The marginal cost of rail infrastructure maintenance; does more data make a difference?

Kristofer Odolinski, Jan-Eric Nilsson, Åsa Wikberg

Swedish National Road and Transport Research Institute, Department of Transport Economics, Box 55685, 102 15 Stockholm, Sweden

Abstract

This paper studies the marginal cost for maintenance of the Swedish rail network, using a unique panel dataset stretching over 14 years. We test different econometric approaches to estimate the relationship between traffic and maintenance costs, and compare our estimates with previous studies using shorter panels. The dynamic model results in this paper are contrasting previous estimates on Swedish data. Our results show that an increase in maintenance cost during one year can increase maintenance costs in the next year. No substantial differences are found for the static models. We conclude that more data made a difference in a dynamic context, but the estimated cost elasticities in European countries are rather robust.

1.0 Introduction

The Swedish government has commissioned VTI to summarize state-of-the-art principles for estimating the marginal costs of infrastructure use and to update cost estimates as well as develop new knowledge if and when feasible. While this is a cost appraisal assignment, the ultimate benefit of these estimates is to provide input for the pricing of infrastructure use.

One component of the marginal cost in the railway sector concerns the way in which track maintenance costs are affected by variations in railway traffic. The relevance of this relationship was formally established after the vertical separation of infrastructure management and train operations introduced by the European Commission in 1991 (see directive Dir. 91/440)[1], and the White Paper on Fair payments for infrastructure use (CEC 1998) endorsing the use of marginal cost pricing to finance infrastructure.

[1] Note the Swedish reform was made in 1988

Previous estimates on Swedish data are summarized in Table 1; Table 2 comprises the current charges for using Sweden's railway network. The cost elasticities for maintenance in table 1 are in line with the estimates in the review of best practice by Link et al. (2008), which reports elasticities from 0.07 to 0.26. In additional studies made within the rail cost allocation project CATRIN, the cost elasticities lies within 0.2 and 0.35 (see Wheat et al. 2009).

The purpose of this paper is to present new marginal cost estimates for maintenance of the Swedish rail network. The analysis departs from the models referenced in table 1. A significant difference is, however, that our data covers a much longer period of time than the previous studies. This does per se motivate the research: since previous studies make use of rather short data panels, it is relevant to consider whether longer time series makes a difference to conclusions.

An additional motive for addressing this question is that the maintenance of Sweden's railways has gone through a far-reaching organizational reform. In 1998, the production unit of what was then the Swedish Rail Administration (*Banverket*) was separated from its administrative unit, creating a client-contractor relationship. This further led to a political decision to introduce competitive tendering of maintenance contracts, with the first contract tendered in 2002. The exposure to competition was gradual, but almost 95 percent of the network had been tendered at least once as of 2012.

Changes in the definition of activities have also been made, with snow removal defined as a maintenance activity as of 2007. Table 1 shows the operation cost elasticities from previous studies, in which snow removal costs constitutes a major part of the operation cost included in the estimations.

Table 1 - Previous estimates on Swedish marginal railway costs

	Model	Output variable	Output elasticity	Marginal cost	Marginal costs in 2012 prices using CPI
Maintenance					
Johansson and Nilsson (2004)	Pooled OLS	Gross tonnes	0.17	0.0012	0.0014
Andersson (2006)	Pooled OLS	Gross tonnes	0.21	0.0031	0.0036

Andersson (2007)	Fixed effects	Gross tonnes	0.27	0.0073	0.0084
Andersson (2008)	Fixed effects	Gross tonnes	0.26	0.0070	0.0081
Andersson (2011)	Box-Cox	Freight gross tonnes	0.05	0.0014	0.0016
		Passenger gross tonnes	0.18	0.0108	0.0124
Operation					
Andersson (2006)	Pooled OLS	Trains	0.37	0.476	0.5481
Andersson (2008)	Fixed effects	Trains	-0.04	0.089	0.1025
Uhrberg and Grenestam (2010)	Fixed effects	Trains	0.18	0.45	0.4975

Table 2 - Current charges

	Track charge, SEK/gross tonne-km	Operating charge, SEK/train-km
2013	0.0040	0.10
2014	0.0045	0.18

The present paper makes use of a panel covering 14 years. This includes a re-assessment of the appropriate choice of functional form and the choice between a static or a dynamic panel data model.

2.0 Methodology

Different approaches have been used in order to determine the cost incurred by running one extra vehicle or vehicle tonne on the tracks. There are examples of a so-called bottom-up approach that use engineering models to estimate track damage caused by traffic (see Booz Allen Hamilton 2005 and Öberg et al. 2007 for examples). Starting with Johansson and Nilsson (2004) previous studies have, however, mainly used econometric techniques to estimate the relationship between costs and traffic, and can be referred to as a top-down approach. To estimate the marginal costs from trains using railway infrastructure first requires the derivation of the cost elasticity when traffic varies and secondly to establish the average maintenance cost.

Most of the top-down approaches use a double log functional form, either a full translog model or quadratic and cubic terms for the output variables. However, another functional form that has recently gained popularity within this area of research is the Box-Cox model, which also can be used to test the appropriateness of different functional forms. See Link et al. (2008) and Wheat et al. (2009) for a list of these studies and their reported cost elasticities.

In this paper we use the econometric – top down – approach, which is briefly presented in section 2.1. There are some intricate challenges that have to be addressed in order to formulate a model that can be expected to deliver the relevant marginal cost estimates. The first concerns the appropriate transformation of variables. We therefore begin with the Box-Cox functional form, which is presented in section 2.2. Another challenge concerns the choice between fixed and random effects assumptions when dealing with a 14-year panel of data; this is addressed in section 2.3. The static double log model to be estimated is presented in section 2.4.

A hypothesis tested by Andersson (2008) was the cyclic fluctuation of maintenance activities, where costs in year t depend on costs in t-1. Section 2.5 considers a modelling approach with lagged maintenance costs as an explanatory variable, i.e. a dynamic double log model.

2.1 An econometric approach

The marginal cost of railway infrastructure wear and tear can be demonstrated to be the product of the cost elasticity of traffic (γ) and average cost (AC). To derive the cost elasticity, a general cost function is given by eq. (1) where there are $i = 1, 2, \dots, N$ track sections and $t = 1, 2, \dots, T$ years of observations. C_{it} is maintenance costs, Q_{it} the volume of output (traffic density as defined below), N_{it} a vector of network characteristics and Z_{it} a vector of dummy variables.

$$C_{it} = f(Q_{it}, N_{it}, Z_{it}) \tag{1}$$

We assume there is low variation in input prices, an assumption suggested by Johansson and Nilsson (2004) as well as by Andersson (2009), arguing that salaries for employees are rather similar across the country. Since then, maintenance activities have however been transferred from using in-house resources, including employees, to being competitively tendered. This may have increased the variation in salaries. A proxy for wages did, however, not affect maintenance costs at the contract area level in the model estimated by Odolinski and Smith (2014). Moreover, prices on the materials used in the production can be assumed to be constant between entrepreneurs (and thus track sections) since the principal, *Trafikverket*, procures these on behalf of the maintenance producers without any price discrimination. Hence, no factor prices are included in the model.

2.2 Box-Cox regression model

Eq. (2) demonstrates a transformation of variable y where λ is a parameter to be estimated, developed by Box and Cox (1964):

$$y^{(\lambda)} = \frac{(y^{\lambda} - 1)}{\lambda} \tag{2}$$

This functional form does not impose a specific transformation of the data, such as the logarithmic transformation in the double log functional form. Instead, the functional form is tested with a logarithmic transformation $y^{(\lambda)} = \ln(y)$ if $\lambda \rightarrow 0$ and a linear functional form $y^{(\lambda)} = y - 1$ if $\lambda = 1$. Eq. (3) is the general cost model to be estimated, referred to as the "theta model":

$$C_{it}^{(\theta)} = \alpha + \beta_m Q_{mit}^{(\lambda)} + \beta_k N_{kit}^{(\lambda)} + \vartheta_p Z_{pit} + \varepsilon_{it} \tag{3}$$

The dependent variable is subject to the transformation parameter θ and the explanatory variables are subject to a different transformation parameter, λ. Q_{it} is gross tons and N_{it} a vector of network characteristics. Z_{it} refers to variables that are not subject to a transformation, representing dummy variables and data that include zeroes. A "lambda model" can also be specified where the dependent and explanatory variables are subject to the same transformation parameter (λ), and is therefore more restrictive than the theta model. Likelihood ratio tests can be used to compare different values of the transformation parameters (for example 0 or 1) with the estimated values.

