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Estimating the marginal maintenance cost of rail infrastructure usage in Sweden; does more data make a difference?

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Abstract

One cornerstone of EU's railway policy is that track user charges should be based on marginal costs for infrastructure use. This paper updates knowledge about the marginal cost of maintaining Sweden's railway network. Using an extended panel dataset, now comprising 16 years, we corroborate previous results using a static model framework. However, the results from the dynamic model show that an increase in maintenance cost during one year increases costs in the next year, which is contrasting previous estimates on a shorter panel dataset. We conclude that more data made a difference in a dynamic setting, but the estimated cost elasticities are rather robust in a European context.

1. Introduction

The way in which railway infrastructure maintenance is affected by variations in train traffic comprises one component of the social marginal costs for using railways. The policy relevance of this relationship was formally established after the vertical separation of infrastructure management and train operations introduced by the European Union in 1991 (Dir. 91/440). This directive required the introduction of track access charges. The charging principles of infrastructure use was further specified in 2001, when Dir. 2001/14 established that track access charges should be set according to the direct cost of running a vehicle on the tracks. This means that train operators (inter alia) should be charged for the wear and tear traffic inflicts on the infrastructure.

The significance of marginal cost pricing is one of the pillars of a policy for using societies' resources in an efficient way. The level of marginal cost of track use at large, and of wear and tear in particular, is therefore highly relevant both from a theoretical perspective and as a platform for EU's infrastructure policy, triggering several research papers referenced below. Against this background, the purpose of this paper is to present new marginal cost estimates for rail infrastructure maintenance in Sweden, using data that covers a much longer period of time than the existing literature. For the first time in this literature, our data set also comprises factor prices. The extended dataset has motivated the title of the paper since it is relevant to consider whether better data in general and longer time series in particular makes a difference to conclusions.

Access to several years of information furthermore makes it possible to assess any dynamic properties of track maintenance costs. A complementary purpose of the paper is therefore to assess whether and how spending on maintenance in one year affect costs in subsequent years. The possibility of dynamic interactions is still within the short run marginal cost paradigm, since it would only mean that the consequences of an activity – of traffic – one year has implications also for maintenance over a longer period.

The long time period also makes it possible to consider the possible consequences for marginal cost estimates of external events in the industry. The maintenance of Sweden's railways has gone through a comprehensive organizational reform with the introduction of competitive tendering in year 2002. The transfer to competition was gradual, but the entire network had been tendered at least once as of 2014. Odolinski and Smith (2016) show that competitive tendering reduced maintenance costs with 11 per cent. Thus the marginal cost may well have been affected by the reform.

Previous research has used different approaches for estimating the cost incurred by running one extra vehicle or vehicle ton on the tracks. There are examples of so-called bottom-up approaches that use engineering models to estimate track damage caused by traffic (see Booz Allen Hamilton 2005 and Öberg et al. 2007). Starting with Johansson and Nilsson (2004), previous studies have, however, mainly used econometric techniques to estimate the relationship between costs and traffic; this is referred to as a top-down approach. This line of research includes a derivation of the cost elasticity with respect to traffic, and calculation of the average maintenance cost. The marginal cost is the product of these two components.

Most of the top-down approaches make use of a double log functional form, either a full translog model or quadratic and cubic terms for the output variables. A survey of econometric rail cost studies is made in Link et al. (2008), who report cost elasticities in the interval 0.13-0.38, which we take as our benchmark or state-of-the-art opinion of the research community.

Table 1 lists some results of previous studies on Swedish data which is the most direct benchmark for our analysis. It is obvious that these elasticity values are within the overall range of cited observations for Europe.

Estimating a dynamic model in order to analyze rail infrastructure costs is rare, Andersson (2008) being one notable exception. He uses a difference generalized method of moments (GMM) estimator on a four-year panel dataset. Our paper adds to this study and the literature on rail infrastructure costs in general, by considering the dynamic aspect of maintenance on a much longer panel.

