THE MARGINAL COST OF RAILWAY TRACK RENEWALS: A SAMPLE SELECTION MODELLING APPROACH

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Abstract

Economic theory advocates marginal cost pricing for efficient utilisation of transport infrastructure. A growing body of literature has emerged on the issue of marginal infrastructure wear and tear costs, but the majority of the work is focused on costs for infrastructure maintenance. Railway track renewals are a substantial part of an infrastructure manager's budget, but in disaggregated statistical analyses, they cause problems for traditional regression models since there is a piling up of values of the dependent variable at zero. Previous econometric work has sought to circumvent the problem by aggregation in some way. In this paper we work with disaggregate (track-section) data, including the zero observations, but apply censored and sample selection regression models to overcome the bias that would result from estimation using OLS. We derive track renewal cost elasticities with respect to traffic volumes and in turn marginal renewal costs using Swedish railway renewal data over the period 1999 to 2009. Our paper is the first paper in the literature that we are aware of to report usage elasticities specifically for renewal costs and therefore adds important new evidence to the previous literature where there is a paucity of studies on renewals and considerable uncertainty over the effects of rail traffic on renewal costs. In the Swedish context, we find that the inclusion of marginal track renewal costs in the track access pricing regime, which currently only reflects marginal maintenance costs, would add substantially to the existing track access charge.

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1. INTRODUCTION

Marginal cost pricing of infrastructure wear and tear is of great importance from an economic efficiency standpoint. Over the last decade, research on the subject has gradually increased for all modes of transport (Nash and Sansom, 2001; Nash, 2003; Thomas et al., 2003; Nash and Matthews, 2005; Wheat et. al., 2009). One of the reasons for the renewed interest in the marginal cost of rail infrastructure costs has been the move in European railways towards vertical separation of rail infrastructure from train operations, driven by successive European legislation. This legislation requires countries to set rail infrastructure charges based on the direct cost of running different services, including: additional “wear and tear” costs of running more trains; scarcity charges; and environmental charges. Non-discriminatory mark-ups are also permitted. The changed model for organising rail transport in Europe has therefore created a key research need; namely to estimate the direct cost of running extra traffic on the network.

Sweden was the first country to undertake such a separation in 1988, with the rest of Europe following later, to a greater or lesser extent (see Nash and Matthews, 2009). The Swedish Railway Act stipulates two types of charges for the use of infrastructure (Banverket, 2009). The first type is special charges, which can be of two different types, either covering the fixed costs of the infrastructure, or costs occurring when new infrastructure has been built as a special project. The other type of charge is based on short run marginal costs. In turn, there are three different types of marginal cost based charges; the track charge, the accident charge and the emission charge. The first, and for our purposes most interesting, is the track charge, which mirrors the maintenance costs incurred by one additional tonne movement as a result of wear and tear on the network. Importantly, to date, the wear and tear track charge has not taken into account incremental renewal costs.

The track charge is based on an analysis of data at track section level, where incurred maintenance costs are seen as a function of output volume (gross tonne-km) and properties of the infrastructure (track section length, rail age, number of switches, tunnels etc). The track charge for 2011 is set to SEK 0.0036/gross tonne-km as a marginal infrastructure cost charge[2]. In the rail marginal cost estimation literature, a track section represents the most disaggregate level at which cost data is recorded. In the case of this study, it is defined by the national track information system (BIS), administered by the Swedish Transport Administration (Trafikverket).

[2] Exchange rate is: Swedish Krona (SEK) 6.75 = US$ 1; SEK 9.30 = € 1 (11 Nov, 2010).

More generally, most research on railway infrastructure wear and tear has rather focused on the relationship between maintenance costs and traffic, while controlling for infrastructure characteristics. The lack of empirical evidence concerning the size of the rail renewal marginal cost has therefore recently drawn some attention in the literature and amongst policy makers (see Nash, 2005 and Wheat et. al., 2009).

A renewal is an activity that will restore the infrastructure to its original standard. Renewals and maintenance are linked in such a way that lack of maintenance will force the infrastructure manager to renew at an earlier stage than if maintenance were undertaken properly and vice versa. An optimally managed railway track has a mix of maintenance and renewal in time over the life cycle and excluding renewals from the total picture of marginal infrastructure costs, would therefore be misleading.

As rail renewals have long life cycles and therefore are rare events, disaggregate renewal cost data contains many zero observations – that is, no renewal is undertaken for a given track section in a given year. In the small number of previous econometric studies on renewals marginal costs, this problem has been addressed by combining maintenance and renewal costs to create a measure of total costs (thus eliminating the zeros); see Andersson (2006; 2007a), and Marti et al. (2009). Alternatively, modelling has proceeded at a less disaggregate level (regional or even national, for a number of countries), thus eliminating zero renewal costs; see Wheat and Smith (2009)[3], Smith (2008) and Smith et al. (2008), though again maintenance and renewals have been combined in the reported, preferred models. Of course, both these types of aggregation merely mask the problem of zero renewals. Further, in general, the models involving renewals have proved to be less robust than maintenance-only modelling and there have also been fewer studies of the former than the latter. The result is that renewal cost elasticities have to be inferred from models based on maintenance and renewals combined, and there is therefore currently much uncertainty over the range of appropriate values that should be used.

As an alternative way of circumventing the problem, Andersson (2007b) uses an analytical expression of marginal rail renewal costs and applies a Weibull survival model to study the effects of increased traffic volumes on the rail renewal cycle. Through observed rail ages and renewals during a six-year time frame, the expected life time of a rail segment is estimated as a function of traffic volume and other track characteristics. By comparing two discounted costs streams of infinite renewal cycles with different traffic volumes, the marginal cost associated with increased traffic can be derived. The analysis contains an estimation of deterioration elasticities for total tonnage, and passenger and freight tonnages separately. Marginal costs are calculated as a change in present values of renewal costs from premature

[3] Even then, maintenance and renewal costs were combined in the preferred model.

renewal following increased traffic volumes. One disadvantage of this approach is that it requires an assumption to be made about unit renewal costs in order to compute marginal costs. It should be noted that the latter is far from trivial given the considerable unit cost variation that can result from different types and volumes (as unit costs vary with scale) of track replacement work.