2.3 Modelling unobserved effects

With access to data for cross-sectional units observed over 14 years, we can estimate panel data models. Following Baltagi (2008), we first consider the linear model in eq. (4). Here, y_{it} is the dependent variable and X_{it} is a vector of observed variables that can change across i (individuals, here track sections) and t (time). μ_i is the individual effect which contains features that predict y, but are not captured by the explanatory variables X_{it}. This value is assumed to be the same for each track unit over time. Finally, v_{it} is the error term that is assumed to be normally distributed, α is a scalar and β a vector of parameters to be estimated:

$$y_{it} = \alpha + X'_{it}\beta + \mu_i + v_{it} \qquad i = 1,2\ldots N \qquad t = 1, 2\ldots T \tag{4}$$

If the unobserved individual effects are constant (or averaged out), we can estimate a pooled model using ordinary least squares (POLS). However, there is often variation in the unobserved individual effects, and a pooled regression would then produce inconsistent and/or inefficient estimates of β.[2] *Fixed effects* and *random effects* are two approaches often used to model this variation. If μ_i is not observed and correlated with X_{it}, the fixed effects model can be used. A transformation is then performed by first using the average over time for each individual in eq. (4) where for example $\bar{y}_i = \sum_t y_{it}/T_i$:

$$\bar{y}_i = \alpha + \bar{X}_i + \mu_i + \bar{v}_i \tag{5}$$

Subtracting (5) from (4) gives (6):

$$y_{it} - \bar{y}_i = \beta(X_{it} - \bar{X}_i) + (v_{it} - \bar{v}_i) \tag{6}$$

The individual effect μ_i is now eliminated and it is possible to estimate $\tilde{\beta}$ from eq. (6). Taking the average across all observations in eq. (4) makes it possible to estimate α (eq. 7), where we use the constraint $\bar{\mu}_i = 0$.

$$\bar{\bar{y}} = \alpha + \beta\bar{\bar{X}} + \bar{\bar{v}} \tag{7}$$

Here, double bars denote averages such as for example $\bar{\bar{y}} = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T_i} y_{it}}{Total\ number\ of\ obs.}$. Summing (6) and (7) gives (8):

$$y_{it} - \bar{y}_i + \bar{\bar{y}} = \alpha + \beta\left(X_{it} - \bar{X}_i + \bar{\bar{X}}\right) + (v_{it} - \bar{v}_i + \bar{\bar{v}}) \tag{8}$$

Equation (8) is used for estimating the fixed effects model, producing unbiased estimates of β as long as the explanatory variables are strictly exogenous. The alternative approach, the random

[2] More specifically, the POLS estimator is inconsistent if the true model is fixed effects. If random effects model is the true model, the POLS estimator will be inefficient.

effects model, makes use of a weighted average of the fixed and between effects estimates from (8) and (5) respectively. Following Wooldridge (2009), the random effects transformations is:

$$y_{it} - \lambda\bar{y}_i = \alpha(1-\lambda) + \beta(X_{it} - \lambda\bar{X}_i) + (v_{it} - \lambda\bar{v}_i) \quad (9)$$

Here $\lambda = 1 - [\sigma_v^2/(\sigma_v^2 + T\sigma_\mu^2)]^{1/2}$. The random effects model assumes that the individual effects are random and normally distributed $\mu_i \sim IID(0, \sigma_\mu^2)$ and independent of v_{it}. However, the crucial assumption is that the unobserved individual effects μ_i are not correlated with X_{it}. Otherwise, the random effects model will produce biased estimates of β.

Since μ_i may be correlated with X_{it}, the random effects model will often produce biased estimates. On the other hand, the fixed effects model may produce high variance in the estimated coefficients, i.e. produce estimates of β that are not very close to the true β. This can be the case when we have a low within-individual variation in the explanatory variable relative to the variation in the dependent variable. In that case, the random effects model will produce lower variance in the estimate of β by using information across individuals. The choice between fixed and random effects is therefore often a compromise between bias and variance (efficiency) in the estimates, considering there is some degree of correlation between μ_i and X_{it} (Clark and Linzer 2013).

The Hausman test (1978) is often used for the choice between the random and fixed effects models, and is a test for systematic differences between the estimates from two models (systematic differences indicate relatively high correlation between μ_i and X_{it}). This test is not used for a robust covariance matrix as it relies on all the random effect model assumptions (Imbens and Wooldridge 2007). Mundlak's (1978) test is an alternative approach to the Hausman test, and Arrellano (1993) extended the test for a robust covariance matrix.

We therefore estimate both the fixed and random effects version of our static double log model and perform the Hausman test and the test suggested by Arrellano (1993).

2.4 Modelling approach; static double log model

We use a double log functional form and start with the flexible translog cost function. Dropping the firm and time subscripts, the translog functional form with M outputs, K network characteristics and P dummy variables is expressed by eq. (10):

$$lnC = \alpha + \sum_{m=1}^{M} \beta_m lnQ_m + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} lnQ_m lnQ_n + \sum_{k=1}^{K} \beta_k lnN_k + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnN_k lnN_l + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} lnN_k lnQ_m + \sum_{p=1}^{P} \vartheta_p Z_p + \mu + v \quad (10)$$

β is the vector of parameters to be estimated, lnQ_m is the m[th] output and lnN_k is the k[th] network characteristic. We estimate a model with gross tons as output as well as a model using freight and passenger gross tons as separate outputs.

The Cobb-Douglas constraints are $\beta_{mn} = 0$, $\beta_{kl} = 0$ and $\delta_{km} = 0$. With symmetry restrictions $\beta_{mn} = \beta_{nm}$ and $\beta_{kl} = \beta_{lk}$, we get eq. (11):

$$lnC = \alpha + \sum_{m=1}^{M} \beta_m lnQ_m + \sum_{m=1}^{M-1}\sum_{n>m}^{M} \beta_{mn} lnQ_m lnQ_n + \frac{1}{2}\sum_{m=1}^{M} \beta_{mm}(lnQ_m)^2 + \sum_{k=1}^{K} \beta_k lnN_k + \sum_{k=1}^{K-1}\sum_{l>k}^{K} \beta_{kl} lnN_k lnN_l + \frac{1}{2}\sum_{k=1}^{K} \beta_{kk}(lnN_k)^2 + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} lnN_k lnQ_m + \sum_{p=1}^{P} \vartheta_p Z_p + \mu + v \quad (11)$$

The ex-ante expectation is that costs increase with traffic so that $\beta_m > 0$. In the baseline formulation of the model, only one proxy for output is used, eliminating the estimation of β_{mn}. It is also worthwhile to consider a distinction between freight and passenger services, but without any prior.

Several of the network characteristics are related to the size of each track section, and it is straightforward to assume that costs increase with track length, length of switches[3] and length of tunnels and bridges. The older the tracks, the more likely it is that higher costs are required, which means we have a prior that $\beta_k > 0$. The expectation goes in the opposite direction for the parameter RATIO_TR. This provides an indication of the length of tracks for a certain route length. For a section with single tracks the ratio is unity. Adding one place for meetings and over taking increases the numerator and for a double track section the ratio is 2. The a priori expectation is that more double tracking will make it easier to maintain the tracks, i.e. that costs are lower and $\beta_k < 0$.

2.5 Modelling approach; dynamic double log model

Maintenance costs during one year can affect maintenance costs the next. Moreover, not all types of maintenance activities are undertaken every year. Hence, the maintenance costs may fluctuate even if traffic and infrastructure characteristics do not change. To address the possibility of inter-temporal interactions, a dynamic-panel data model with a lagged dependent variable as an explanatory variable is tested. Both the Arellano and Bond (1991) and the Arellano-Bover/Blundell-Bond (1995; 1998) estimators are used. These estimators essentially use first differencing and lagged instruments to deal with the unobserved individual effect and the autocorrelation.

For a Cobb-Douglas functional form the model is expressed by eq. (12):

$$lnC_{it} = \beta_0 lnC_{it-1} + \sum_{m=1}^{M} \beta_m lnQ_{mit} + \sum_{k=1}^{K} \beta_k \, lnN_{kit} + \sum_{p=1}^{P} \vartheta_p Z_{pit} + \mu_i + v_{it} \qquad (12)$$

[3] The quality of the information about the number of switches seems to be lower than the quality of switch length information in that the variation between years in the first statistic is higher than for the second.

Lagged maintenance costs lnC_{it-1} are correlated with the individual effects μ_i, and estimating this model with OLS would therefore produce biased estimates. First differencing (12) gives eq. (13).

$$lnC_{it} - lnC_{it-1} = \beta_1(lnC_{it-1} - lnC_{it-2}) + \sum_{m=1}^{M}\beta_m(lnQ_{mit} - lnQ_{mit-1}) + \sum_{k=1}^{K}\beta_k(lnN_{kit} - lnN_{kit-1}) + \sum_{p=1}^{P}\vartheta_p(Z_{pit} - Z_{pit-1}) + (\mu_i - \mu_i) + (v_{it} - v_{it-1}) \quad (13)$$

This makes the individual effect μ_i disappear. However, lnC_{it-1} and the lagged independent variables are correlated with v_{it-1}. To deal with this endogeneity it is necessary to use instruments. We first consider lnC_{it-2} as an instrument for $(lnC_{it-1} - lnC_{it-2}) = \Delta lnC_{it-1}$. This instrument is not correlated with v_{it-1} under the assumption of no serial correlation in the error terms. Holtz-Ekin et al (1988) show that further lags can be used as additional instruments without reducing sample length. To model the differenced error terms $(v_{it} - v_{it-1})$, Arellano and Bond (1991) propose a generalized method of moment (GMM) estimator, estimating the covariance matrix of the differenced error terms in two steps.

