimation, we would assess economies of density to be as high as 4.72. However, reflecting

[11] In our case, since we do have the UIC dummy variable data, it may be possible to consider a more complex model whereby economies of density are computed based on the traffic elasticity plus the cost impact of different UIC categories, combined with an estimate of the probability that a traffic increment would produce a change in preventative maintenance regime. That approach could be an avenue for future research.

the between-variation in the data through use of the between estimator leads to much higher traffic elasticities and in turn lower estimates of economies of density (3.20).

Table 7. Overall traffic elasticities and economies of density*

Model	Overall traffic elasticity*	Measure of economies of density
FE	0.212	4.72
BE	0.313	3.20
RE	0.230	4.35

* Note this is the sum of the elasticities of costs with respect to passenger and freight volumes (and are based on traffic-weighted averages of the elasticities estimated for each track section)

To summarise: based on our prior reasoning and on the empirical results in this paper we consider that estimates of the elasticity of cost with respect to traffic – holding the infrastructure fixed, and in turn its reciprocal, economies of density – should be estimated using models that capture the between variation in the data. That is, we recommend that the between estimator or the random effects[12] estimator should be used. This is because we want to capture both the pure traffic effect and the effects of changes in preventative maintenance regime, where the latter only varies across the cross-section. An important caveat here is that researchers need to be confident – as we are in our empirical case – that the wider problem of omitted variable bias with respect to characteristics of the fixed infrastructure can be avoided through the use of appropriate control variables included in the model.

Our main purpose therefore has been to demonstrate the importance of preventative maintenance effects in rail infrastructure data, which in turn justifies the use of the between or random effects estimator in computing economies of density for rail datasets. This is an important finding because the literature (starting with Caves et. al., 1985) has argued for the

[12] Random effects is of course a weighted average of the between and within estimator. It could be considered as an alternative to the between estimator in some circumstances e.g. in economic regulation, for example, where there is greater familiarity with random effects, or where datasets are relatively small, or simply to avoid over-reliance on one particular approach.

use of fixed effects to estimate economies of density. Further, as noted, our approach is analogous to the arguments used by Caves et. al. (1985) for the use of the between estimator for estimating scale elasticities because we want to correctly include the associated preventative maintenance effects in our traffic elasticity and economies of density, in the same way that Caves et. al. (1985) wished to include the associated network effects in their estimate of economies of scale. We therefore consider that these results demonstrate the central point of the paper – namely that, because of the between-variation in preventative maintenance regimes, triggered by increases in traffic, researchers should not rely solely on within variation in the data (fixed effects) when deriving economies of density for rail infrastructure costs.

6.2 Comparison of marginal costs across models

The final step is to calculate marginal costs based on traffic estimates for the different panel estimators. These are important as they would form the basis for setting track access charges.

The fixed effects model generates a marginal cost at 0.166 euro per 1000 freight ton-km and 0.755 euro per 1000 passenger ton-km. The marginal cost for freight traffic is substantially higher when using between effects (0.581) or random effects (0.314), while the estimate for passenger traffic likewise increases substantially to 0.928 when the between estimator is used (in this case, for passenger, the fixed and random effects marginal costs are rather similar).

Table 10. Weighted average marginal costs, euro/1000 ton-km

Model	Freight	Passenger
FE	0.166	0.755
BE	0.581	0.928
RE	0.314	0.766

The results in Table 10 shows the marginal cost implications of the finding already noted – namely that fixed effects estimation will understate the elasticity of cost with respect to traffic

/ overstate the extent of economies of density. In turn then marginal costs and ultimately track access charges would be set too low.

This finding therefore calls for the utilisation of between variation in rail datasets, either the between estimator or random effects. We further note that the differences between the different estimators is particularly pronounced for freight traffic. The past literature has noted that rail infrastructure cost function estimation can result in marginal costs for freight traffic (per ton-km) that are much lower than passenger traffic, which could be seen as surprising when considered against engineering evidence (see e.g. Wheat et. al., 2009). In Table 10 we see that the estimators that rely on between variation produce freight and passenger marginal costs that are closer together. The latter is intuitive, given the increased weighting that freight is given in defining the preventative maintenance regimes as shown in equation (1) above.