Given the lack of previous evidence on rail renewals marginal cost, and the associated methodological problems experienced in previous studies, new approaches to the problem and new evidence is therefore called for. In this paper we utilise an alternative set of econometric models that are workable even for disaggregated data with a large proportion of zero renewals (Tobit, Heckit and the Two-part model). These approaches derive marginal costs directly from the econometric cost model (avoiding the aforementioned problems associated with survival analysis), whilst ensuring that the zero data observations are utilised and modelled appropriately to ensure consistent estimates of the model parameters (a more satisfactory approach than simply aggregating the data). We explore the results of these alternative approaches using Swedish railway renewal cost data.

To our knowledge this paper is the first attempt in the literature to apply these techniques to disaggregate renewal cost data in railways (characterised by a data structure comprising a large fraction of zero values for the dependent variable). We consider this to be an important addition to the literature, particularly given the paucity of studies of marginal rail renewal costs in general and its importance in the context of setting track access charges in vertically separated rail systems.

We find that the Tobit and Heckit models have limitations in modelling our renewal data, while the Two-part model performs best. The renewal cost elasticity with respect to output of gross tonne-km is around 0.55, which is higher than estimates of maintenance cost elasticities from the previous literature, but in line with a priori expectations (given that engineering evidence suggests that renewals expenditure is likely to be more variable with traffic than maintenance; see Abrantes et al., 2008). Our findings put the estimated elasticity with respect to renewal cost at the top end of the range of estimates from previous, aggregated maintenance and renewals econometric work.

As noted above, the few aggregated studies that have been done are based on aggregating maintenance and renewals together and these studies have produced a wide range of estimates for the total maintenance and renewal cost elasticities. The result is that renewal cost elasticities have to be inferred from models based on maintenance and renewals combined, and there is therefore currently much uncertainty over the range of appropriate values that should be used. Our paper is the first paper in the literature that we are aware of to report usage elasticities[4] specifically for renewal costs (in our case, track renewal costs) and therefore adds important new evidence to the previous literature. In the Swedish context, the estimated marginal cost is approximately SEK 0.009 per gross tonne-km or two and a half times higher than the current infrastructure wear and tear track access charge for 2011, which is based purely on maintenance marginal cost.

The paper is organised as follows. In section 2, we introduce the modelling approach followed by a description of the data set in section 3. Section 4 covers the econometric specifications and results, while we discuss the results and draw some conclusions in section 5.

2. MODELLING APPROACH

2.1 Regression models for truncated and censored data

There exists an extensive literature on statistical modelling techniques for use when data are censored or truncated. When a relevant part of the population generating the data is unobserved, the data is said to be truncated. In this case, data on both the dependent and independent variables is not observed. For example, in a study of household income, the sample may only contain data for low-income households.

Censored data is different. In this case, the dependent variable is not observable for some part of the population (though data on the independent variables are available). Again, using the study of household income as an example, above a certain threshold, income may only be recorded as being above that threshold (the actual income level is not recorded in the data set, perhaps for confidentiality reasons). This type of censoring is referred to as top-coding. Another example is demand for tickets to major sporting events, where the latent (or potential) demand is not observed because in the case of a sell-out, observed ticket sales are limited to the capacity of the venue. In the income example, all income values above a certain threshold are censored to be equal to that threshold. In the ticketing example, observed ticket sales are a “censored version” of potential demand (see Greene, 2007).

A second model, which is sometimes described as being a type of censored data model, is the corner solution model. Wooldridge (2002) describes this model as being relevant to a situation where a firm or household makes an (observable) choice for a variable, *y*, where *y* takes the value zero (the corner solution) with a positive probability, and otherwise is a continuous, strictly positive random variable. Examples might include

[4] The term ’usage elasticity’ was first used by Wheat et al (2009) to refer to the elasticity of cost (be it maintenance and/or renewal) with respect to traffic.

household expenditure on life insurance or health services, or firm expenditure on R&D activity. In these cases researchers are analysing continuous variables (expenditure) containing a spike or probability mass at zero. The zeros are not censored versions of some underlying variable, they are "true" zeros, since they are the actual choices of the relevant decision maker. For this reason, Greene (2007) states that the corner solution model is not actually a censored model, though noting that it produces the same model specification and can thus be treated as the same in terms of estimation[5].

Since our empirical application concerns observations on track renewal costs, which may be positive or zero, resulting from the choice of the infrastructure manager, we proceed to describe the estimation strategies for the corner solution interpretation of the censored regression model. Following the treatments in Wooldridge (2002) and Greene (2007), the censored model considers the classical regression model for the underlying dependent variable y^*[6]:

$$y_i^* = x_i'\beta + \varepsilon_i, \varepsilon_i \sim N[0, \sigma^2] \quad (1)$$

For the censored model the observed data, y_i, is generated as follows:

$$y_i = \max(0, y_i^*) \quad (2)$$

Proceeding using ordinary least squares (OLS), regressing y_i on x, gives biased and inconsistent estimates of β, since if $E(y^*|x) = x'\beta$, the censoring in the data means that $E(y|x)$ will be non-linear in $x'\beta$. Therefore, $E(\varepsilon|x)$ is a function of x (so is not equal to zero). As Greene (2007, p. 703) notes, this non-linearity means that OLS on the observed data is "unlikely to produce an estimate that resembles β". Further, OLS opens up the possibility of negative predicted values of y_i. Intuitively, the problem arises from trying to fit a linear model, with constant partial effects, to a sample with a set of values (the zeros) where changes in the x value have no impact on the dependent variable.

A natural question to ask then is whether the researcher should throw away the zero observations and apply OLS to the remaining data points. In this case, a "truncated regression model", estimated via maximum likelihood (ML), should be applied (see Greene, 2007). However, in our case, where the zeros are "true zeros" and thus contain useful information, it is inappropriate to proceed in this way.

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[5] Though not necessarily interpretation as explained further below.

[6] In the context of the corner solution model, y^* is simply a construct to help us formulate the model. In the corner solution model, y is both the observed data and the variable that we are interested in understanding. Explaining y^* has little value in the corner solution model, in contrast to the censored interpretation.

For our case, the corner solution model, there are broadly three ways to proceed in terms of estimation: the Tobit model (Tobin, 1958; Amemiya, 1985), the Two-part model (Cragg, 1971) and the sample selection model first proposed by Heckman (1979), which is often referred to as the Heckit model. Each of these is discussed in turn below.