Note that as T increases, the number of instruments also increases. For example, with T=3 (minimum number of time periods needed), one instrument, lnC_{i1}, is used for ΔlnC_{i2}. With T=4, both lnC_{i1} and lnC_{i2} can be used as instruments for ΔlnC_{i3}. The present data set comprises T=14. We therefore need to consider a restriction of the number of instruments used because too many instruments can over-fit the endogenous variables[4] (see Roodman 2009a). If independent variables are *predetermined* ($E(X_{is}v_{it}) \neq 0$ for $s<t$ and zero otherwise), it is feasible to include lagged instruments for these as well, using the same approach as for the lagged dependent variable.

The approach by Blundell and Bond (1998), which is a development of the Arellano and Bover (1995) estimation technique, is called system GMM and does not employ first differencing of the independent variables to deal with the fixed individual effects. Instead, they use differences of the lagged dependent variable as an instrument. In our case lnC_{it-1} is instrumented with ΔlnC_{it-1} and assuming that $E[\Delta lnC_{it-1}(\mu_i + v_{it})] = 0$; this must also hold for any other instrumenting

[4] We use the "collapse" alternative that reduces the number of instruments, even though this set of instruments contains less information.

variables. This means that a change in an instrument variable must be uncorrelated with the fixed effects, that is $E(\Delta C_{it}\mu_i) = 0$.

A lagged difference of the dependent variable as an instrument is appropriate when the instrumented variable is close to a random walk. Roodman explains this neatly (2009b; p. 114): "For random walk-like variables, past changes may indeed be more predictive of current levels than past levels are of current changes…" Hence, the system GMM will perform better if the change in maintenance costs between *t*-2 and *t*-1 is more predictive of maintenance cost in *t*-1, compared to how maintenance costs in *t*-2 can predict the change in maintenance cost between *t*-2 and *t*-1.

In addition to using lagged differences as instruments for levels, the system GMM also uses lagged levels as instruments for differences; the system GMM estimator is based on a stacked system of equations in differences and levels in which instruments are observed (Blundell and Bond 1998)

Alonso-Borrego and Arellano (1999) perform simulations showing that the GMM estimator based on first differences (the Arellano and Bond (1991) model) have finite sample bias. Moreover, Blundell and Bond (1998) compare the first difference GMM estimator with the system GMM using simulations. They find that the first difference GMM estimator produces imprecise and biased estimates (with persistent series and short sample periods) and estimating the system GMM as an alternative can lead to substantial efficiency gains.

Against this background, we estimate a Cobb-Douglas model[5] (including a quadratic term for traffic) with lnC_{it-1} as an explanatory variable using the approach by Arellano-Bover/Blundell-Bond (1995, 1998) system GMM (*Model 2A*) as well as the Arellano and Bond (1991) model (*Model 2B*). Traffic is assumed to be *predetermined* (not strictly exogenous) and is instrumented with the same approach as the lagged dependent variable.

[5] Testing the comprehensive Translog model turned out to be very sensitive to the number of instruments included. Moreover, some of the estimated coefficients for the network characteristics had reversed signs compared to model 1. We also note that the Arellano and Bond (1991) and Arellano-Bover/Blundell-Bond (1995; 1998) estimators were designed for situations with a linear functional relationship (Roodman 2009b).

3.0 Data

The publicly owned Swedish railway network is divided into approximately 260 track sections. The sections of today have a long history and are not defined based on a specific set of criteria. As a result, the structure of the sections varies greatly. For example, section length ranges from 1.9 to 219.4 kilometres, and the average age of sections range from one (i.e. new tracks) to 83 years; see table 3.

Table 3 - Descriptive statistics for track units for the 1999-2012 period (No. obs. 2486)

Variable	Mean	Std. Dev.	Min	Max
Maintenance cost incl. snow removal, SEK*	11 795 864	13 520 001	8 747	183 783 983
Maintenance cost, SEK*	10 916 954	12 580 344	8 747	154 341 916
Train gross tonnes	7 801 181	8 438 352	567	59 571 928
Passenger train gross tonnes	2 951 660	5 433 973	0	48 813 129
Freight train gross tonnes	4 632 609	5 349 039	0	30 332 703
Track length, metres	69 327	51 323	4 200	290 654
Route length, metres	53 190	41 283	1 889	219 394
Track length over route length	1.61	1.06	1	8.1
Average rail age, years	20.30	10.42	1	83
Quality class**	3.20	1.20	1	6
No. joints	167	134	1	1 203
Length of switches, metres	1 766	1 721	58	14 405
Average age of switches, years	20.73	9.27	1	55
Length of bridges and tunnels, metres	1 141	2 722	3	23 212
Average amount of snow per year, mm water	117	64	2.1	342.7

***** Costs have been inflated to 2012 price level using CPI, ** Track quality class ranges from 0-5, but 1 have been added to avoid observations with value 0.

In the same way as in Anderson et al. (2012), as well as all other Swedish rail cost studies, most of information derives from the systems held by *Trafikverket* to report about the technical aspects about the network and about costs. Traffic data emanates from different sources. Andersson (2006) collected data from train operators for the period 1999-2002. Björklund and Andersson (2012) interpolated traffic using access charge declarations for years 2003-2006. *Trafikverket* has provided traffic data for 2007-2012. Weather data – for example average amount of snow – has been collected from the Swedish Metrological and Hydrological Institute (SMHI).

Previous cost analyses made a distinction between operations, primarily costs for snow clearance, and on-going maintenance. As of 2007 *Trafikverket* no more makes this separation and the (previously) separate observations of the two items have therefore been merged for previous years. Maintenance costs therefore comprise all activities included in tendered maintenance contracts which thus include costs for snow removal as well as other activities that in previous studies have been defined as operation. Though, the other activities - i.e. operation costs excluding snow removal – are rarely reported at the track section level and therefore constitutes a very small part of the total operation cost for track sections. A sensitivity analysis with maintenance costs that do not include snow removal costs is also carried out.

Many track sections includes one (or more) railway station(s). This is at least partly captured by the number of switches per track section; the larger the number of stations or places for meetings and overtaking on single track lines, the larger the number of switches. In some situations, a train station is however defined to be a track section of its own. Odolinski (2014) describes an algorithm for estimating traffic at stations-cum-track-sections based on information about traffic on adjacent track sections. As a result, an additional 24 cross section observations are included each year. A dummy is used to capture the possibility of different principles for handling the allocation of resources to stations compared to the main line sections (see *Model 1*).

It is not feasible to include all track sections of the network in the analysis, one reason being that important information is missing. In particular, information about traffic is not available for many sections with low traffic density and sections used for industrial purposes. Moreover, marshalling yards have been omitted since the cost structure at these places can be expected to differ from track sections at large. Neither are privately owned sections, heritage railways, nor sidings and track sections that are closed for traffic included in the dataset.

Data from previous studies has been supplemented with more years of observations and all in all, about 250 track sections are observed for the 1999 to 2012 period. A comprehensive matrix would therefore comprise (250 x 14 years =) 3500 observations. Due to missing information and changes in the number of sections on the network, 2486 observations are available for analysis and the panel is thus unbalanced.

It is important to note that gradually more observations become available during the period of analysis. In particular, information of 18 more track sections is available for 2007 than for 2006;

see table 3. This gradual addition of information seems to primarily concern older parts of the network, increasing the average age of tracks and structures more than the additional year net of reinvestment that same year.