Table 1 - Previous estimates on the marginal maintenance cost of rail infrastructure usage in Sweden

	Model	Output variable	Cost elasticity	MC*	MC* 2014 Prices**
Johansson and Nilsson (2004)	Pooled OLS	Gross ton	0.17	0.0012	0.0014
Andersson (2006)	Pooled OLS	Gross ton	0.21	0.0031	0.0036
Andersson (2007)	Fixed Effects	Gross ton	0.27	0.0073	0.0084
Andersson (2008)	Fixed Effects	Gross ton	0.26	0.0070	0.0080
	Difference GMM	Gross ton	0.34^{S} 0.22^{L}	0.0092^{S} 0.0060^{L}	0.0106^{S} 0.0069^{L}
Andersson (2011)	Box-Cox	Freight gross ton	0.05	0.0014	0.0016
		Passenger gross ton	0.18	0.0108	0.0124

*Marginal Cost, **Inflation adjusted using the Swedish consumer price index, S=short-run, L=long-run

The focus in this paper is on maintenance costs – that is, spending on day to day activities. The relevance of renewal costs for appropriate charging is addressed in Andersson et al. (2012) and Andersson et al. (2016). Since a reduction in maintenance can front-load renewals and/or increase the level of renewals and vice versa, there is a possible interdependence between these cost categories. These links are beyond the scope of this paper.

The outline of the rest of the paper is as follows. The methodology Section (2) is followed by a description of the available dataset in Section 3. We present the results in Section 4. Section 5 comprises a discussion and conclusion of the results.

2. Methodology

Several intricate challenges have to be addressed in order to formulate a model that can be expected to deliver estimates of marginal costs. Section 2.1 addresses the econometric approach and appropriate transformation of variables. The static model to be estimated is presented in Section 2.2 while section 2.3 considers the possibility that maintenance activities in year t depend on costs in $t-1$.

2.1 Econometric approach

From an engineering perspective, the weight of the rolling stock is a main driver of the rail infrastructure wear and tear. Gross ton-km (GTKM, i.e. an additional ton using the tracks) has therefore become the preferred charging unit in Europe and is the output measure used in marginal cost calculations. When the impact of an additional ton-km on maintenance costs is estimated, there is reason to separate scale (track length) and density (tons) effects, as these dimensions of track use may have different effects. In particular, scale effects are related to long-run expansion of the railway network and the size of the maintenance production areas. Similar to the literature in this field, we instead use the cost elasticity with respect to gross tons (GT) and multiply with the average cost ($\frac{C}{GTKM}$) to derive the marginal cost per ton-km:

$$MC = \frac{\partial C}{\partial GTKM} = \frac{GTKM}{C}\frac{\partial C}{\partial GTKM}\frac{C}{GTKM} = \frac{\partial lnC}{\partial lnGT}\frac{C}{GTKM}, \tag{1}$$

where C is maintenance costs.[1] To derive the cost elasticity with respect to gross tons, we use a cost function given by equation (2) where there are $i = 1, 2, \ldots, N$ track sections and $t = 1, 2, \ldots, T$ years of observations.

$$C_{it} = f(\boldsymbol{P}_{it}, \boldsymbol{Q}_{it}, \boldsymbol{F}_{it}, \boldsymbol{Z}_{it}), \quad (2)$$

$\boldsymbol{P}_{it}$ are input prices, $\boldsymbol{Q}_{it}$ the volume of output (gross ton) and $\boldsymbol{F}_{it}$ is a vector of network characteristics such as track length and rail age. $\boldsymbol{Z}_{it}$ is a vector of dummy variables which includes year dummies and variables indicating whether or not a track section belongs to a contract area tendered in competition. Since the introduction of competitive tendering in an area rarely starts at the beginning of a calendar year, we include a dummy variable for years when there is a mix between tendered and not tendered in competition. See Odolinski and Smith (2016) for more details.

