THE MARGINAL COST OF RAILWAY 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 renewals are a substantial part of an infrastructure manager's budget, but in disaggregated statistical analyses, they cause problems for traditional regression models from a pile of zero observations. 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 renewal cost elasticities with respect to traffic volumes and marginal renewal costs using Swedish railway renewal data over the period 1999 to 2007.

1. INTRODUCTION

Marginal cost pricing of infrastructure wear and tear is of great importance from an 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).

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 term marginal costs.

Sweden has a long tradition of marginal cost pricing in the transport sector, but to date, railway infrastructure wear and tear charges have excluded costs for rail renewal. There are currently three different 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.

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 tonnes) and properties of the infrastructure (track section distance, rail age, number of switches, tunnels etc). The track charge for 2011 is set to SEK 0.0036/gross tonne kilometre as a marginal infrastructure cost charge[1].

The marginal infrastructure cost issue has drawn some attention recently regarding the lack of empirical evidence on the size of the rail renewal marginal cost (Nash, 2005). Most research on railway infrastructure wear and tear has rather focused on the relationship between maintenance costs and traffic, while controlling for infrastructure characteristics.

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. A railway track has an optimal 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, the lack of comprehensive time-series data have questioned the adequacy of applying standard regression analysis techniques to the renewal problem on disaggregate data. The main problem is that disaggregate renewal cost data contains many zero observations, i.e. 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,

[1] Exchange rate is: SEK 7.65 = US$ 1; SEK 9.59 = € 1 (14 May, 2010).

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)[2], Smith (2008) and Smith et al. (2008). In general, the models involving renewals have proved to be less robust than maintenance-only modelling, and a wide range of marginal costs has resulted.

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 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.

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 therefore derive marginal costs directly from the econometric cost model, whilst ensuring that the zero data observations are utilised and modelled appropriately to ensure consistent estimates of the model parameters. We explore the results of these alternative approaches using Swedish railway renewal cost data.

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 tonnes is around 0.5, which is higher than what has previously been found in empirical analyses of maintenance costs, 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[3]). The results are also broadly in line with previous, aggregated econometric work. The estimated marginal cost is approximately SEK 0.01 per gross tonne kilometre or three times higher than the charge for 2011.

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

[2] Even then, maintenance and renewal costs were combined in the preferred model.
[3] See Abrantes et al. (2008).

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, 2005).

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 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 (2005) 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[4].

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 (2005), consider the classical regression model for the underlying dependent variable *y**:

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

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 $x'\beta$. There, $E(\varepsilon|x)$ is a function of x (so is not equal to zero). As Greene (2005) 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, 2005). However, in our case, where the zeros are "true zeros" and thus contain useful information, it would seem inappropriate to proceed in this way.

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 briefly in turn below.

The fundamentals of the Tobit model is to correct for the pile 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

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

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 (following the notation used in Dow and Norton, 2003):

$$\Pr[y > 0 \mid X] = \Phi(X\beta_2, \varepsilon_2) \quad (3)$$

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

$$E[y \mid y > 0, X] = X\beta_4 + E[\varepsilon_4 \mid y > 0, X] = X\beta_4 \quad (4)$$

The model here implies that the value of y (say expenditure), given that it is positive, 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, its motivation lies in the fact that the decision to participate - in our case, to renew or not - is determined independently of the decision concerning how much to spend, given that expenditure will be positive. Fin and Schmidt (1984) offer a good example, 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. Second, 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[5]. Third, 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 $\alpha = \beta$ then the Two-part model simplifies to the Tobit case (and this restriction is testable).

Finally, the Heckit model has been proposed and used extensively for censored and truncated data. The motivation behind this model is to address the potential problem of sample selection bias. That is, it 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

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

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 to 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 additional variables included, computed based on the parameter values from the probit model (see Greene, 2005). The errors in the two equations can be correlated in this model as well, unlike in the Two-part model where the decision to participate is independent of the level of expenditure.

Using the terminology in Dow and Norton (2003), the Heckit can be formalised as a selection equation (5) and an outcome equation (6).

$$\Pr[y > 0 \mid X] = \Phi(X\beta_2, \varepsilon_2) \tag{5}$$

$$\begin{aligned} E[y \mid y > 0, X] &= X\beta_3 + E[\varepsilon_3 \mid y > 0, X] = \\ & X\beta_3 + \rho\sigma_3\lambda(X\beta_2) \end{aligned} \tag{6}$$

where $\lambda(X\beta_2)$ is the inverse Mills ratio $\phi(X\beta_2)/\Phi(X\beta_2)$.