Table 4 - Descriptive statistics for track sections for 1999, 2006 and 2012. Numbers in brackets refers to stations that constitute a track section

	1999		**2006**		**2012**	
Variable	Obs.	Mean	Obs.	Mean	Obs.	Mean
Maintenance + snow cost, m SEK	169 [21]	9 [25.1]	168 [19]	11 [25.4]	182 [22]	16 [23.5]
Maintenance costs only, m SEK	169 [21]	8 [22.5]	168 [19]	10 [22.7]	182 [22]	15 [21.1]
M train gross tonnes	169 [21]	6.7 [13.7]	168 [19]	8.1 [13.8]	182 [22]	8.0 [13.2]
M passenger train gross tonnes	169 [21]	2.5 [6.3]	168 [19]	2.8 [6.6]	182 [22]	3.5 [6.0]
M freight gross tonnes	169 [21]	4.2 [6.7]	168 [19]	5.0 [6.5]	182 [22]	4.3 [6.6]
Track length, km	169 [21]	55.8 [9.0]	168 [19]	54.3 [8.7]	182 [22]	52.0 [8.8]
Route length, km	169 [21]	68.3 [29.3]	168 [19]	72.1 [28.7]	182 [22]	69.4 [28.3]
Track length over route length (RatioTLRO)	169 [21]	1.36 [3.57]	168 [19]	1.66 [3.62]	182 [22]	1.72 [3.54]
Average rail age, years	169 [21]	18.7 [20.3]	168 [19]	19.9 [20.3]	182 [22]	22.6 [19.7]
Quality class (no. 0-5, +1)	169 [21]	3.3 [3.7]	168 [19]	3.1 [3.7]	182 [22]	3.1 [3.8]
No. Joints	169 [21]	135.5 [228.8]	168 [19]	178.4 [231.3]	182 [22]	176.7 [215.9]
Length of switches, km	169 [21]	1.6 [3.5]	168 [19]	1.8 [3.5]	182 [22]	1.8 [3.3]
Average age of switches	169 [21]	18.3 [22.6]	168 [19]	21.1 [22.1]	182 [22]	22.2 [22.1]
Track length of bridges and tunnels, km	169 [21]	0.9 [1.7]	168 [19]	1.2 [1.8]	182 [22]	1.5 [1.5]
Average amount of snow per year, mm water	169 [21]	136.4 [135.1]	168 [19]	118.3 [128.7]	182 [22]	137.5 [137.3]

4.0 Results

Three models are estimated. *Model 1* uses the Box-Cox regression model. *Model 2* is a static model with a restricted translog functional form. *Models 3A* and *3B* consider the dynamic dimension, estimating how past levels of maintenance costs affect current levels. Estimations are carried out using Stata 12 (StataCorp.11).

4.1 Model 1 – Box-Cox regression results

The results from *Model 1* are presented in table 5 where train gross tons is the output variable. Results from the Box-Cox regression with passenger and freight gross tons as separate outputs are presented in the appendix.

We only present results with maintenance costs excluding snow costs as the dependent variable. The reason is that the theta model had problems converging when snow costs are included in the dependent variable.

The transformation parameters are significantly different from zero in both models, suggesting that the log-transformation is not optimal. Table 6 shows the results from likelihood ratio tests of different values of the transformation parameters, i.e. functional forms, compared to the estimated values in table 5. The log-transformation ($\lambda = 0$) have the highest log likelihood compared to the other functional forms ($\lambda = -1, \lambda = 1$).

Table 5 - Results from Box-Cox models

	Lambda model		*Theta model*	
	Coef.	Std. Err.	Coef.	Std. Err.
Lambda	0.1745***	0.0117	0.0625**	0.0253
Theta	-	-	0.1746***	0.0113
Not transformed	Coef.	P>chi2(df)	Coef.	P>chi2(df)
Cons.	-4.1932		-48.8730	
JOINTS	0.0189	0.000	0.0220	0.000
D.STATION SECTION	5.7084	0.000	5.9336	0.000
YEAR00	-1.0223	0.262	-1.1394	0.210
YEAR01	0.3797	0.675	0.2281	0.801
YEAR02	2.5848	0.004	2.4578	0.006
YEAR03	1.1752	0.200	0.9137	0.319
YEAR04	2.6305	0.004	2.3511	0.010
YEAR05	2.7008	0.003	2.4101	0.009
YEAR06	1.2564	0.172	0.9878	0.283
YEAR07	1.6268	0.070	1.5248	0.088
YEAR08	2.5388	0.005	2.3849	0.008
YEAR09	3.3889	0.000	3.2390	0.000

YEAR10	2.3042	0.010	2.1446	0.017
YEAR11	4.7804	0.000	4.5656	0.000
YEAR12	6.3986	0.000	6.0719	0.000
Transformed				
TGTDEN	0.2747	0.000	1.4231	0.000
TRACK_M	1.2752	0.000	4.2571	0.000
RATIOTLRO	-3.5066	0.000	-3.1187	0.000
QUALAVE	2.8759	0.000	3.1774	0.000
SWITCH_M	1.0538	0.000	2.0925	0.000
RAIL_AGE	0.3797	0.098	0.7357	0.019
SWITCH_AGE	0.5426	0.035	0.6597	0.057
Sigma	8.3665		8.3405	
No. obs.	2486		2486	
Log likelihood	-41146.071		-41136.387	

Note: ***, **, * : Signif. at 1%, 5%, 10% level.

Definition of variables in table 5:

JOINTS = Nr. of joints

D.STATION SECTION = Dummy variable for station track sections

YEAR00-YEAR12= Year dummy variables, 2000-2012

TGTDEN = ln (Tonne-km/route-km)

TRACK_M = ln (Track length metres)

RATIOTLRO = ln (Track length/Route length)

QUALAVE = ln (average quality class); note a high value of average quality class implies a low speed line

SWITCH_M = ln (Switch length metres)

RAIL_AGE = ln (average rail age)

SWITCH_AGE = ln (average age of switches)

Table 6 - Likelihood ratio tests of functional forms

Test H0:	Restricted log likelihood	chi2	Prob>chi2

lambda = -1	-49895.967	17499.79	0.000
lambda = 0	-41271.957	251.77	0.000
lambda = 1	-42957.204	3622.27	0.000
theta=lambda = -1	-49895.967	17519.16	0.000
theta=lambda = 0	-41271.957	271.14	0.000
theta=lambda = 1	-42957.204	3641.63	0.000

The parameter estimates have the expected signs and most are statistically significant. The coefficient for stations sections show that these have a higher cost level compared to other track sections.

In order to calculate the cost elasticity of output, we use the following expression (Andersson 2011):

$$\hat{\gamma}_{mit} = \hat{\beta}_m \left(\frac{Q_{mit}^{\lambda}}{C_{it}^{\theta}}\right) \qquad (14)$$

where θ=λ in the lambda-model. Eq. (14) shows that the output elasticities vary with the level of costs and output. The cost elasticity with respect to gross tons is 0.2505 (standard error 0.0011) in the lambda model and 0.2360 (standard error 0.0007) in the theta model.

The marginal cost is calculated by multiplying the average cost by the cost elasticities:

$$MC_{it} = \widehat{AC}_{it} \cdot \hat{\gamma}_{it} \qquad (15)$$

We use the predicted average costs, which is the fitted cost divided by gross tonnes kilometres:

$$\widehat{AC}_{it} = \hat{C}_{it}/GTKM_{it} \qquad (16)$$

Similar to Andersson (2008), we estimate a weighted marginal cost for the entire railway network included in this study, using the traffic share on each track section (see eq. 17).

$$MC_{it}^{W} = MC_{it} \cdot \frac{TGTKM_{it}}{(\sum_{it} TGTKM_{it})/N} \qquad (17)$$

The estimated average costs, marginal costs and weighted marginal costs for the two models are presented in table 7. The weighted marginal cost in the theta model (0.0058 SEK) is lower than the corresponding cost in the lambda model (0.0066 SEK). Both estimates have standard errors at 0.0001.

Table 7 - Estimated costs; Box-Cox models

Variable	Obs.	Mean	Std. Err.	[95% Conf.	Interval]
Average cost[a]	2486	0.2428	0.0445	0.1556	0.3300
Average cost[b]	2486	0.3432	0.0809	0.1846	0.5018
Marginal cost[a]	2486	0.0550	0.0090	0.0374	0.0726
Marginal cost[b]	2486	0.0453	0.0066	0.0323	0.0583
Weighted marginal cost[a]	2486	0.0058	0.0001	0.0056	0.0060
Weighted marginal cost[b]	2486	0.0066	0.0001	0.0064	0.0069

[a] Theta model, [b] Lambda model

4.2 Model 2 estimation results; restricted translog model

The results from *Model 2* - with train gross tons as the output variable - are presented in table 8. Estimation results from a restricted translog model using passenger and freight gross tons as separate outputs are presented in the appendix but do not show a significant difference in cost elasticity for these outputs.

Table 9 presents the results from the diagnostic tests. We first note that the Breusch and Pagan's (1980) test show that random effects model is preferred to Pooled OLS. However, the test proposed by Hausman (1978) indicates that the fixed effects estimator is preferred. Moreover, the test developed by Arellano (1993) indicates that the random effects specification do not meet the orthogonality conditions ($E(X_{it}\mu_i) \neq 0$). Even more important, the main coefficient of interest for the present paper - gross tons - does not differ substantially between the fixed and random effects models. Hence, a low within-individual variation for output does not seem to be a problem in the fixed effects estimation. Accordingly, the results from this estimator are in focus for the following discussion.

Rho ($\rho = \sigma_\mu^2/\left(\sigma_\mu^2 + \sigma_v^2\right)$ is a measure of the fraction of variance due to differences in the unobserved individual effects, and is lower in the random effects model compared to the fixed effects model (see table 8). This is what one would expect considering that the random effects estimator also uses variation between track sections, as opposed to the fixed effects (within) estimator.

As is standard in the literature we started with the full translog functional form, and tested down. In the end, based on tests of linear restrictions - using the fixed effects model results - we could only retain a quadratic term for track lengths and the interaction term between track length and gross tons from the translog expansion.