The Tobit model corrects for the piling up of zeros, which violates the standard OLS assumption of the dependent variable following a conditional normal distribution, avoid negative predictions and also give more reasonable estimates of partial effects (Wooldridge, 2009). The Tobit model proceeds by applying maximum likelihood estimation to all of the data points (including the zeros). This procedure results in consistent estimates of the model in (1).

However, Cragg (1971) proposes an alternative Two-part model that nests the Tobit model as a special case. The Two-part model can be written as the probability of observing y > 0, given X:

$$\Pr[y > 0 \mid x] = \Phi(x_1^{'}\beta_1, \varepsilon_1) \tag{3}$$

where a probit model is the natural choice for the first part. The second part is then a truncated regression model:

$$E[y \mid y > 0, x] = x_2^{'}\beta_2 + E[\varepsilon_2 \mid y > 0, x] = x_2^{'}\beta_2 \tag{4}$$

The model here implies that the value of y (say expenditure), given that it is positive, and after controlling for the regressors (x), is independent of the decision whether to make any expenditure at all.

A number of points are worth noting in respect of the Two-part model. First the Two-part model considers that the data generating process (DGP) for the decision to participate – in this case, to renew or not – maybe different from the DGP for the decision of how much to spend. This flexibility arises, firstly since the regressors can differ in each decision equation (x_1 need not equal x_2) and second, even if the regressors are the same, the coefficients can be different (β_1 need not equal β_2). A much quoted example in the literature as to the usefulness of this model is given by Fin and Schmidt (1984) in which it is pointed out that the probability of a fire occurring in a building, and the cost of repair in the event of a fire, might both be affected by the age of the building, but the two effects might take opposite signs. We may expect *a priori* that some of the candidate regressors for this study maybe statistically significant in one equation but not in the other or take different signs (see section 2.2 for further discussion of this point in respect of this study).

Second, the Two-part model imposes that the errors in each part are independently distributed. Thus, whilst correlation is allowed for in the measured regressors between parts, the residuals are not correlated. Correlation between residuals often arises if the reason for censoring was due to sample selection. However there is no sample selection issue in the corner solution interpretation; the zeros are true zeros. However correlation in residuals could result due to correlation between unobserved effects in each part of the model. Thus it is an empirical matter as to whether the assumption is reasonable and importantly, through estimation of the Heckit model (discussed below), we can test the validity of this assumption.

Third, the Two-part model enables a log-linear specification to be adopted in the second part of the model, which is useful from a cost modelling perspective. This is because only strictly positive values of y are taken forward into the second stage and so ln(y) is defined for all observations in the truncated regression[7]. Fourth, the Two-part model permits, but does not require the same regressors to appear in both parts of the model. If the same regressors appear in both parts, and $\beta_1 = \beta_2$ then the Two-part model simplifies to the Tobit case (and this restriction is testable).

The final class of model that we consider is the Heckit model which has been extensively used for censored and truncated data (Heckman, 1979). The motivation behind this model is to address the potential problem of sample selection bias. That is, there is assumed to exist a model that applies to the underlying data, but the sample selected has not been selected randomly from the population. Therefore if OLS is carried out only on the observed values, biased estimates will result. The Heckit was developed for wage equation estimation and the model includes the effect on wages for both actual and potential workers. Those who do not work are not observed, and this group is also likely to have relatively low wages, when they do work. The Heckit explicitly models the sample selection process (via a probit model), and then applies OLS to a second outcome equation, utilising just the observed data (in the censored case, excluding the censored data), but with an additional variable included, computed based on the parameter values from the probit model (see Greene, 2007). The additional variable facilitates correlation between errors in the two equations. As such the model can be thought of as an extension of the Two-part model. Importantly, the restriction that the coefficient on the additional variable is equal to zero can be tested.

The Heckit can be formalised as a selection equation (5) and an outcome equation (6).

$$\Pr[y > 0 \mid x] = \Phi(x_1^{'}\beta_1, \varepsilon_1) \tag{5}$$

[7] The log-linear specification can be done in a Tobit model as well, but requires some data manipulation, which is described in 4.2.

$$E[y \mid y > 0, x] = x_2^{'}\beta_2 + E[\varepsilon_2 \mid y > 0, x] =$$

$$x_2^{'}\beta_2 + \sigma_{12}\lambda(x_1^{'}\widehat{\beta}_1) \qquad (6)$$

where $\lambda(x_1'\widehat{\beta_1})$ is the estimated inverse Mills ratio $\phi(x_1'\widehat{\beta_1})/\Phi(x_1'\widehat{\beta_1})$. The correlation between the errors in the two stages is given as $\rho = \sigma_{12}/\sigma_2$. A simple *t* test of whether or not $\sigma_{12} = 0$ (or ρ = 0) can be used to test the null hypothesis that the Two-part model is correct (the alternative hypothesis being that the Heckit model is the correct model)[8].

As alluded to above, the motivation for the Heckit model is less strong in the corner solution interpretation than in the censoring interpretation, given that sample selection bias is not applicable to the corner solution case. The zeros do not represent observations for which the potential (or latent) outcome is missing, but are instead actual outcomes. Instead it is an empirical matter as to whether there is correlation between errors in the two stages. This may arise if unobserved effects are correlated between the two equations. It should be noted that while the Heckit model is identified with $x_1 = x_2$, identification is likely to be weak since it is only identified by the parameter non-linearity of the Inverse-Mills ratio (the additional variable in the second stage)[9]. Identification is stronger if $x_1 \neq x_2$ at least for some elements, however as noted extensively in the literature, it is often difficult to *a priori* justify which regressors to drop from one of the parts (see, e.g. Dow and Norton, 2003, and Cameron and Trivedi, 2009). However it should be noted that the significance of individual coefficients is not of primary interest in the corner solution approach, instead the unconditional marginal effects (or alternatively elasticities) are of more importance. These are combinations of individual coefficients and so may be well identified even if the individual coefficients are not. So while there is less compulsion to adopt a Heckit model (and indeed there is some evidence to suggest that the Two-part model performs better (Dow and Norton, 2003), the Heckit model is a viable alternative for a corner solution model (Leung and Yu, 1996).