The Heckit model contains as a special case the truncated regression model, where for the latter the sample selection is on the basis of y_i (that is, the sample excludes, say, households with high incomes). The Heckit bases sample selection on another variable, and is sometimes therefore referred to as an “incidental truncation” model (see Greene, 2005 and Wooldridge, 2002)[6]. It should also be noted that sample selection bias can occur in censored regression models as well, if those observations for which full information is missing differ in a systematic way from the uncensored observations (see Dow and Norton, 2003). However, Dow and Norton (2003) argue that as long as the censored data represent true values, there is no sample selection problem. The zeros do not represent observations for which the potential (or latent) outcome is missing, but are instead actual outcomes.

Dow and Norton (2003) nevertheless point out that the Heckit model can be used for the corner solution model, though they put forward evidence to suggest that the Two-part model performs better. This led to considerable debate in the literature, the conclusion of which is that the Heckit model is a candidate model for estimation for corner solution applications, which can be compared against the Two-part model (Leung and Yu, 1996).

[6] For example, in the classic wage studies, the wage offer is only observed for working people. That is, wage is not observed because of the value taken by another variable, namely labour force participation.

An important final point to note here is that the Heckit can suffer from muliticollinearity problems, leading to parameter instability. One solution to this problem is the inclusion of at least one variable in the selection equation that is not in the outcome equation, but this often requires strong arguments for it not to appear in the outcome equation. Another is to rely on functional form assumptions (see Dow and Norton, 2003 and Wooldridge, 2002). 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).

2.2 Application to the problem of modelling railway renewal costs

The key issue in this section is to understand how the above methods can be applied to our problem of obtaining marginal costs for railway infrastructure renewal. From the above model review, there appear to be three main candidates for application to our dataset:

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

The important question is how to obtain consistent and efficient estimates for disaggregate cost data, where a large fraction of the dataset contains zero values for the dependent variable. How can we deal correctly with the fact that the dependent variable comprises discrete and continuous portions (to be precise, large numbers of zero observations, where cost does not vary with the explanatory variables, x, followed by positive renewals, which have some relationship with x)? The models outlined above ensure 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 truncated data.

The literature supports the estimation of all these models in our case, including the Heckit, even though there is no sample selection problem given that our zero observations are true zeros. From a pragmatic point of view, therefore, we estimate all of these and compare the results, but first take a brief look at the data available.

3. THE DATA

There is no readily available 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*)[7].

The total sample contains 1709 observations and covers approximately 190 track sections for a period of nine years, from 1999 to 2007. However, missing traffic data on some peripheral lines and station areas restricts us to use 1519 observations 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 almost 73 kilometres. The number of annual observations varies between 186 in 1999 and 192 in 2007. The reason for this variation is that some track sections have been merged or abandoned, while some new sections have been formed during this period.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis
Renewal cost[1]	1519	6465078	1.93e+07	0	2.53e+08	6.821	62.028
Section length[3]	1519	72890	52854	3719	261561	1.122	3.959
Gross tonnes[1]	1519	7766147	8817919	6426.95	88459900	2.841	18.627
Trains[1]	1519	16887	20681	14.655	185681	3.328	18.657
Quality class[4]	1519	2.131	1.129	0	5	-0.190	2.191
Tunnels[3]	1519	369.880	1418.900	0	13799.14	6.434	53.043
Bridges[3]	1519	677.879	1132.218	0	9821.985	4.688	30.423
Joints[2]	1519	170.440	136.711	0	1119	2.065	10.676
Switches[3]	1519	1772.283	1780.861	0	14404.7	3.015	17.187
Switches[4]	1519	50.211	47.670	0	376	2.898	16.170
Switch age[4]	1519	19.758	8.932	1	67.665	0.646	3.582
Rail weight kg[4]	1519	50.802	4.920	32	60	0.023	2.810
Rail age[4]	1519	17.925	10.924	1	98	2.269	13.139
Iron ore line[5]	1519	0.050	0.218	0	1	4.128	18.040
Secondary lines[5]	1519	0.248	0.432	0	1	1.166	2.359
High speed lines[5]	1519	0.203	0.403	0	1	1.474	3.171
Stations[5]	1519	0.109	0.312	0	1	2.505	7.273