Before elaborating on the elasticity with respect to traffic, it is first reason to comment on the other parameter estimates. The coefficients for most year dummies are significant with 1999 as the baseline year. Tests of differences between the year dummies show that years 1999-2001 have a lower cost level compared to other years. No significant difference is found between years 2002 to 2010, while 2011 and 2012 have a significantly higher cost level than other years. These changes may be due to variables not included in the model and/or that unit maintenance costs increase.

In line with the findings in Odolinski and Smith (2014), the results show that the gradual transfer from using in-house resources to competitive procurement reduced maintenance costs (a reform that started in 2002). The parameter estimate is -0.1099 (p-value 0.020) which translates to a 10,4 per cent[6] decrease in maintenance costs due to competitive tendering.

Table 8 - Model 2 results; fixed and random effects

	Fixed effects		*Random effects*	
MaintC	Coef.	Robust s.e.	Coef.	Robust s.e.
Cons.	15.9300***	0.0778	16.0854***	0.0613
MIX	-0.0021	0.0355	0.0043	0.0355
CTEND	-0.1099**	0.0467	-0.1059**	0.0458
TGTDEN	0.1856***	0.0674	0.2121***	0.0422
TRACK_M	0.8115***	0.2062	0.6551***	0.0573
RATIOTLRO	-0.1578	0.0965	-0.1415**	0.0723
RAIL_AGE	0.1000**	0.0398	0.0454	0.0395
QUALAVE	-0.2872	0.1832	0.0949	0.0846
SWITCH_M	0.1723**	0.0777	0.2928***	0.0511

6 EXP(-0.1099)-1 = -0.1041

SWITCH_AGE	0.1293**	0.0509	0.0956**	0.0480
SNOWMM	0.0706***	0.0259	0.0910***	0.0265
YEAR00	0.0197	0.0368	0.0200	0.0390
YEAR01	-0.0275	0.0371	-0.0450	0.0367
YEAR02	0.1991***	0.0469	0.1989***	0.0471
YEAR03	0.1698***	0.0516	0.1845***	0.0523
YEAR04	0.1957***	0.0563	0.1979***	0.0577
YEAR05	0.2222***	0.0464	0.2293***	0.0484
YEAR06	0.1589***	0.0455	0.1701***	0.0479
YEAR07	0.2099***	0.0482	0.2249***	0.0487
YEAR08	0.2196***	0.0609	0.2373***	0.0621
YEAR09	0.2508***	0.0633	0.2615***	0.0671
YEAR10	0.2458***	0.0571	0.2523***	0.0613
YEAR11	0.3847***	0.0594	0.4307***	0.0619
YEAR12	0.4491***	0.0612	0.4845***	0.0640
TRACK_M2	0.4620***	0.1308	0.2569***	0.0751
TGTDENTRACK_M	0.1110*	0.0568	-0.0225	0.0290
No. obs.	2486		2486	
$\rho = \sigma_\mu^2 / (\sigma_\mu^2 + \sigma_v^2)$	0.7397		0.4422	

Note: ***, **, * : Significance at 1%, 5%, 10% level.

Definition of variables in table 8:[a,b]

MIX = Dummy for years when mix between tendered and not tendered in competition, which is the year when tendering starts

CTEND = Dummy for years when tendered in competition

TGTDEN = ln (Tonne-km/route-km)

TRACK_M = ln (Track length metres)

RATIOTLRO = ln (Track length/Route length)

RAIL_AGE = ln (Average rail age)

QUALAVE = ln (Average quality class); note a high value of average quality class implies a low speed line

SWITCH_M = ln (Switch length metres)

SWITCH_AGE = ln (Average age of switches)

SNOWMM = ln (Average mm of precipitation (liquid water) when temperature < 0˚Celcius)

YEAR00-YEAR12= Year dummy variables, 2000-2012

TRACK_M2 = TRACK_M^2

TGTDENTRACK_M = TGTDEN*TRACK_M

[a] We have transformed all data by dividing by the sample mean prior to taking logs

[b] Quadratic terms are divided by 2

Table 9 - Results from diagnostic tests; Model 2

Breusch-Pagan LM-test for Random effects	$Chi^2(1)=1639.21$, P=0.000
Hausman's test statistic*	$Chi^2(12)=113.51$, P=0.000
Arellano bond (1993) test: Sargan-Hansen statistic*	$Chi^2(12)=87.29$, P=0.000

*Year dummies are excluded in the test (see Imbens and Wooldridge 2007)

The parameter estimates for track length, rail age, switch length, average age of switches and average amount of snow are significant and have the expected signs.

The cross product between traffic and track length is included in the model. In order to evaluate the cost elasticity with respect to traffic, it is therefore necessary to use eq. (18) where $\hat{\beta}_1$ is the first order coefficient for gross tonnes and $\hat{\beta}_2$ for the interaction variable. Based on this, table 10 reports cost elasticities of traffic with respect to mean length of tracks. The mean cost elasticity is 0.1534 with standard error 0.0555[7] (significant at the 1 per cent level).

$$\hat{\gamma}_{it} = \hat{\beta}_1 + \hat{\beta}_2 \cdot lnTRACK\_m_{it} \quad (18)$$

To calculate the marginal costs we use eq. (15), (16) and (17). However, we now use a fitted cost, $\hat{C}_{it}$, as specified in eq. (19), which derives from the double-log specification of our model that assumes normally distributed residuals (Munduch et al. 2002, and Wheat and Smith 2008).

$$\hat{C}_{it} = \exp(\ln(C_{it}) - \hat{v}_{it} + 0.5\hat{\sigma}^2) \quad (19)$$

[7] Calculated using the Delta method

Table 10 - Mean cost elasticity of traffic (gross tonnes)

MaintC	Coef.	Std. Err	T	P>t	[95% Conf.	Interval]
$\hat{\gamma}_{it}$	0.1534	0.0555	2.76	0.006	0.0439	0.2629

The average and marginal costs are summarized in table 11. The lower value of costs deriving from the weighting procedure indicates that track sections with relatively more traffic have lower marginal costs than average.

Table 11 - Estimated costs; Model 2

Variable	Obs.	Mean	Std. Err.	[95 % Conf.	Interval]
Average cost	2486	0.4049	0.1241	0.1616	0.6483
Marginal cost	2486	0.0317	0.0083	0.0153	0.0479
Weighted marginal cost	2486	0.0061	0.0002	0.0057	0.0064

The mean weighted marginal cost is 0.0061 SEK (in 2012 prices), with standard error at 0.0002.

Model 2 was also estimated with snow costs excluded from the dependent variable. We experience no noteworthy changes in the parameter estimates, except for the expected non-significance of the coefficient for snow. The mean output elasticity is 0.1543 which is very close to the first estimate (0.1534). As expected, the weighted marginal cost is slightly lower with mean 0.0053 SEK and standard error 0.0001.

Moreover, we estimate *Model 2* using data for 2007-2012 as a robustness check; i.e. if cost elasticities with respect to traffic and weighed marginal cost differ significantly depending on which period is analysed. We find that the mean cost elasticity is 0.1990 with standard error 0.0706 and the weighted marginal cost is 0.0097 SEK (standard error at 0.0005).

4.2 Model 3 estimation results; a dynamic model

Two dynamic models have been estimated: the system GMM (*Model 3A*) – proposed by Arellano-Bover/Blundell-Bond (1995, 1998) – and the difference GMM model (*Model 3B*), proposed by Arellano and Bond (1991). As described in section 2.5, both are used in order to estimate how the level of maintenance cost during one year affect the level of maintenance costs in the next. The estimation results are presented in table 12, where MAINTC t-1 is the variable for lagged maintenance costs. A lagged variable for traffic was tested in the estimations which did not result in significantly different results but generated a second-order autoregressive process in first differences.

We use the Windmeijer (2005) correction of the variance-covariance matrix of the estimators, and we therefore only report the two-step results[8].

Table 12 - Model 3 results

	Model 3A		*Model 3B*	
MaintC	Coefficient	Corrected Std. Err.	Coefficient	Corrected Std. Err.
Cons.	1.9541	1.6729	-	-
MAINTC t-1	0.1708***	0.0602	0.1561**	0.0699
TGTDEN	0.2690*	0.1385	0.1350	0.2102
TRACK_M	0.4670***	0.0532	-0.1855	0.2191
RAIL_AGE	0.1087	0.0939	-0.0388	0.0796
SWITCH_M	0.1844*	0.0996	0.1688*	0.0919
SNOWMM	0.0733***	0.0260	0.0279	0.0238
YEAR01	-0.0342	0.0400	0.0148	0.0343
YEAR02	0.1738***	0.0418	0.2251***	0.0416
YEAR03	0.1159**	0.0487	0.1834***	0.0445
YEAR04	0.1380**	0.0551	0.2326***	0.0499
YEAR05	0.1260***	0.0484	0.2120***	0.0467
YEAR06	0.0478	0.0502	0.1349***	0.0482
YEAR07	0.1142**	0.0537	0.2023***	0.0483
YEAR08	0.0982	0.0612	0.1873***	0.0586
YEAR09	0.1376**	0.0577	0.2426***	0.0566
YEAR10	0.1031	0.0671	0.2444***	0.0659
YEAR11	0.2337***	0.0634	0.3365***	0.0577
YEAR12	0.2793***	0.0646	0.4021***	0.0600
No. obs.	2269		2269	
No. instruments	32		30	

Note: ***, **, * : Significance at 1%, 5%, 10% level.