2.2 Application to the problem of modelling railway renewal costs

The key issue in this section is to determine how the above methods can be applied to our problem of obtaining marginal costs for railway infrastructure renewal. Our data set (see section 3) comprises data on 190 track sections where in any given year the observed track

[8] As discussed in Dow and Norton (2003), the *t* test can still be used even though the Two-part model is not generally nested within the Heckit (see also Leung and Yu, 1996).
[9] The *t* test that can be used to distinguish between the Two-part and the Heckit model is also affected by multicollinearity problems (see Leung and Yu, 1996).

renewal costs are either positive or zero (and where almost 60% of the observations are zeros, since track has a long asset life). Further, as noted earlier, the zero observations are true zeros, and thus the corner solution interpretation is the relevant one in our case.

From the above literature review, the three main candidates for application to our data set are:

- Single equation Tobit model
- Cragg's Two-part model
- Heckman's selection model

Adopting the appropriate model from this model class ensures that consistent estimates are produced, which would not be the case if analysis proceeded by simply carrying OLS on all the data, or OLS on the positive values.

There is a further question as to which of these three models is, a priori, likely to be the most appropriate to our particular problem. At a conceptual level, it seems reasonable to think of track renewal costs being explained by a two part process: firstly there is a decision whether to renew, and secondly, there is a decision about the quality of the renewal to be undertaken, which will determine the unit cost and thus overall cost of the renewal.

The probability of a renewal occurring will depend on the state of the asset relative to relevant asset condition and safety standards. This in turn will depend on the age and characteristics of the track and the volume and type of traffic that has run on the section. The quality, and in turn overall cost of the renewal, will depend on a range of factors, for example the type of track being replaced, and the loads that it is expected to bear. The age of the track may also affect the cost of the work carried out, as it could impact on whether the rail, sleepers, and ballast all need replacing together (or not), and indeed whether major work is required on the sub-structure.

It is therefore possible to think of the variables included in the two-stages having different coefficients, possibly also with different signs. For example, higher quality track may, other things equal, reduce the probability of a renewal occurring, but would be expected to cause the cost of the renewal undertaken to be higher. Older track would, other things equal, be expected to increase the probability of renewal, as the asset reaches the end of its life, but its impact on the cost of renewal is driven by different factors as noted above. It is however not easy to think of variables that would only be included in one stage. The kinds of variables that are typically available for rail marginal cost studies (see section 3), such as traffic volumes, track age and characteristics are all likely to influence both the probability of and cost of renewal undertaken, though perhaps with different coefficients as noted.

As noted in section 2.1, the problem of finding a variable that is included in the first (selection) equation but not in the second (outcome) equation, has been well documented in the literature; and the failure in this matter is likely to result in identification problems with the Heckit model. Further, as noted in section 2.2, there has been some discussion of whether the Heckit model is appropriate for corner solution applications, given that there is no sample selection problem, and Dow and Norton (2003) have presented evidence to show that the Two-part model performs better in such cases. It is, however, an empirical matter as to which model fits the data better, and in this paper we therefore estimate both the Two-part model and the Heckit and perform appropriate testing.

Since we have good reasons to expect that the explanatory variables will affect the decision to participate, and decision of how much to spend on renewals, differently, we would expect the Two-part model to perform better than the more restrictive Tobit. Again, however, this is an empirical matter, and we therefore also estimate the Tobit and perform the relevant tests. In line with the literature, we therefore estimate and compare the results of all three of the candidate models noted above.

3. THE DATA

There is no readily available, single database containing all data on costs, traffic and infrastructure required for our analysis. Therefore, our data used been gathered from different sources within the Swedish Transport Administration (*Trafikverket*)[10]. The collection and assimilation of this data was therefore, in itself, a major undertaking.

The total data set contains 2093 observations and covers approximately 190 track sections for a period of eleven years, from 1999 to 2009. However, missing traffic data on some peripheral lines and station areas restricts us to use a sample of 1663 observations on 166 track sections in our estimations. Descriptive statistics are given in table 1. The track sections are defined by the national track information system (BIS), administered by Trafikverket. The length of the track sections, including multiple tracks, varies from 2.6 kilometres to over 260 kilometres, with an average of about 78 kilometres. The number of annual observations varies between 145 and 159. One reason for this variation is that some track sections have been merged or abandoned, while some new sections have been formed during this period.

The cost data originates from Trafikverket's accounting system, Agresso. The cost data covers track renewal costs at a track section level. Track renewals make up roughly half of total rail infrastructure renewal costs. Out of the 1663 observations, 958 or almost 60 per

[10] The Swedish Rail Administration (Banverket) merged with the Swedish Road Administration (Vägverket) on April 1, 2010 and formed the Swedish Transport Administration (Trafikverket). All our data has been collected from Banverket, but we refer to Trafikverket as the provider of information as Banverket no longer exists.

cent of the track renewal cost observations equals zero, i.e. for many observations, no renewal has occurred, which gives an accumulation of zeros in the data set. Further, approximately 2 per cent of the track sections have had track renewals in all of the studied years, while roughly 11 per cent of the track sections have not had track renewals in any of the years. At the overall network level, there has been a notable variation and increase in total track renewal costs during the period in question, as illustrated by figure 1. This reflects a generally increased focus on track renewals, as well as an allocation of further resources to this area.