A common functional form in the literature on rail infrastructure costs is the double-log specification. Indeed, agents in maintenance production are more likely to have the same reactions to relative changes than to changes in absolute levels, and a logarithmic transformation of the variables can reduce skewness and heteroscedasticity (Heij et al. 2004). Which transformation that is most appropriate can however be tested empirically using the model proposed by Box and Cox (1964) which does not impose a specific transformation of the data. Instead, the functional form is tested. We estimate the Box Cox model and the results confirm that a logarithmic transformation is preferred.[2]

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[1] In equation (1), the fact that $\frac{\partial C}{\partial GTKM} = \frac{\partial C}{\partial GT}\frac{1}{KM}$ implies that an extra ton that runs on a track section will not change the length of that section. An interaction term between GT and track length can also be added in the model estimation to allow for the cost elasticity with respect to GT to vary with track length. It should also be noted that a comprehensive measure of marginal costs also includes the impact of traffic on the date for track renewal. This dimension of the analysis is, however, dealt with in a separate paper; cf. Yarmukhamedov et al. (2016).

[2] More specifically, the estimates of the transformation parameters show that the logarithmic transformation is preferred when rounding the parameters to the closest functional form, as suggested by Sheather (2009).

2.2. Translog model

We start with the flexible translog cost function which, for example, allows economies of scale to vary with different output levels and the production structure can be non-homothetic (input demands can vary for different output levels). See for example Christensen and Greene (1976). The translog functional form is expressed as:

$$lnC_{it} = \alpha + \sum_{r=1}^{R} \beta_r lnP_{rit} + \frac{1}{2}\sum_{r=1}^{R}\sum_{s=r}^{R} \beta_{rs}\, lnP_{rit} lnP_{sit} + \sum_{m=1}^{M} \beta_m lnQ_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn}\, lnQ_{mit} lnQ_{nit} + \sum_{k=1}^{K} \beta_k lnF_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnF_{kit} lnF_{lit} + \sum_{r=1}^{R}\sum_{m=1}^{M} \beta_{rm} lnP_{rit} lnQ_{mit} + \sum_{r=1}^{R}\sum_{k=1}^{K} \beta_{rk} lnP_{rit} lnF_{kit} + \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{km} lnF_{kit} lnQ_{mit} + \sum_{d=1}^{D} \vartheta_d Z_{dit} + \mu_i + v_{it} \quad (3)$$

Equation (3) comprises *R* inputs, *M* outputs, *K* network characteristics, and D dummy variables. $\boldsymbol{\beta}$ and $\boldsymbol{\vartheta}$ are vector of parameters to be estimated, and the symmetry restrictions $\beta_{mn} = \beta_{nm}$, $\beta_{kl} = \beta_{lk}$, $\beta_{rm} = \beta_{mr}$, $\beta_{rk} = \beta_{kr}$ and $\beta_{km} = \beta_{mk}$ are used. The Cobb-Douglas constraint is $\beta_{rs} = \beta_{mn} = \beta_{kl} = \beta_{rm} = \beta_{rk} = \beta_{km} = 0$, which we examine using an F-test. Hence, the Cobb-Douglas model implies the homotheticity ($\beta_{rm} = 0$) and homogeneity ($\beta_{rm} = \beta_{mn} = 0$) restrictions. A cubic term for output is also considered in the model estimation so that we allow for turning points in the cost elasticity with respect to output.

v_{it} is the error term in our model and α is a scalar. μ_i is the impact of generic features of each track section which may contain features that predict lnC_{it} but are not captured by the explanatory variables. This value is the same for each track unit over time. *Fixed effects* and *random effects* are two approaches often used to model this variation. A crucial assumption in the random effects approach is that the unobserved individual effects μ_i are uncorrelated with the explanatory variables. Otherwise, the model will produce biased estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\vartheta}$. We use the Hausman test (1978) for the choice between the random and fixed effects models.

In the baseline formulation of the model, only total annual gross tons is used to represent output. We also consider a distinction between freight and passenger gross tons as the characteristics of these vehicle types may cause different levels of wear and tear.

Several 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 and length of tunnels and bridges. The older the tracks, the more likely it is that maintenance costs are higher. The expectation goes in the opposite direction for the ratio between track and 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 with less work during night hours, that is, costs are lower.