[1] Annual volume; [2] Number of; [3] Meters; [4] Track section average; [5] Dummy variable

The cost data originates from Trafikverket's accounting system, Agresso. The cost data covers total infrastructure renewal costs at a track section level. Out of the 1519 observations, 583 or almost 40 percent of the total infrastructure 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 20 percent of the track sections

[7] 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 will use Trafikverket as the provider of information as Banverket no longer exists.

have had renewal in all of the studied years, while roughly 5 percent of the track sections have not had renewal in any of the years. There has been a substantial increase in renewal costs during the period in question. The average size of an infrastructure renewal has risen from SEK 3.3 million in 1999 to 7.3 million in 2007 (2007 prices).

Since the separation of train operation from infrastructure management in 1988, the supply of traffic data has been limited. A higher level of competition on the tracks has further impaired the collection of accurate traffic data. Detailed traffic data has therefore been retrieved from different sources such as train operators and published timetables, and for later years from Trafikverket. Generally, train traffic has risen in the period in question from an average of 7.2 million gross tonnes per track section in 1999 to 7.7 million in 2007, peaking at 8.2 million in 2006.

Data on characteristics of the infrastructure have been retrieved from the national track information system, BIS. This data contains inter alia on quality class, age, switches, track lengths, bridges and tunnels. Quality class is measured in six categories where 0 is the highest and 5 is the lowest quality. The quality determines inter alia the maximum speed allowed on the track section and will work as a proxy variable for speed.

A number of indicator variables describing the overall use of the track section are also available. The Iron ore line variable is used to identify some track sections used for heavy haul freight traffic from the northern iron ore mines in the Kiruna region to the harbours in Luleå, Sweden, and Narvik, Norway. There are also indicator variables for high speed track sections, secondary lines and stations.

4. ECONOMETRIC RESULTS

As pointed out in section 2, we have three different model candidates that would suit our data. Each one is discussed in order below. To compare the different alternatives, we have used the same model specification in all three cases. This should be seen as a starting point to assess the merits of the alternatives. However, as there are different assumptions underlying these alternatives, this is not a definite solution. More emphasis will be put on the individual model specifications in future work.

The general specification is to use renewal costs or the probability of a renewal as dependent variables. The cost variable 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 log of track section length (*lntsl*), total gross tonnes (*lntgt*), track length of switches (*lnswit_tl*), switch age (*swag*) as well as average quality class in levels (*qc_ave*), a dummy variable for secondary lines (*sec_line*), and eight dummy variables for year 2000 – 2007 (*year200X*). All other variables in table 1 have not been found to improve our models.

The length of a track section, total gross tonnes, length and age of switches and quality class (with its definition) are all expected to have a positive effect on both the probability and the size of renewal costs. Secondary lines are expected to reduce both the probability of a renewal and the size. We finally include the year dummy variables to capture budget fluctuations and other time trends, but with no a priori expectation on signs.

All estimations are done in Stata 10 (StataCorp, 2007).

4.1 Tobit regression model

The Tobit model is originally developed to deal with expenditure data (Tobin, 1958), but expenditure data it is often more convenient to model this type of data in logarithmic form to alleviate the problems of skewness (see table 1). To estimate the Tobit model in log form, we need to transform our data as pointed out by Cameron and Trivedi (2009). The key is to take the natural logarithm of our cost data, which will generate 583 missing observations. 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.

The Tobit model estimates both the outcome and selection process jointly under a normality assumption using the natural logarithm of annual renewal costs as dependent variable.

The estimated coefficients are given in table 2. All coefficients are significant and with expected signs, except year 2000 and 2001 who are insignificantly different from our baseline year 1999.

The Tobit gives a first impression of reasonable estimates, but relies on the normality assumption to give consistent estimates of the regression coefficients. A normality test following Cameron and Trivedi (2009) shows that this assumption is violated and we conclude that the Tobit model is unsuitable for our data, despite the logarithmic transformation.