Table 1. Descriptive statistics

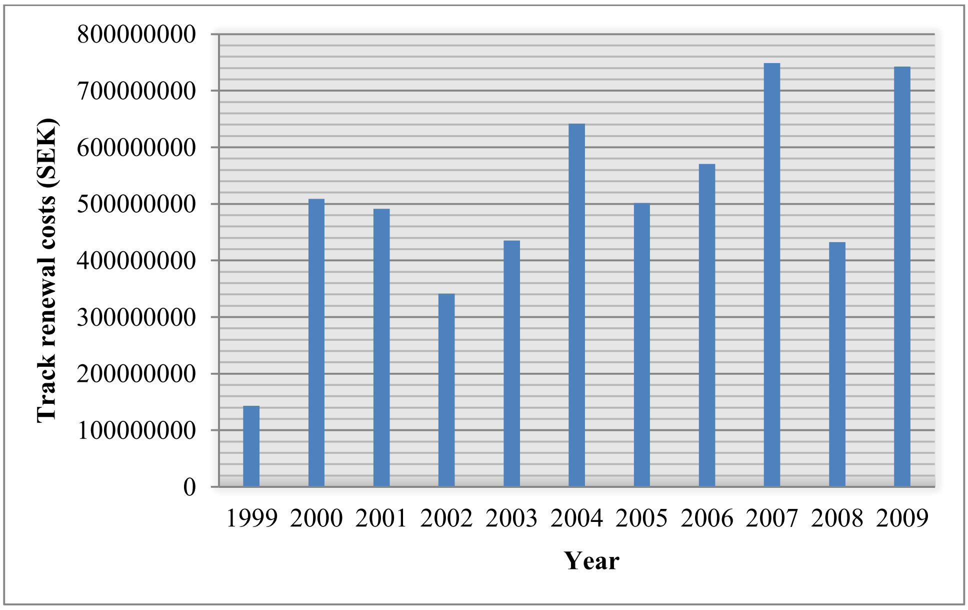
Variable	Mean	Std.Dev.	Min	Max	Variable name[3]
Track renewal cost (SEK)[1]	3 342 144	16 100 000	0	243 000 000	lnccr
Section length (meters)	77 801.3	52 394.8	2 642	261 561	lntsl
Gross tonnes per track section (tonnage density)[2]	7 183 785	7 588 555	15.8	46 900 000	lntgt
Number of trains	15 583.8	17 866.3	0.2193	132 501	lntt
Tunnels (meters)	383.1	1 487.0	0	13 802.4	lntun_tl
Bridges (meters)	649.7	983.8	0	9 822	lnbri_tl
Number of joints	173.4	121.8	0	730	lnjoints
Number of switches	52.0	46.9	2	353	lnswit
Switches (meters)	1575.8	1374.6	58.03	9 070	lnswit_tl
Switch age (years)	20.4	9.1	1	67.7	lnswag
Rail weight (kg)	50.9	5.1	32	60	lnrlwgh
Rail age (years)	20.2	11.5	1	98	lnrail_age
West region (dummy variable)	0.1606	0.3672	0	1	treg_wes
North region (dummy variable)	0.1294	0.3356	0	1	treg_nth
Central region (dummy variable)	0.1990	0.3994	0	1	treg_ctr
South region (dummy variable)	0.2592	0.4383	0	1	treg_sth

[1] Annual cost in 2009 prices. [2] Defined as gross tonne-km divided by track-km. [3] In logs where relevant

Since the separation of train operation from infrastructure management in Sweden in 1988, the supply of traffic data has become more problematic, particularly in view of the higher level of competition on the tracks. Detailed traffic data has therefore been retrieved from different sources such as train operators and published timetables, and for later years from Trafikverket. Generally, traffic has risen in the period in question from an average of 6 million gross tonnes per track section in 1999 to 7.7 million in 2009, peaking at 7.9 million in 2008.

Data on characteristics of the infrastructure have been retrieved from the national track information system, BIS. This data contains inter alia rail age, switches, track length, bridges and tunnels. Further, dummy variables representing different track management regions of Sweden are included the data set. These variables will represent geographical differences, such as need for winter services, and potentially differences in managerial skills.

Figure 1: Total Track Renewal Cost Between 1999 and 2009 (2009 Prices).



Overall we have been able to collect a high quality substantial data set that enables us to explore the relationship between track renewal costs and traffic volume, taking account of a range of infrastructure characteristics and regional (dummy) variables. We now proceed to present and discuss the results.

4. ECONOMETRIC RESULTS

4.1 Model specification

As discussed in section 2, we have three different model candidates that would suit our data and we report the results of all three models and carry out appropriate testing to arrive at a preferred model. The general specification is to use track renewal costs or the probability of a track renewal as dependent variables. The cost variable (in log form) is used in the Tobit and the outcome equations of the Two-part and Heckit models. The probability variable is used in the selection equations of the latter two models.

As independent variables, we use the logs of track section length (*lntsl*), total gross tonnes per track section (or tonnage density; *lntgt*), switch age (*lnswag*), and rail weight (*lnrlwgh*), together with four regional dummy variables (*treg_yyy*) that should pick up remaining unobserved heterogeneity between the sections. We also include ten dummy variables for year 2000 – 2009 (*year200X*). All other variables in table 1 have not been found to improve our models.

Our primary concern in this paper is with the unconditional elasticity of cost with respect of tonnage density. However, it is worth briefly commenting on the expected signs of the coefficients in the selection and outcome equations for the Two-part and Heckit models. First, the length of a track section (*lntsl*) is included in both the selection and outcome parts of the model because the track sections are not of equal length. Thus, in the first stage, a longer track section is more likely to see part of the section renewed. Whilst some data exists at a further level of disaggregation (track segment), cost data is not available at that level. Our data set is therefore the most disaggregate level at which cost and cost driver information exists in Sweden. In the second stage section length is a proxy for the size of the renewal undertaken. In both stages we expect the coefficient on section length to be positive.

Likewise, we expect total gross tonnes per track section (tonnage density) to increase both the probability of a renewal and the cost of renewal undertaken. At this point we note that in the first stage, (annual) tonnage density is acting as a proxy for cumulative tonnage. At present we do not have a robust measure of cumulative tonnage, but we hope to develop this and utilise it in future work. In the second stage, tonnage density is again likely to have a positive effect, but its effect may come through in respect of expected future tonnage, as that would affect the quality of a renewal to be done. To the extent that current tonnage is a good proxy for both past and future traffic, this distinction may be unimportant.

Switch age is a proxy for track age and is included in place of rail age, which, surprisingly, proved to be insignificant in both stages of the model. We would expect older track (proxied here via switch age), other things equal, to have a higher probability of a renewal, though its effect on the cost of renewal is ambiguous for the reasons outlined in section 2.2. Increased rail weight would, other things equal, be expected to reduce the probability of a rail renewal, since the rail quality is higher. In the second stage rail weight would be expected to increase the cost of renewals as higher quality rail is being installed, but at the same time other factors, such as the age and type of sleepers and the condition of the sub-structure could come into play. Finally, we include regional and year dummy variables to capture unobserved heterogeneity between sections, budget fluctuations and other time trends, but with no a priori expectation on signs. All estimations are done in Stata 10 (StataCorp, 2007).

4.2 Estimation outputs

The basic model estimation outputs for the Tobit, Two-part and Heckit models are shown in Tables 2 to 4 below. These are shown for completeness. Our key interest is in the elasticity of cost with respect tonnage density (and the associated marginal cost), which we discuss in section 4.3 below.