[8] Without the Windmejer (2005) correction, the standard errors are downward biased in the two-step results, which is a motivation for reporting the one-step estimation results together with the two-step results (Roodman 2009a).

To test for the validity of the lagged instruments, autocorrelation in the differences of the idiosyncratic errors is tested for. We expect to find a first-order autoregressive process – AR(1) – in differences because Δv_{it} should correlate with Δv_{it-1} as they share the v_{it-1}term. However, a second-order autoregressive process – AR(2) – indicates that the instruments are endogenous and therefore not appropriate in the estimation. We maintain the null hypothesis of no AR(2) process in our models according to the Arellano and Bond test, though in *Model 3B* we cannot reject the presence of an AR(2) process at a 10 per cent level of significance (see table 13). The test results presented in table 13 further show that we have valid instruments. The Sargan test of over-identifying restrictions is a test of the validity of the instruments. We cannot reject the null hypothesis that the included instruments are valid. The null hypothesis of the Hansen test excluding groups of instruments is that these are not correlated with independent variables. Hence, a rejection is what we expect as we excluded them to avoid endogeneity.

Table 13 - Results from diagnostic tests; models 3A and 3B

	Model 3A		*Model 3B*	
A-B test AR(2) in first diff.	z=1.61, Pr>z=0.108		z=1.70, Pr>z=0.090	
Sargan test of overid. restr.	Chi2(13)=12.03, Pr>chi2=0.525		Chi2(12)=10.45, Pr>chi2=0.576	
GMM instruments for levels				
Hansen test excl. group	Chi2(12)=12.02	Pr>chi2=0.444	N/A	N/A
Difference (null H = exogenous):	Chi2(1)=0.01	Pr>chi2=0.912	N/A	N/A
gmm(MaintC L1, collapse lag(1 .))				
Hansen test excl. group	chi2(0)=0.00	Pr>chi2= .	chi2(0)=0.00	Pr>chi2= .
Difference (null H = exogenous)	chi2(13)=12.03	Pr>chi2=0.525	chi2(12)=10.45	Pr>chi2=0.576
gmm(tgtden, collapse eq(diff) lag(3 4))				
Hansen test excl. group	chi2(11)=7.84	Pr>chi2=0.727	chi2(10)=7.36	Pr>chi2=0.692
Difference (null H = exogenous)	chi2(2)=4.19	Pr>chi2=0.123	chi2(2)=3.10	Pr>chi2=0.213

The results from the Arellano and Bond (1991) model (*Model 3B*) are unsatisfactory with respect to significance levels and the coefficients for track length and rail age have an unexpected negative sign. As mentioned in section 2.5, Alonso-Borrego and Arellano (1999) and Blundell and Bond (1998) show that the GMM estimator based on first differences (*Model 3B*) can produce imprecise and biased estimates. We therefore focus on *Model 3A* estimation results, which according to Blundell and Bond (1998) can lead to efficiency gains.

The estimation results from *Model 3A* suggest that an increase in maintenance costs in year *t*-1 increases costs in year *t*, which is opposite to the results in Andersson (2008). The cost elasticity with respect to gross tonnes is 0.2690 with a standard error at 0.1385 (significant at the 10 per cent level). With a lagged dependent variable in our model, we are able to calculate cost elasticities for output that account for how changes in costs in the previous year affect costs in the current year:

$$\hat{\gamma}_{it} = \frac{1}{(1-\hat{\beta}_1)} \cdot [\hat{\beta}_2] \qquad (20)$$

where $\hat{\beta}_1$ is the estimated coefficient for the lagged dependent variable and $\hat{\beta}_2$ is the cost elasticity for gross tonnes. The cost elasticity with respect to output and lagged costs is 0.3245 with standard error at 0.1609 (significant at the 5 per cent level). We choose to call this elasticity the dynamic cost elasticity. The dynamic cost elasticity is significantly different from the direct cost elasticity (0.2690) at the 10 per cent level (p-value 0.070).

Similar to equations (15), (16), (17) and (19), we use the predicted cost to estimate average cost and marginal costs, which are summarized in table 14.

Table 14 - Estimated costs; model 3A

Variable	Obs.	Mean	Std. Err.	[95% Conf.	Interval]
Average cost	2269	0.1530	0.0215	0.1109	0.1951
Marginal cost	2269	0.0412	0.0058	0.0298	0.0525
Weighted marginal cost	2269	0.0078	0.0001	0.0075	0.0081
Dynamic marginal cost	2269	0.0496	0.0070	0.0360	0.0633
Dynamic weighted marginal cost	2269	0.0094	0.0002	0.0091	0.0097

The weighted marginal cost is 0.0078 SEK. The dynamic weighted marginal cost is 0.0094 SEK with a standard error at 0.0002.

5.0 Discussion and conclusion

In this paper we have tested different econometric approaches for estimating the relationship between maintenance costs and traffic. The results are summarized in table 15.

Table 15 - Cost elasticities and marginal costs with standard errors in parentheses

Model	Method	Cost elasticity	Weighted marginal cost, SEK
Model 1	Box-Cox, theta model	0.2360 (0.0007)*	0.0058
Model 2	Fixed effects	0.1543 (0.0597)	0.0053[a]
Model 2b**	Fixed effects 2007-2012	0.1990 (0.0706)	0.0097
Model 3A**	GMM	0.2690 (0.1385), 0.3245[b] (0.1609)	0.0078, 0.0094[c]

* not cluster-adjusted, ** snow removal costs included in maintenance costs, [a] 0.0061 SEK incl. snow removal, [b] Dynamic cost elasticity, [c] Dynamic weighted marginal cost

The cost elasticity from the Box-Cox regression is higher than the elasticity produced by the restricted translog model (*Model 2*), while the weighted marginal cost is similar in both models. The Box-Cox results show that the double log functional form is preferred over the linear transformation. Though, the estimates of the transformation parameter are significantly different from zero which indicates that the double log transformation is not optimal (see table 5 and 6). However, the Box-Cox functional form does not fully use the panel structure of the data. Unobserved individual effects are assumed to be the same for all individuals, which introduce omitted variable bias if this assumption is wrong. The assumption of constant unobserved individual effects is strongly rejected in *Model 2* (see table 9). Thus, despite the similar weighted marginal cost estimates, the results from the Box-Cox regression should be interpreted with care.[9]

[9] We tested the inclusion of a set of dummy variables for track sections in the Box-Cox regression in order to capture individual effects, though we are aware of the incidental parameters problem that may lead to inconsistent estimates (Neyman and Scott 1948)[9]. With this in mind, the estimated cost elasticities with respect to output is 0.1460 (standard error 0.0026) in the theta-model and 0.1219 (standard error 0.0047) in the lambda model when dummy variables are included to capture the individual fixed effects. These estimates are closer to the elasticity in *Model 2* (0.1513[9]), which is a restricted translog model estimated with fixed effects. We also estimated *Model 2* using Pooled OLS, which estimates a constant that is assumed to be the same for all individuals (similar to the Box-Cox regression). Interestingly, the mean cost elasticity is 0.2587 which is close to the elasticities from the Box-Cox regression.

We can conclude that more data did not make a difference with respect to the Box-Cox regression results. The estimated cost elasticity for total output is 0.236, and the cost elasticity is 0.156 for passenger traffic and 0.076 for freight traffic in the model with separate outputs. The Box-Cox estimates from Andersson (2011), using 4 years of data, are similar (the cost elasticity for passenger traffic is 0.179 and 0.052 for freight traffic).

When modelling unobserved individual effects using the fixed effects estimator (*Model 2*) excl. snow removal costs, we have slightly lower cost elasticity (0.1543 compared to 0.26 and 0.27) and weighted marginal cost (0.0053 SEK compared to 0.0081 and 0.0084 SEK) than earlier studies on Swedish data using the fixed effects estimator. A change in results from previous studies is not surprising considering the longer time period of our data, during which major changes in the organisation of railway maintenance have been carried out (though we account for the effect of competitive tendering which lowered costs with about 10 per cent). Moreover, a major difference between our model and previous models by Andersson (2007 and 2008) is that we include more infrastructure characteristics. These were assumed to be constant in previous models, which can be a reasonable assumption using a fixed effects model on a short panel. Estimating model 2 using data over 2007-2012 results in a cost elasticity at 0.1990 and a weighted marginal cost at 0.0097 SEK (snow removal costs included). This cost elasticity is more in line with earlier studies on Swedish data and a number of European studies showing elasticities which lies in the interval 0.20-0.35 (Wheat et al. 2009).