Table 2. Tobit regression estimates of renewal costs (natural log)

```
Tobit regression                                  Number of obs   =       1519
                                                  F(  14,   1505) =      66.45
                                                  Prob > F        =     0.0000
Log pseudolikelihood = -2816.1907                 Pseudo R2       =     0.1055
```

lncr	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
lntsl	1.585041	.1320168	12.01	0.000	1.326085	1.843998
lntgt	.7752157	.1055832	7.34	0.000	.5681099	.9823215
lnswit_tl	.4631595	.1252789	3.70	0.000	.2174198	.7088992
lnswag	.4295909	.242359	1.77	0.077	-.0458062	.9049881
qc_ave	.5519064	.1041411	5.30	0.000	.3476294	.7561834
sec_line	-1.693554	.3438309	-4.93	0.000	-2.367992	-1.019115
year00	-.2468901	.4473078	-0.55	0.581	-1.124303	.6305228
year01	.4691002	.4272652	1.10	0.272	-.3689982	1.307199
year02	1.392079	.4085209	3.41	0.001	.5907486	2.19341
year03	2.276469	.4157668	5.48	0.000	1.460925	3.092013
year04	2.336511	.4128418	5.66	0.000	1.526704	3.146317
year05	3.119542	.3973395	7.85	0.000	2.340144	3.898939
year06	2.336329	.4161931	5.61	0.000	1.519949	3.152709
year07	2.605205	.405241	6.43	0.000	1.810308	3.400103
_cons	-23.86542	2.124153	-11.24	0.000	-28.03203	-19.6988
/sigma	3.169526	.0739856			3.024401	3.314652

```
  Obs. summary:        583  left-censored observations at lncr<=10.129713
                       936     uncensored observations
                         0 right-censored observations
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4.2 Cragg's Two-part model

The estimates from Cragg's Two-part model are given in table 3. The selection equation (Tier 1) reveals a similar pattern as the Tobit above, with significant estimates and expected signs. Conversely, the outcome equation (Tier 2) shows some differences worth noting. Switch age and secondary lines have no significant impact on the size of the renewal and likewise this holds also for all of the year dummies. These variables only affect the probability of observing a renewal.

It is emphasised in both Dow and Norton (2003) and Burke (2009) that even if the probit and the truncated normal regression model are estimated under an independence assumption (as in the Cragg model), interpretation does not follow in line with this. Hence, we cannot simply look at the coefficients in the outcome equation and interpret these as elasticities. The elasticity calculation is given in 4.4.

Table 3. Cragg's Two-part regression estimates of renewal costs (natural log)

Number of obs = 1519
Wald chi2(14) = 441.65
Log pseudolikelihood = -2557.268
Prob > chi2 = 0.0000

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Tier1						
lntsl	.4766672	.0585342	8.14	0.000	.3619423	.5913921
lntgt	.2541964	.0426202	5.96	0.000	.1706624	.3377304
lnswit_tl	.1501142	.0495701	3.03	0.002	.0529586	.2472698
lnswag	.1665014	.0866042	1.92	0.055	-.0032398	.3362426
qc_ave	.1671896	.0465803	3.59	0.000	.0758939	.2584852
sec_line	-.5828532	.1307894	-4.46	0.000	-.8391956	-.3265107
year00	-.0574681	.1417041	-0.41	0.685	-.3352031	.2202668
year01	.238595	.1391502	1.71	0.086	-.0341345	.5113245
year02	.5480916	.1416412	3.87	0.000	.27048	.8257033
year03	.9493353	.1617025	5.87	0.000	.6324042	1.266266
year04	.908378	.159655	5.69	0.000	.59546	1.221296
year05	1.377972	.1789365	7.70	0.000	1.027263	1.728681
year06	1.012478	.1653089	6.12	0.000	.6884781	1.336477
year07	1.144615	.16466	6.95	0.000	.821887	1.467342
_cons	-11.07393	.8770961	-12.63	0.000	-12.79301	-9.354856
Tier2						
lntsl	.66311	.0856247	7.74	0.000	.4952887	.8309313
lntgt	.3391584	.0681036	4.98	0.000	.2056777	.472639
lnswit_tl	.2462626	.0716361	3.44	0.001	.1058585	.3866668
lnswag	.0164457	.1563216	0.11	0.916	-.289939	.3228304
qc_ave	.2743875	.0651506	4.21	0.000	.1466947	.4020804
sec_line	-.2071685	.2014442	-1.03	0.304	-.6019919	.1876549
year00	-.2449077	.2741505	-0.89	0.372	-.7822328	.2924175
year01	-.3769725	.2684551	-1.40	0.160	-.9031348	.1491899
year02	-.1163623	.2343907	-0.50	0.620	-.5757597	.343035
year03	.030376	.2480273	0.12	0.903	-.4557486	.5165005
year04	.1424889	.2398812	0.59	0.553	-.3276695	.6126474
year05	.1703779	.2318537	0.73	0.462	-.2840471	.6248029
year06	-.109714	.2469081	-0.44	0.657	-.593645	.3742171
year07	-.0614133	.2394694	-0.26	0.798	-.5307647	.4079381
_cons	-.1636237	1.442691	-0.11	0.910	-2.991246	2.663999
sigma						
_cons	1.68801	.038276	44.10	0.000	1.612991	1.76303

4.3 Heckit selection model

Finally, we estimate the Heckit model using the same specification as in the Tobit and Two-part cases. The estimates once again are in line with the both the Tobit and Two-part estimates, and even giving significant estimates secondary lines and some year dummies. However, we find that the model has serious problems, with ρ constrained to 1. This is a sign of misspecification, which questions the Heckit in this case. We therefore refrain from interpreting the results given in table 4.

Table 4. Heckit model – two-step estimates