The Tobit model was originally developed to deal with expenditure data (Tobin, 1958), and with expenditure data it is often more convenient to model this type of data in logarithmic form to alleviate the problems of skewness. Further, cost function estimation in the literature generally proceeds using a logarithmic functional form. Given that our data set contains zero observations for the dependent variable, to estimate the Tobit model in log form, we first need to transform our data as pointed out by Cameron and Trivedi (2009). By finding the minimum log value of our positive observations, we set the missing observations infinitesimally below the minimum value. We need to redefine the lower limit for censoring not being zero, but rather just below the minimum log value.

Table 2. Tobit Results

Variable	Coefficient	Standard error	t	P value	95% conf. Interval	
lntsl	3.177319	0.331984	9.57	0.000	2.526164	3.828475
lntgt	2.033007	0.224192	9.07	0.000	1.593275	2.472738
lnswag	1.632077	0.535632	3.05	0.002	0.581485	2.682669
lnrlwgh	-7.601759	3.269037	-2.33	0.020	-14.013670	-1.189846
treg_nth	1.584977	0.777734	2.04	0.042	0.059525	3.110429
treg_ctr	0.044501	0.704283	0.06	0.950	-1.336884	1.425886
treg_sth	1.554795	0.706620	2.20	0.028	0.168825	2.940765
treg_eas	1.547125	0.712152	2.17	0.030	0.150304	2.943946
year00	-0.898373	1.127719	-0.80	0.426	-3.110289	1.313544
year01	1.519132	1.071565	1.42	0.156	-0.582643	3.620906
year02	3.911651	1.036689	3.77	0.000	1.878281	5.945020
year03	4.035787	1.052588	3.83	0.000	1.971234	6.100341
year04	4.321607	1.050723	4.11	0.000	2.260711	6.382503
year05	3.774779	1.054585	3.58	0.000	1.706308	5.843250
year06	5.085104	1.045593	4.86	0.000	3.034271	7.135937
year07	5.173595	1.048477	4.93	0.000	3.117105	7.230085
year08	5.716598	1.038124	5.51	0.000	3.680414	7.752781
year09	7.706843	1.033130	7.46	0.000	5.680455	9.733231
constant	-39.916250	11.674660	-3.42	0.001	-62.815020	-17.017480
Sigma	7.250160	0.222141			6.814451	7.685869

Number of obs = 1663, LR chi2(18)= 396.52, Prob > chi2 = 0.0000, Log likelihood = -2935.8088, Pseudo R2 = 0.0633
958 left-censored observations at lnccr_tob<=6.0532551, 705 uncensored observations

Concerning model selection, the Tobit gives a first impression of reasonable estimates. However, a likelihood ratio test of the Tobit model as compared to the more flexible Two-part model shows that the Tobit restriction can be rejected at any reasonable levels of significance. With regard to the choice between the Two-part and Heckit models, we carry out the standard *t* test on the lambda coefficient (defined here as $\rho \cdot \sigma_2$); see section 2. As shown in Table 3, we cannot reject the null hypothesis that the correlation between the errors in the two stages is zero even at the 10% level. This finding leads us to prefer the Two-part model. However, since the power of this test is affected by the multi-collinearity problems that often beset the Heckit model in empirical applications, we follow the approach recommended in Dow and Norton (2003), and utilise the empirical mean square error

(EMSE) criterion (computed based on the main elasticity of interest, the estimated elasticity with respect to tonnage density). We find that the Two-part model has the lower empirical MSE for this estimate, which again favours the Two-part model according to this criterion.

Table 3. Two-Part Model Results

Variable/ Equation	Coefficient	Robust standard error	z	P value	95% conf. interval	
Selection equation						
lntsl	0.454107	0.051307	8.85	0.000	0.353548	0.554668
lntgt	0.302315	0.035914	8.42	0.000	0.231924	0.372706
lnswag	0.219649	0.093094	2.36	0.018	0.037189	0.402109
lnrlwgh	-1.083273	0.521021	-2.08	0.038	-2.104454	-0.062091
treg_nth	0.241668	0.123099	1.96	0.050	0.000398	0.482937
treg_ctr	-0.002100	0.109703	-0.02	0.984	-0.217214	0.212814
treg_sth	0.208522	0.110179	1.89	0.058	-0.007426	0.424469
treg_eas	0.284138	0.113048	2.51	0.012	0.062568	0.505708
year00	-0.123794	0.163989	-0.75	0.450	-0.445207	0.197619
year01	0.188312	0.163064	1.15	0.248	-0.131286	0.507911
year02	0.624562	0.157700	3.96	0.000	0.315280	0.933844
year03	0.599936	0.160912	3.73	0.000	0.284555	0.915317
year04	0.633515	0.162522	3.90	0.000	0.314977	0.952053
year05	0.558197	0.165490	3.37	0.001	0.233842	0.882552
year06	0.779137	0.167183	4.66	0.000	0.451466	1.106809
year07	0.814997	0.165403	4.93	0.000	0.490812	1.139181
year08	0.950275	0.164088	5.79	0.000	0.628668	1.271882
year09	1.307138	0.169716	7.70	0.000	0.974400	1.639776
constant	-6.908049	1.868068	-3.70	0.000	-10.569400	-3.246702
Outcome equation						
lntsl	0.787886	0.144696	5.45	0.000	0.504287	1.071485
lntgt	0.284667	0.096559	2.95	0.003	0.095414	0.473910
lnswag	0.544509	0.270409	2.01	0.044	0.014517	1.074500
lnrlwgh	-2.468350	1.361774	-1.81	0.070	-5.137378	0.200679
treg_nth	0.106308	0.312252	0.34	0.734	-0.505694	0.718300
treg_ctr	-0.121240	0.309452	-0.39	0.695	-0.727754	0.485276
treg_sth	0.493809	0.299598	1.65	0.099	-0.093392	1.081009
treg_eas	-0.368183	0.277127	-1.33	0.184	-0.911343	0.174977
year00	-0.185250	0.657958	-0.28	0.778	-1.474824	1.104323
year01	0.224342	0.504700	0.44	0.657	-0.764852	1.213536
year02	-0.651508	0.484902	-1.34	0.179	-1.601898	0.298881
year03	-0.189770	0.480178	-0.40	0.693	-1.130902	0.751362
year04	-0.066083	0.466494	-0.14	0.887	-0.980394	0.848228
year05	-0.231088	0.489100	-0.47	0.637	-1.189707	0.727531
year06	-0.376985	0.476650	-0.79	0.429	-1.311203	0.557232
year07	-0.484181	0.465505	-1.04	0.298	-1.396553	0.428191
year08	-0.696808	0.441673	-1.58	0.115	-1.562470	0.168855
year09	-0.420119	0.440876	-0.95	0.341	-1.284220	0.443982
constant	8.986663	4.820211	1.86	0.062	-0.460776	18.434100
Sigma	2.306333	0.068140	33.85	0.000	2.172781	2.439885