2.3 Dynamic model

Some maintenance activities are not implemented every year. The level of tamping, rail grinding etc. during one year may therefore affect maintenance costs required the next. Hence, costs may fluctuate even if traffic and infrastructure characteristics do not change. Moreover, it may be difficult for the infrastructure manager (subsequently the IM) to give an immediate and appropriate response to a sudden and large change in traffic or in other cost drivers. To address the possibility of the intertemporal effect(s), a dynamic model with a lagged dependent variable as an explanatory variable will be 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 autocorrelation.

For a Cobb-Douglas functional form the model is expressed as:

$$lnC_{it} = \beta_0 lnC_{it-1} + \sum_{r=1}^{R} \beta_r lnP_r + \sum_{m=1}^{M} \beta_m lnQ_{mit} + \sum_{k=1}^{K} \beta_k lnF_{kit} + \sum_{d=1}^{D} \vartheta_d Z_{dit} + \mu_i + v_{it} \quad (4)$$

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. This is handled taking first differences of (4), giving equation (5).

$$\begin{aligned} lnC_{it} - lnC_{it-1} &= \beta_0(lnC_{it-1} - lnC_{it-2}) \\ &+ \sum_{r=1}^{R} \beta_r(lnP_{rit} - lnP_{rit-1}) + \sum_{m=1}^{M} \beta_m(lnQ_{mit} - lnQ_{mit-1}) \\ &+ \sum_{k=1}^{K} \beta_k(lnF_{kit} - lnF_{kit-1}) + \sum_{d=1}^{D} \vartheta_d(Z_{dit} - Z_{dit-1}) \\ &+ (\mu_i - \mu_i) + (v_{it} - v_{it-1}) \end{aligned} \quad (5)$$

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.

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}. Since the present dataset comprises 16 periods, we need to consider a restriction of the number of instruments used because too many instruments can over-fit the endogenous variables (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, differences of the lagged dependent variable are used 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 variables.

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…". We expect this to be the case for maintenance costs. The reason is that, for example, a large change in maintenance costs indicates that something is going on (e.g. a large increase in traffic), and contains information about maintenance costs in the following year (costs will be either low or high due to the change). Moreover, a very small change is more likely to imply that business is as usual. The past level, on the other hand, does not contain much information on how maintenance costs will change; it can be either business as usual or a large change in costs. In other words, based on this intuition, we expect the system GMM to perform better - using past changes as instruments for current levels - than the difference GMM, which uses past levels as instruments for current changes.

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 with lnC_{it-1} as an explanatory variable using the approach by Arellano-Bover/Blundell-Bond (1995, 1998) system GMM as well as the Arellano and Bond (1991) model.[3] Traffic is assumed to be predetermined (not strictly exogenous) and is instrumented with the same approach as the lagged dependent variable. This type of instruments is also used for a lagged track quality variable. Track geometry requirements are linked to this track quality class, where high speed lines have stricter requirements than low speed lines. We expect that a change in this particular variable in one year may have a nontrivial effect on maintenance costs in the following year.

3. Data

The publicly owned Swedish railway network is divided into track sections, administered by five regional units and a central planning unit within the Swedish Transport Administration (the IM). All in all, about 250 track sections are observed for the 1999 to 2014 period. A comprehensive matrix would therefore comprise (250 x 16 years =) 4000 observations. However, marshalling yards have been omitted since the cost structure at these places can be expected to differ from track sections at large. Neither is privately owned sections, heritage railways, nor track sections that are closed for traffic, included in the dataset. Also due to

[3] The comprehensive Translog model turned out to be sensitive to the number of instruments included. Moreover, some of the estimated coefficients for the network characteristics had reversed signs compared to the static model.

missing information and changes in the number of sections on the network, 2819 observations are available for analysis and the panel is thus unbalanced.

In the same way as in all other Swedish rail cost studies, most of the information derives from the systems held by the IM that reports on the technical aspects about the network and about costs. 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 (route) length ranges from 1.8 to 219.4 kilometres, and the average age of sections ranges from one to 84 years; see Table 2.

Table 2 - Descriptive statistics for track section for the 1999-2014 period (2819 obs.)