```
note: two-step estimate of rho = 1.1423862 is being truncated to 1

Heckman selection model -- two-step estimates   Number of obs      =      1519
(regression model with sample selection)        Censored obs       =       583
                                                Uncensored obs     =       936

                                                Wald chi2(14)      =     52.13
                                                Prob > chi2        =    0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnccr_n						
lntsl	1.315319	.2569277	5.12	0.000	.81175	1.818888
lntgt	.6182977	.1437332	4.30	0.000	.3365857	.9000096
lnswit_tl	.4385236	.1321267	3.32	0.001	.17956	.6974872
lnswag	.3208623	.2389535	1.34	0.179	-.1474781	.7892026
qc_ave	.4548586	.1229345	3.70	0.000	.2139113	.6958058
sec_line	-1.101886	.4286028	-2.57	0.010	-1.941932	-.2618401
year00	-.2754085	.4003289	-0.69	0.491	-1.060039	.5092217
year01	.0658258	.411752	0.16	0.873	-.7411932	.8728448
year02	.7122018	.4725919	1.51	0.132	-.2140613	1.638465
year03	1.293094	.584344	2.21	0.027	.1478007	2.438387
year04	1.38025	.5783169	2.39	0.017	.2467702	2.513731
year05	1.894092	.7059851	2.68	0.007	.510387	3.277798
year06	1.254665	.6065703	2.07	0.039	.0658091	2.443521
year07	1.471279	.6457791	2.28	0.023	.2055754	2.736983
_cons	-16.62209	6.051257	-2.75	0.006	-28.48233	-4.761842
select						
lntsl	.4936214	.0583256	8.46	0.000	.3793055	.6079374
lntgt	.2465994	.0436179	5.65	0.000	.1611098	.332089
lnswit_tl	.1504713	.0482978	3.12	0.002	.0558094	.2451332
lnswag	.1786906	.0837836	2.13	0.033	.0144777	.3429036
qc_ave	.1570574	.0451098	3.48	0.000	.0686437	.245471
sec_line	-.5895243	.1212579	-4.86	0.000	-.8271854	-.3518633
year00	-.0580865	.1466099	-0.40	0.692	-.3454366	.2292636
year01	.2286824	.1463119	1.56	0.118	-.0580837	.5154485
year02	.5466931	.1469428	3.72	0.000	.2586905	.8346957
year03	.9106426	.156472	5.82	0.000	.6039631	1.217322
year04	.8947271	.1564569	5.72	0.000	.5880773	1.201377
year05	1.362091	.1676336	8.13	0.000	1.033535	1.690646
year06	1.001067	.1591725	6.29	0.000	.689095	1.31304
year07	1.130684	.1627031	6.95	0.000	.8117914	1.449576
_cons	-11.15166	.944346	-11.81	0.000	-13.00255	-9.30078
mills						
lambda	2.89979	.9532659	3.04	0.002	1.031424	4.768157
rho	1.00000					
sigma	2.8997903					
lambda	2.8997903	.9532659				