Number of obs = 1663, Log pseudolikelihood = -2535.9913, Wald chi2(18) = 326.51, Prob > chi2 = 0.0000

Table 4. Heckit (two step) Model Results

Variable/ Equation	Coefficient	Standard error	z	P value	95% conf. interval	
Selection equation						
lntsl	0.454107	0.052144	8.71	0.000	0.351907	0.556308
lntgt	0.302315	0.035914	8.42	0.000	0.231925	0.372705
lnswag	0.219649	0.083756	2.62	0.009	0.055490	0.383808
lnrlwgh	-1.083273	0.523503	-2.07	0.039	-2.109320	-0.057226
treg_nth	0.241668	0.126954	1.90	0.057	-0.007157	0.490493
treg_ctr	-0.002100	0.113599	-0.02	0.985	-0.224850	0.220451
treg_sth	0.208522	0.113840	1.83	0.067	-0.014601	0.431645
treg_eas	0.284138	0.115858	2.45	0.014	0.057061	0.511215
year00	-0.123794	0.173099	-0.72	0.475	-0.463061	0.215474
year01	0.188312	0.164735	1.14	0.253	-0.134563	0.511187
year02	0.624562	0.160832	3.88	0.000	0.309338	0.939787
year03	0.599936	0.163593	3.67	0.000	0.279299	0.920572
year04	0.633515	0.163402	3.88	0.000	0.313254	0.953776
year05	0.558197	0.162900	3.43	0.001	0.238918	0.877475
year06	0.779137	0.162617	4.79	0.000	0.460415	1.097860
year07	0.814997	0.163665	4.98	0.000	0.494219	1.135774
year08	0.950275	0.163720	5.80	0.000	0.629370	1.271179
year09	1.307138	0.166874	7.83	0.000	0.980071	1.634204
constant	-6.908049	1.867916	-3.70	0.000	-10.569100	-3.247000
Outcome equation						
lntsl	1.504084	0.599180	2.51	0.012	0.329713	2.678456
lntgt	0.763474	0.399647	1.91	0.056	-0.019819	1.546768
lnswag	0.913202	0.394487	2.31	0.021	0.140022	1.686382
lnrlwgh	-4.281429	2.183206	-1.96	0.050	-8.560435	-0.002424
treg_nth	0.447206	0.466730	0.96	0.338	-0.467567	1.361979
treg_ctr	-0.115036	0.345665	-0.33	0.739	-0.792528	0.562455
treg_sth	0.780079	0.421626	1.85	0.064	-0.046293	1.606452
treg_eas	0.070373	0.494565	0.14	0.887	-0.898957	1.039703
year00	-0.334629	0.631496	-0.53	0.596	-1.572338	0.903080
year01	0.581040	0.640964	0.91	0.365	-0.675225	1.837306
year02	0.436196	1.020355	0.43	0.669	-1.563662	2.436054
year03	0.864800	1.001267	0.86	0.388	-1.097648	2.827248
year04	1.030518	1.029039	1.00	0.317	-0.986361	3.047397
year05	0.720949	0.937829	0.77	0.442	-1.117163	2.559061
year06	0.926991	1.173352	0.79	0.430	-1.372737	3.226719
year07	0.891946	1.223472	0.73	0.466	-1.506015	3.289908
year08	0.853952	1.345720	0.63	0.526	-1.783612	3.491515
year09	1.617156	1.710504	0.95	0.344	-1.735370	4.969681
constant	-3.795208	11.68794	-0.32	0.745	-26.703150	19.112740
mills lambda	2.59351	2.050877	1.26	0.206	-1.426135	6.613156
rho	0.85007					
sigma	3.05095					
lambda	2.59351	2.050877				

Number of obs = 1663, Censored obs = 958, Uncensored obs = 705, Wald chi2(36) = 350.70, Prob > chi2 = 0.0000

Before turning to the main results of interest, namely the cost elasticities with respect to tonnage, we briefly comment on the coefficient estimates in the preferred, Two-part model. As expected, section length and tonnage density both have positive coefficients in both the probability (Selection) and conditional regression (Outcome) equations. Switch age also has the expected positive coefficient in the first equation. As discussed earlier, its sign in the second equation is ambiguous, and in this case found to be positive. Rail weight also has the expected, negative sign in the first equation, and as discussed earlier, its sign in the second equation is ambiguous, and in this case found to be negative also.

4.3 Cost predictions and elasticities

Our main interest is in the cost elasticity with respect to tonnage density, as the marginal cost is the product of the estimated cost elasticity and the predicted average cost. Dow and Norton (2003) argue that where the Two-part and Heckit models are applied to corner solution data then it is the cost elasticities and marginal costs associated with the actual values of the dependent variable (cost) that are of interest rather than the elasticities and marginal costs of the latent variable. This is in contrast to the standard interpretation of these models where they are applied to data which is subject to sample selection.

Importantly note that both the marginal costs and the elasticities for both models depend on the coefficients from both stages of the models; the decision to renew and the cost of the renewal should it go ahead. Thus they represent the effect of increasing usage on cost taking into account the change in likelihood of undertaking a renewal and any change in the cost of a renewal should it be undertaken. It should be emphasised that both marginal costs and elasticities are non-linear functions of multiple parameters. Dow and Norton derive the formula for the elasticity when the dependent variable is in log form (independent variables in non-logged form). In our case, when the dependent and independent variables are all in log-form, the formula for the Two-part and Heckit models are shown in equations (7) and (8) respectively (see van de Ven and van Praag, 1981):

$$\frac{\partial E[y]}{\partial x_k} \times \frac{x_k}{E[y]} = \beta_{2k} + \beta_{1k}\lambda(x_1^{'}\beta_1) \tag{7}$$

$$\frac{\partial E[y]}{\partial x_k} \times \frac{x_k}{E[y]} = \beta_{2k} + \beta_{1k}\lambda(x_1^{'}\beta_1 + \rho\sigma_2) \tag{8}$$

Table 5 shows the elasticities, together with their standard errors and confidence intervals for the preferred Two-part model, together with the results for the comparator models. The (average) marginal cost estimate for the Two-part model is shown in Table 6, together with its standard error.