Variable	Median	Mean	Std. Dev.	Min	Max
Maintenance cost, million SEK*	8.37	12.57	15.32	0.01	277.52
Maintenance cost excl. snow removal, million SEK*	7.75	11.62	13.98	0.01	209.22
Hourly wage, SEK*	155.80	156.63	11.90	128.87	187.44
Iron and Steel, price index	112.90	100.47	31.22	52.30	140.90
Total ton density**	4.66	7.83	8.58	0.00	65.85
Passenger train ton density**	1.11	3.03	5.67	0.00	56.55
Freight train ton density**	2.36	4.59	5.41	0.00	39.72
Track length, km	56.32	68.99	50.950	4.20	290.65
Route length, km	39.47	53.04	41.26	1.79	219.39
Ratio track- and route length	1.14	1.61	1.05	1.00	8.08
Average rail age	19.17	20.53	10.38	1.00	84.01
Average quality class***	3.25	3.18	1.19	1.00	6.00
Switch length, km	1.32	1.75	1.70	0.06	14.40
Average age of switches, years	20.00	20.92	9.35	1.00	55.25
Length of bridges and tunnels, km	0.36	1.19	2.85	0.00	23.21
Max. axle load allowed	22.50	23.15	1.83	16.00	30.00
Snow mm precipitation when temp. <0 C°	97.94	111.77	63.79	2.14	343.76
Dummy when tendered in competition	0	0.47	0.50	0	1
Dummy when mix between tend. and not tend.	0	0.06	0.24	0	1

* Costs are deflated to the 2014 price level using the consumer price index (CPI), ** Million ton-km/route-km, ***Track quality class ranges from 0-5 (from low to high line speed), but 1 has been added to avoid observations with value 0.

A price index for iron and steel was obtained from Statistics Sweden, and is used as an input price variable. This variable only varies over time. Another input price variable is the gross hourly wage for workers within the occupational category 'building frame and related trade workers', which was obtained from the Swedish Mediation Office (via Statistics Sweden), and varies between eight different regions as well as over time.[4]

Previous analyses made a distinction between operations, primarily costs for snow clearance, and other, around-the-year maintenance. As of 2007 the IM does not make this separation and the (previously) separate observations of the two items have been merged for previous years. Maintenance costs therefore comprise all activities included in tendered maintenance contracts, including costs for snow removal. To control for weather variations between different track sections, information from the Swedish Metrological and Hydrological Institute (SMHI) has been used to create a variable for the amount of snowfall during a year and each track section, using millimetre of precipitation each day when the daily mean temperature is below zero degrees Celsius.

4. Results

Two models are estimated and the output tables are presented in the appendix together with variable definitions. The results of *Model 1*, a static panel data model, are presented in Section 4.1. Here we use heteroscedastic-robust standard errors that are adjusted for correlation within track sections. However, there may also be correlation between track sections. The year dummies in our model will pick up this cross-sectional dependence to the extent that it is similar for every pair of track sections. We test if correlation between track sections is still present in our model using Pesaran's (2004) test, which indicates that we need to address this type of

[4] Unfortunately, the occupational categories changed in 2014. We therefore assume that workers in our occupational category have the same percentage change in wages between 2013 and 2014 as workers in the construction industry, for which we have data.

correlation (see end of Table 8 in appendix for the test results). Our fixed effects model is therefore estimated with Driscoll and Kraay (1998) standard errors that are robust to cross-sectional and temporal dependence.[5] Moreover, the Hausman also indicated that the fixed effects estimator is preferred to the random effects estimator.

In Section 4.2 we present the results from *Model 2* which considers the dynamic dimension of maintenance costs, estimating how past levels of maintenance affect current levels. In addition to the rationale for including lagged maintenance costs as an explanatory variable (provided in section 2.3), we test the presence of serial correlation when this variable is dropped from equation (4). The Wooldridge (2002) test for serial correlation in panel data, which takes within-panel (track section) correlation into account, shows that we can reject the null hypothesis of no first order autocorrelation (F(1, 196)=12.56, prob>F=0.0005), indicating that there is indeed a dynamic process to be captured.