4.4 Cost predictions and elasticities

Our main interest is in the cost elasticity with respect to total gross tonnes as the marginal cost is the product of the 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 necessary equations for cost prediction when the dependent variable is in log form (7) and the elasticity (8) in the Two-part model. Table 5 summarises the key estimates from the Two-part model.

$$E[y] = \Phi(X\beta_2)\exp(X\beta_{4k} + 0.5\sigma_4^2) \tag{7}$$

$$\frac{\partial E[y]}{\partial x_k} \times \frac{x_k}{E[y]} = [\beta_{4k} + \beta_{2k}\lambda(X\beta_2)]x_k \tag{8}$$

Table 5. Output elasticity, total, average and marginal cost

	Estimate	Std. Err.	[95% Conf.	Interval]
Elasticity	0.518	0.075	0.371	0.664
TC	8722095	248238	8235168	9209023
AC	0.0498	0.0018	0.0463	0.0534
MC-uw	0.0253	0.0009	0.0235	0.0271
MC-w	0.0106	0.0003	0.0101	0.0111

The mean elasticity is around 0.52, i.e. a 10 percentage change in traffic will increase renewal costs by 5.2 percent. Average cost is SEK 0.05 per gross tonne kilometre, which gives an average marginal cost estimate of SEK 0.025 per gross tonne kilometre. This estimate is the mean of track section specific estimates of the marginal cost. For policy purposes, it is often easier for the infrastructure manager to charge a unit rate for all track sections and a revenue neutral marginal cost is weighted by traffic volume. This gives higher weight to track sections with large volumes and the weighted average marginal renewal cost falls below the un-weighted marginal cost at around SEK 0.011 per gross tonne kilometres.

5. DISCUSSION AND CONCLUSIONS

In this paper, we have analysed railway renewal costs using Swedish track section data from 1999-2007. 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. Our preferred model is the Two-part model, which performs best in terms of model assumptions and cost prediction.

We find that the cost elasticity with respect to output of total gross tonnes is around 0.5, which is higher than previously found for analyses of maintenance costs. However, this is in line with a priori expectations (since engineering evidence suggests that renewals are more variable with traffic than maintenance). The results also conform to previous infrastructure cost studies finding higher elasticities for renewal (or maintenance and renewal together) than for maintenance (see Table 6).

Table 6. Studies on railway infrastructure renewal costs

Study	**Data**	**Cost category**	**Average elasticity***
This paper	Track section level Sweden 1999 – 2007	Renewals only	0.52
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
Smith (2008)	National level 13 European countries 1996 – 2006	Renewals only	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

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. The reported elasticity of 0.52 from our preferred model does indeed lie just above the top of the range of previous estimates, though we might have expected the difference to be greater. It is however in line with the only previous renewals-only model reported (Smith, 2008), although that model was reported to be less robust than its M&R counterpart. It should be noted that the high M&R elasticities in Table 6 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) more similar in nature to that used in the present study. Overall, we conclude that our results are in line with previous work, although the different cost categories used make a more in-depth comparison problematic.

The weighted marginal cost per gross tonne kilometre is estimated to approximately SEK 0.01 or 0.1 Euro cent. This is higher than previously found in Andersson (2007b), using survival analysis and a unit cost for track renewal. We expect the present estimates to be higher as they both cover a larger renewal cost share. 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). Since the current pricing scheme 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 kilometre.

This paper presents some initial efforts on disaggregate modelling of renewal costs. One improvement for further research is to refine the model specifications and make them more suitable to each method adopted. The use of the same specification in all three cases might disadvantage the Tobit and the Heckit. Another option for future research is to involve panel data estimators as an alternative to the pooled models presented here. Furthermore, an alternative approach to modelling the costs at the disaggregate level would be to aggregate the track sections to a higher management level. This would eliminate the zeros and make it possible to use OLS or other standard estimators.

Finally, there is the question about the extent to which these approaches address the problem of obtaining marginal cost estimates due to the cyclical and lumpy nature of renewals. 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. Using annual tonnage measures on the right hand side of the model, together with capability, condition and age measures, is a first attempt to explain this heuristic, but more research is needed to reveal the answer if this approach addresses the lumpy renewal problem or not.

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