7.0 Conclusion

Economies of density in the railway cost structure literature is concerned with the question of what happens to costs as traffic increases on a fixed network. The past literature on railway cost function estimation has therefore emphasised that estimates of economies of density should be derived from fixed effects estimation, thus utilising only the within-variation in the data (see e.g. Caves et. al., 1985). The reason is that utilisation of between-variation in the data would run the risk of omitted variable bias as there may be unobserved factors relating to the fixed infrastructure that are correlated with traffic that vary over the cross-section – i.e. the network does not remain fixed in the cross-sectional dimension of railway datasets.

Similar concerns have been raised in the more recent rail infrastructure cost literature where the aim is to obtain a measure of cost variability and in turn the short-run marginal cost of running an extra train service on a fixed network. In the EU, track access charges are set based on such marginal cost estimates, and the level of track access charges is hugely important in ensuring efficient use of rail capacity and also allowing new competitors to gain fair access to the network. In this context the concern is that use of between-variation runs the risk of capturing long-run rather than short-run marginal costs for the same reason as noted in the wider rail cost literature – namely that the network does not remain fixed over the cross-section.

This paper offers a new perspective, and provides a motivation for the use of between-variation in rail cost datasets because of the need to capture the changes in preventative maintenance that occurs when moving from one line category to another. Since such changes are rarely observed in the within-variation in the data (at least over short panels), this means that fixed effects estimation will miss the preventative maintenance element of marginal cost.

The foregoing discussion therefore emphasises that on the one hand utilisation of between-variation runs the risk of overstating marginal costs because of omitted variable bias, whilst on the other, use of fixed effects risks understating marginal costs because it ignores (marginal) preventative maintenance costs. Since the literature shows that rail infrastructure cost studies typically have access to an extensive set of control variables for track characteristics and capability and thus avoid the associated omitted variable bias, we argue that the greater danger is therefore the risk of omitting an important element of marginal costs – namely that part relating to preventative maintenance. We therefore argue for the use of between variation in the data to estimate economies of density for rail infrastructure, which implies using the between estimator or random effects rather than fixed effects.

It is also important to note that our argument for the use of the between estimator for estimating economies of density is analogous to that put forward by Caves et. al. (1985) in respect of estimating economies of scale. In the same way that Caves et. al. (1985) argued for the need to capture associated changes in unobserved network effects within the estimate of economies of scale as network size changes across the cross-section, we argue that it is necessary to capture the associated changes in preventative maintenance regimes as traffic changes across the cross-section within the estimate of economies of density. In both cases (ours and Caves et. al., 1985) the estimates are "biased" but in a good way – in our case, use of the between variation allows the unobserved preventative maintenance effects to be correctly conflated with the estimate of a pure traffic effect (that latter would capture only reactive maintenance), thus giving a true reflection of what happens to costs as traffic increases across the cross-section. In our case it is also important to note that the changes in preventative maintenance regime are not related to changes in the fixed infrastructure and that we have an extensive set of control variables to capture the fixed infrastructure characteristics.

`Compared to the between estimator or random effects, our work shows that fixed effects produces considerably lower elasticities of cost with respect to traffic, thus producing higher estimates of the degree of economies of density, and lower marginal costs. The differences are particularly pronounced in respect of freight traffic, where fixed effects estimation produces elasticities that are close to zero and not statistically significant. The choice of estimator therefore impacts not just estimates of economies of density but also marginal costs (for different types of traffic), with consequent implications for the setting of track access charges in the EU context, which are required to be based on short-run marginal cost (referred to in the legislation as "direct costs").

Overall, we consider that our work makes a strong case for the utilisation of between-variation when estimating rail infrastructure cost functions, either through the between estimator or random effects. Indeed these arguments also suggest that previous estimates of economies density derived from overall rail system cost datasets – which include rail infrastructure maintenance as an important part – might need to be re-considered.

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