The elasticity at the sample mean for the preferred model is around 0.55. That is, a 1 per cent change in traffic will increase renewal costs by 0.55 per cent. The point estimates for the comparator models are higher, though in the case of the Heckit model, this is estimated rather imprecisely. As noted above, based on relevant testing, the Two-part model is our preferred model and, as discussed in the next section, the estimated elasticity from this model is supported by engineering and other evidence. The preferred model produces a weighted average marginal cost estimate of SEK 0.009 per gross tonne-km.

Table 5: Elasticities With Respect To Tonnage Density

Model	Elasticity* (*lntgt*)	Standard error	z	p value	95 % Conf. Interval	
Two-part	0.547	0.105	5.190	0.000	0.341	0.754
Heckit	0.771	0.400	1.930	0.054	-0.012	1.555
Tobit	0.687	0.074	9.258	0.000	0.542	0.832

* Calculated at the sample mean

Table 6: Marginal Cost Estimates: Two-part Model

	Obs.	Weighted mean*	Standard error	95 % Conf. Interval	
Marginal cost	1663	0.009	0.002	0.0088	0.0097

* The marginal cost is weighted by gross tonne-km's per track section

5. DISCUSSION AND CONCLUSIONS

In this paper, we have analysed railway track renewal costs using Swedish track section data from 1999-2009. We have estimated three different regression models; the Tobit, the Two-part and the Heckit. All of these models have properties to make them suitable for estimation when data holds a large fraction of true zeros in the dependent variable. Our preferred model is the Two-part model, which performs best in comparison with the Tobit and Heckit models.

We find that the cost elasticity with respect to output (gross tonne-km) is around 0.55. This is higher than previously found for analyses of maintenance costs, which suggests a range of 0.20-0.35 (Wheat et. al., 2009). However, this finding is in line with a priori expectations, since engineering evidence suggests that renewals are more variable with traffic than maintenance (see Abrantes et. al., 2008).

We now turn to consider how our results fit into the previous literature (see Table 7). A few points need to be borne in mind at this stage. First, as compared to studies of maintenance marginal costs, there is a relative shortage of studies involving renewals costs. Second, and perhaps more importantly, all of the previous studies have modelled maintenance and renewals together, and these studies have produced a wide range of estimates for the total maintenance and renewals cost elasticities. The result is that renewals cost elasticities have to be inferred from models based on maintenance and renewals combined, and there is therefore currently much uncertainty over the range of appropriate values that should be used. Our paper is therefore the first paper in the literature that we are aware of to report usage elasticities specifically for renewals costs (in our case, track renewal costs).

Table 7. Studies on railway infrastructure renewal costs

Study	Data	Cost category	Average elasticity*
This paper	Track section level Sweden 1999 – 2009	Renewals only	0.55
Andersson (2006)	Track section level Sweden 1999 – 2002	Maintenance and Renewals	0.26
Marti et al. (2009)	Track section level Switzerland 2003 – 2007	Maintenance and Renewals	0.28
Wheat and Smith (2009)	Maintenance delivery unit level Great Britain 2006	Maintenance and Track renewals	0.49
Smith et al. (2008)	Regional level 5 European countries 2002-2006	Maintenance and Track renewals	0.43-0.44
Smith (2008)	National level 13 European countries 1996 – 2006	Maintenance and Renewals	0.48-0.51
Wheat et al. (2009)	A range of country case studies	Maintenance only	0.20-0.35
Andersson (2007b)	Track segment level Sweden 1999 – 2005	Renewals only	-0.1**

* Elasticity of cost w.r.t. traffic volume; ** Elasticity of expected life time w.r.t. traffic volume

Nevertheless, it is interesting to consider how our results compare against previous work. Given difference in network quality between countries resulting in substantial differences in average cost, Wheat et. al. (2009) recommend that generalisation from one study to other networks should be based on elasticities. As noted, the majority of the studies reported in Table 6 cover both maintenance and renewals (M&R) cost, and we would thus expect our results to have a higher elasticity than in those studies based on engineering evidence. The reported elasticity of 0.55 from our preferred model does indeed lie above the top of the range of previous estimates for maintenance and renewals. It should be noted, however, that the high M&R elasticities in Table 7 derive from the results of more aggregated data (national, regional or maintenance delivery unit), whereas Andersson (2006) and Marti et al. (2009) report much lower elasticities using disaggregate (track section) data more similar in nature to the data set used in the present study.

Overall, we conclude that our results make sense in the context of previous work, though the different cost categories used make a more in-depth comparison problematic. Importantly, by presenting the first renewals-only study, we consider that we have added new clarity to the literature, and indeed increased certainty regarding the elasticity of renewal costs with respect to traffic (at least for track renewals).

The average marginal cost per gross tonne-km is estimated to be approximately SEK 0.009 or €c 0.10. Marginal cost estimates are either not reported in the other previous studies shown in Table 6, or are non-comparable since they are based different cost bases (i.e. they include maintenance); and as noted above, generalisation from one country to another should proceed based on elasticities rather than marginal costs in any case. Turning to the evidence in respect of Sweden, our estimates are higher than previously found in Andersson (2007b), using survival analysis and a unit cost for track renewal, specifically rail replacements. We expect the present estimates to be higher as they cover a larger track renewal cost share. Since the current pricing scheme in Sweden only covers the marginal infrastructure cost for maintenance activities, the inclusion of our estimate of marginal infrastructure renewal costs would add substantially to the current track charge, which is SEK 0.0036 per gross tonne-km.

Of course, if the track access charges in Sweden are to be made truly cost reflective, as required by EU legislation, then marginal renewal costs should be incorporated into current charging structures. Given the evidence provided by this paper, the inclusion of marginal renewal cost would lead to an increase in charges of approximately 250 per cent.

This paper presents some initial efforts at disaggregate modelling of track renewal costs. A key development would be the incorporation of cumulative tonnage into the analysis. Cumulative tonnage is considered a key for renewal decisions in the rail technology literature, but this type of data is normally not available. If it is not available, then decisions will have to follow some other heuristic. In this paper, we have attempted to model renewal costs using annual tonnage measures on the right hand side of the model, together with capability, condition and age measures. Whilst a robust measure of cumulative tonnage is not yet available in Sweden, this could be a realistic possibility with additional data collection and analysis in the future.

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