The estimation result from the dynamic model stands out. Adding 10 years to the dataset certainly made a difference. A lower estimate for the cost elasticity and marginal cost is found in *Model 3A*, compared to the estimate in the dynamic model in Andersson (2008). More importantly, the dynamic cost elasticity and marginal cost is higher than the cost elasticity for output. The reason is that the results from our dynamic model show that an increase in maintenance costs in year *t*-1 predicts an increase in maintenance costs in year *t*. This is opposite to the previous results and might to some extent be counterintuitive. One would expect that an increase of maintenance costs should lower the need to maintain the track the following year. However, the crux of the matter is that we have two main types of maintenance activities: preventive and corrective maintenance. A possible explanation (summarized in table 16) is the following: an increase in preventive maintenance should decrease the need for corrective maintenance the following year (*scenario 1*). An increase in corrective maintenance will, however, not reduce the level of maintenance the following year, rather the opposite. An increase in the frequency of corrective maintenance is in fact a sign of a track with quality problems, and is therefore expected to require further corrective maintenance the following year. The following year might even require additional corrective maintenance as the deterioration rate is likely to increase if mainly corrective maintenance is carried out (*scenario 2b*). Preventive maintenance can stop this, and is likely to be carried out on a track with high corrective maintenance the previous year (*scenario 2a*).

Table 16 - Scenarios for preventive and corrective maintenance

	Scenario 1		*Scenario 2*	
Year	Preventive maint.	Corrective maint.	Preventive maint.	Corrective maint.
t	+			+
t+1	-	-	+[a]	+[b]

[a] scenario 2a, [b] scenario 2b

Our results therefore suggest that we are in *scenario 2* more often than in *scenario 1*; we have an increase in corrective maintenance compared to preventive maintenance. According to a report by *Trafikverket* (2012) the amount of corrective maintenance has indeed increased more than preventive maintenance since 2008. Though, this statement is a bit uncertain as almost a third of total maintenance costs are not registered as being corrective or preventive.

Estimations with freight and passenger gross tonnes as separate outputs have been made (results are presented in the appendix). The restricted translog model estimation did not generate significantly different cost elasticities. The Box-Cox regression results confirm the result found by Andersson (2011), with higher cost elasticity with respect to passenger gross tonnes compared to freight gross tonnes. This is an unexpected result for track engineers in Sweden and should be interpreted with care, especially since we have reason to suspect a bias in the estimates when assuming unobserved individual effects to be constant.[10]

[10] We estimated the lambda model (the theta model did not converge) with dummy variables for track sections (which can cause the incidental parameters problem) to capture unobserved individual heterogeneity, resulting in similar cost elasticities for passenger and freight gross tonnes.

In summary, we can determine that the cost elasticity estimates are rather robust with respect to the previous estimates in European countries. Adding more data has not made a big difference for the static models. There seem to be strong evidence that cost elasticities for rail maintenance are generally below 0.4.

Future research should aim at examining the dynamic costs more in depth. Budget restrictions and maintenance strategies will affect the amount and type of maintenance that can be carried out one year, which will have an effect on the required maintenance in future years. It is therefore important to consider the dynamics in maintenance costs. Data on the type of maintenance (preventive and corrective) carried out together with contract design can help to explain how current maintenance affect future maintenance.

References

Andersson, M. (2006): 'Marginal Cost Pricing of Railway Infrastructure Operation, Maintenance, and Renewal in Sweden, From Policy to Practice through Existing Data', *Transportation Research Record*, 1943, 1-11

Andersson, M. (2007): 'Fixed Effects Estimation of Marginal Railway Infrastructure Costs in Sweden', *Scandinavian Working papers in Economcis* (SWoPEc) 2007:11, VTI, Sweden

Andersson, M. (2008): 'Marginal Railway Infrastructure Costs in a Dynamic Context', *EJTIR*, 8, 268-286

Andersson, M. (2011): 'Marginal cost of railway infrastructure wear and tear for freight and passenger trains in Sweden', *European Transport\Transporti Europei*, 48, 3-23

Andersson, M., and G. Björklund (2012): 'Marginal Railway Track Renewal Costs: A Survival Data Approach', *Centre for Transport Studies (CTS)* Working Paper 2012:29, Stockholm

Andersson, M., A.S.J. Smith, Å. Wikberg, and P. Wheat (2012): ‘Estimating the Marginal Cost of Railway Track Renewals Using Corner Solution Models’, *Transportation Research Part A*, 46(6), 954-964

Arellano, M., and S. Bond (1991): ‘Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations’, *The Review of Economic Studies*, 58(2), 277-297

Arellano, M. (1993): ‘On the Testing of Correlated Effects with Panel Data’, *Journal of Econometrics*, 59(1), 87-97

Arellano, M., and O. Bover (1995): ‘Another look at the instrumental variable estimation of error-components models’, *Journal of Econometrics*, 68, 29-51.

Baltagi, B.H. (2008): ‘Econometric Analysis of Panel Data’, Third edition, John Wiley & Sons, Chichester, England

Booz Allen Hamilton, and TTCI (2005): ‘Review of Variable Usage and Electrification Asset Usage Charges: Final Report‘, Report R00736a15, London, June 2005

Box, G.E.P., and D.R. Cox (1964): ‘An Analysis of Transformations’, *Journal of the Royal Statistical Society. Series B (Methodological)*, 26(2), 211-252

Blundell, R., and S. Bond (1998): ‘Initial conditions and moment restrictions in dynamic panel data models’, *Journal of Econometrics*, 87, 115-143.

Breusch, T.S. and A.R. Pagan (1980): 'The LM test and Its Applications to Model Specification in Econometrics', *Review of Economic Studies*, 47(1), 239-253

Clark T.S., and D.A. Linzer (2013): 'Should I use fixed or random effects?', Working Paper, January 30, 2013

Grenestam, E., and E. Uhrberg, (2010): 'Marginal Cost Pricing of Railway Infrastructure - An econometric analysis', Kandidatuppsats i Nationalekonomi, Linköpings Universitet, (In Swedish).

Hausman, J.A. (1978): 'Specification Tests in Econometrics', *Econometrica*, 46(6), 1251-1271

Holtz-Ekin, D., W. Newey, and H.S. Rosen (1988): 'Estimating vector autoregressions with panel data', *Econometrica*, 56(6), 1371-1395

Imbens, G., and J. Wooldridge (2007): 'What's new in Econometrics?', The National Bureau of Economic Research (NBER) Summer Institute 2007. Lecture notes 2: http://www.nber.org/WNE/WNEnotes.pdf

Johansson, P., and J-E. Nilsson (2004): 'An economic analysis of track maintenance costs', *Transport Policy*, 11, 277-286.

Lancester, T. (2000): 'The incidental parameter problem since 1948', *Journal of Econometrics*, 95, 391-413

Link, H., A. Stuhlehemmer, M. Haraldsson, P. Abrantes, P. Wheat, S. Iwnicki, C. Nash, and A.S.J Smith (2008): 'CATRIN (Cost Allocation of TRansport INfrastructure cost), Deliverable D 1, Cost allocation Practices in European Transport Sector. Funded by Sixth Framework Programme. VTI, Stockholm, March 2008

Mundlak, Y. (1978): 'On the Pooling of Time Series and Cross Section Data', *Econometrica*, 46(1), 69-85

Munduch, G., A. Pfister, L. Sögner, and A. Siassny (2002): 'Estimating Marginal Costs for the Austrian Railway System', *Vienna University of Economics & B.A., Working Paper* No. 78, February 2002

Neyman J., and E.L. Scott (1948): 'Consistent Estimates Based on Partially Consistent Observations', *Econometrica*, 16(1), 1-32

Odolinski, K. (2014): 'PM: Trafikdata 1999-2012, järnväg', Memorandum, VTI (In Swedish)

Roodman, D. (2009a): 'Practioners' corner. A Note on the Theme of Too Many Instruments', *Oxford Bulletin of Economics and Statistics*, 71 (1), 135-158.

Roodman, D. (2009b): 'How to do xtabond2: An introduction to difference and system GMM in Stata', *The Stata Journal*, 9(1), 86-136.

StataCorp.2011. *Stata Statistical Software: Release 12*. College Station, TX: StataCorp LP

Trafikverket (2012): ’Organisering av underhåll av den svenska järnvägsinfrastrukturen’, Dnr: TRV2012/63556, (in Swedish)

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

Wheat, P., A.S.J. Smith, and C. Nash (2009): ‘CATRIN (Cost Allocation of TRansport INfrastructure cost)’, Deliverable 8 – Rail Cost Allocation for Europe. VTI, Stockholm

Windmeijer, F. (2005): ‘A finite sample correction for the variance of linear efficient two-step GMM estimators’, *Journal of Econometrics*, 126, 25-51

Wooldridge, J.M. (2009): ‘Introductory Econometrics. A Modern Approach’, Fourth Edition, South-Western Cengage Learning, Mason, USA

Öberg, J., E. Andersson, and J. Gunnarsson (2007): ‘Track Access Charging with Respect to Vehicle Characteristics’, second edition, Rapport LA-BAN 2007/31, Banverket (In Swedish)

Appendix

Table 17 - Restricted translog model with separate outputs

	Fixed effects		*Random effects*	
MaintC	Coef.	Robust s.e.	Coef.	Robust s.e.
Cons.	16.0011***	0.0781	16.2255***	0.0695
PGTDEN	0.0251	0.0399	0.1082***	0.0324

FGTDEN	0.0408	0.0401	0.0527**	0.0229
TRACK_M	0.7730***	0.2371	0.6610***	0.0553
RATIOTLRO	-0.1201	0.1015	-0.1598**	0.0742
RAIL_AGE	0.1111***	0.0402	0.0811**	0.0392
QUALAVE	-0.2183	0.1764	0.2404***	0.0890
SWITCH_M	0.1791*	0.0953	0.3011***	0.0463
SWITCH_AGE	0.0406	0.0743	0.0122	0.0745
SNOWMM	0.0842***	0.0244	0.1024***	0.0261
YEAR00	0.0184	0.0372	0.0153	0.0405
YEAR 01	-0.0049	0.0405	-0.0203	0.0404
YEAR 02	0.1894***	0.0497	0.1744***	0.0495
YEAR 03	0.2130***	0.0558	0.2020***	0.0559
YEAR 04	0.2058***	0.0632	0.1870***	0.0632
YEAR 05	0.2135***	0.0497	0.2020***	0.0488
YEAR 06	0.1267**	0.0490	0.1179**	0.0465
YEAR 07	0.1941***	0.0483	0.1951***	0.0459
YEAR 08	0.1835***	0.0505	0.1829***	0.0499
YEAR 09	0.2602***	0.0509	0.2502***	0.0488
YEAR 10	0.1963***	0.0522	0.1853***	0.0517
YEAR 11	0.3129***	0.0553	0.3305***	0.0533
YEAR 12	0.3686***	0.0542	0.3673***	0.0533
PGTDEN2	0.0041	0.0078	0.0159***	0.0060
FGTDEN2	0.0119*	0.0068	0.0147***	0.0048
TRACK_M2	0.2471***	0.0714	0.1111***	0.0328
SWITCH_AGE2	-0.0709	0.0787	-0.0787	0.0656
PGTDENFGTDEN	-0.0212***	0.0080	-0.0234***	0.0059
PGTDENSWITCH_AGE	0.0591**	0.0204	0.0370**	0.0161
FGTDENSWITCH_AGE	-0.0099	0.0263	-0.0116	0.0225
No. obs.	2216		2216	
$\rho = \sigma_\mu^2/(\sigma_\mu^2 + \sigma_v^2)$	0.6120		0.3623	

Note: ***, **, * : Significance at 1%, 5%, 10% level.

Definition of new variables in table 17: [a,b]

PGTDEN = ln (Passenger train tonne-km/route-km)

FGTDEN = ln (Freight train tonne-km/route-km)

PGTDEN2 = PGTDEN^2

FGTDEN2 = FGTDEN^2

SWITCH_AGE2 = SWITCH_AGE^2

PGTDENFGTDEN = PGTDEN*FGTDEN

PGTDENSWITCH_AGE = PGTDEN*SWITCH_AGE

FGTDENSWITCH_AGE = FGTDEN*SWITCH_AGE

[a] We have transformed all data by dividing by the sample mean prior to taking logs

[b] Quadratic terms are divided by 2

Table 18 - Results from diagnostic tests; restricted translog model

Breusch-Pagan LM-test for Random effects	$Chi^2(1)=1481.37$, P=0.000
Hausman's test statistic*	$Chi^2(16)=75.35$, P=0.000
Arellano bond (1993) test: Sargan-Hansen statistic*	$Chi^2(16)=75.63$, P=0.000

In order to estimate the cost elasticities with respect to passenger train gross tonnes and freight train gross tonnes, we use the following expressions:

$$\hat{\gamma}_{it}^{P} = \hat{\beta}_1^P + \hat{\beta}_2^P \cdot lnPGTDEN_{it} + \hat{\beta}_3^P \cdot lnFGTDEN_{it} + \hat{\beta}_4^P \cdot lnSWITCH\_AGE_{it} \quad (21)$$

$$\hat{\gamma}_{it}^{F} = \hat{\beta}_1^F + \hat{\beta}_2^F \cdot lnFGTDEN_{it} + \hat{\beta}_3^F \cdot lnPGTDEN_{it} + \hat{\beta}_4^F \cdot lnSWITCH\_AGE_{it} \quad (22)$$

The estimated cost elasticities are summarized in table 19.

Table 19 - Estimated cost elasticities for passenger and freight gross tonnes

Variable	Coef.	Std. Err.	[95% Conf.	Interval]
$\hat{\gamma}_{it}^{P\,a}$	0.0351	0.0304	-0.0249	0.0951
$\hat{\gamma}_{it}^{F\,a}$	0.0550*	0.0326	-0.0092	0.1193
$\hat{\gamma}_{it}^{P\,b}$	0.1089***	0.0253	0.0593	0.1586
$\hat{\gamma}_{it}^{F\,b}$	0.0669***	0.0179	0.0318	0.1020

Note: ***, **, * : Significance at 1%, 5%, 10% level. [a] Fixed effects estimator, [b] Random effects estimator

The estimated cost elasticities from the fixed effects model are low, though only the estimate for freight gross tonnes is significant at the 10 per cent level. The cost elasticities with respect to output from the random effects estimator are higher and significant at the 1 per cent level.

However, the difference between the freight and passenger cost elasticity is not significant (chi2(1)=1.74[11], Prob>chi2=0.187). Moreover, according to the Hausman test and the test suggested by Arellano (1993), the fixed effects model is our preferred model. We note that the Box-Cox regression produce similar results as the random effects estimator, with respect to the difference in cost elasticities between freight and passenger gross tonnes (see table 22 below).

Table 20 - Results from Box-Cox models with separate outputs

	Lambda		*Theta*	
Maintc	Coef.	Std. Err.	Coef.	Std. Err.
/lambda	0.1490***	0.0119	0.1794***	0.0214
/theta	-	-	0.1419***	0.0127
Not transformed	Coef.	P>chi2(df)	Coef.	P>chi2(df)
Cons.	-4.4239		3.0521	
JOINTS	0.0110	0.000	0.0089	0.000
D.STATION SECTION	3.5364	0.000	3.0975	0.000
YEAR00	-0.5214	0.384	-0.4098	0.444
YEAR01	-0.5397	0.348	-0.4372	0.395
YEAR02	1.6101	0.005	1.4852	0.004
YEAR03	1.8285	0.002	1.7195	0.001
YEAR04	1.7048	0.003	1.6016	0.002
YEAR05	1.7939	0.002	1.6867	0.001
YEAR06	1.0203	0.077	0.9880	0.056
YEAR07	1.9784	0.000	1.8100	0.000
YEAR08	1.9298	0.001	1.7860	0.001
YEAR09	2.6948	0.000	2.4449	0.000
YEAR10	2.0617	0.000	1.8518	0.000
YEAR11	3.7082	0.000	3.3748	0.000
YEAR12	4.4303	0.000	4.0003	0.000
Transformed				
PGTDEN	0.1952	0.000	0.1186	0.000
FGTDEN	0.0889	0.000	0.0520	0.000
TRACK_M	1.2730	0.000	0.8232	0.000
RARTIOTLRO	-1.5771	0.000	-1.5289	0.000
QUALAVE	3.9118	0.000	3.4812	0.000

[11] Wald test

SWITCH_M	0.7955	0.000	0.5912	0.000
SNOWMM	0.4974	0.000	0.4055	0.000
/sigma	5.0511		4.5088	
No. obs.	2290		2290	
Log likelihood	-37993.231		-37991.717	

Note: ***, **, * : Significance at 1%, 5%, 10% level.

Table 21 - Likelihood ratio tests of functional forms

Test H0:	Restricted log likelihood	chi2	Prob>chi2
lambda = -1	-42156.258	8326.05	0.000
lambda = 0	-38074.997	163.53	0.000
lambda = 1	-39657.921	3329.38	0.000
theta=lambda = -1	-42156.258	8329.08	0.000
theta=lambda = 0	-38074.997	166.56	0.000
theta=lambda = 1	-39657.921	3332.41	0.000

We use expression (14) to calculate the cost elasticities with respect to passenger train gross tonnes and freight train gross tonnes.

Table 22 - Estimated cost elasticities for passenger and freight train gross tonnes

Variable	Obs.	Mean	Std. Err.	[95% Conf.	Interval]
$\hat{\gamma}_{m=P,it}{}^{a}$	2336	0.1489	0.0008	0.1472	0.1506
$\hat{\gamma}_{m=F,it}{}^{a}$	2336	0.0735	0.0004	0.0727	0.0742
$\hat{\gamma}_{m=P,it}{}^{b}$	2336	0.1565	0.0010	0.1545	0.1585
$\hat{\gamma}_{m=F,it}{}^{b}$	2336	0.0755	0.0005	0.0746	0.0764

[a] Lambda model, [b] Theta model