Before elaborating on the parameter estimates, we note that 17 outliers were detected. The average cost (maintenance cost per ton-km) for 14 of these observations were 200 times larger than the sample median, while three outliers had extremely low average costs with a ratio over 50 between the sample median and their respective average cost. These 17 outliers are excluded from the estimations. All estimations are carried out using Stata 12 (StataCorp.2011).

4.1 Estimation results: static panel data model

We start with the full translog functional form. Based on F-tests of linear restrictions on the fixed effects model results, with two exceptions, the full translog model is retained; both the parameter for wages and for structures (tunnels and bridges) are dropped due to their negative parameter estimates. Moreover, the input price for iron and steel only varies over time and is

[5] These standard errors rely on asymptotic theory, which we consider appropriate for our panel data that stretches over 16 years.

therefore collinear with one of the dummy variables. Hence, we only include interactions with this input price variable in the estimations. We also considered dividing maintenance cost and the input price for iron and steel with wages in order to impose linear homogeneity in input prices. However, we prefer the non-normalized formulation of our model as specified in eq. 3, in view of the negative estimate for wages in the model estimations which indicates that this input price variable may be a poor proxy for actual wages. Moreover, we are able to test if the sum of the input price variable's interaction terms is zero, which is required for linear homogeneity in input prices.[6] We cannot reject this restriction at the 5 per cent level of significance (F(1, 202)=2.71, Prob>0.0983).

Estimation results from a translog model with passenger and freight gross ton as separate outputs did not result in a significant difference in cost elasticity between these outputs.[7] We therefore present the results with total gross ton as output, meaning that it is impossible in our data to detect any – *ceteris paribus* – difference in wear and tear from a passenger and a freight train.

Before elaborating on the elasticity with respect to traffic, it is reason to comment on the other parameter estimates. The year dummy coefficients for 2002-2014 are significantly different from 1999, which is the baseline year. Moreover, tests of differences between the year dummies show that years 1999-2001 have the lowest cost level, while the years 2011-2014 have a significantly higher cost level than other years. These changes may be due to general effects over the rail network, such as an increase in unit maintenance costs and/or a change in the allocation of budget resources for maintenance purposes.

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[6] Other conditions required for linear homogeneity in input prices are that the sum of their second order terms is zero, as well as the sum of their first order coefficients.

[7] It can be noted that 190 track sections (out of 203) are included in this estimation as the separation between freight and passenger gross tons results in 13 track sections having a zero value in either of the outputs (these sections are dropped in the logarithmic transformation).

In line with the findings in Odolinski and Smith (2016), the gradual transfer from using in-house resources to competitive procurement has reduced maintenance costs. The parameter estimate for tendering in competition (Ctend) is -0.1060 (*p*-value 0.005), which translates to a 10.1 per cent[8] reduction in maintenance costs as a result of competitive tendering.

The first order coefficients (evaluated at the sample median) for track length (Track_l) and average rail age (Rail_age) are significant and have the expected signs. The estimate for maximum axle load allowed (Max.axle_load) is positive, which indicates that these tracks require more maintenance due to the heavy axle loads they experience, even though they are designed for this type of traffic. We also note that the first order coefficients for switch length (Switch_tl) and snowfall (Snowmm) have the expected signs, but are only nearly significant at the 10 per cent level (*p*-values 0.130 and 0.136, respectively).

The focus of the inquiry is on the impact of traffic on costs. The first order coefficient for traffic (Tgtden), evaluated at the sample median, is 0.1437 and statistically significant (*p*-value=0.000). However, we have a squared and cubic term for traffic as well as interaction terms between traffic, input prices, network characteristics and the weather variable (snow). Hence, in order to get an estimate of the cost elasticity with respect to gross ton at the observed levels of the variables in the interaction terms, it is necessary to use equation (6) where $\hat{\beta}_1$ is the first order coefficient for gross ton and $\hat{\beta}_2, \hat{\beta}_3, \dots, \hat{\beta}_{12}$ are the coefficients for the interaction variables. As a result, the static cost elasticity at the sample mean is 0.1729 with a standard error at 0.0421 (*p*-value=0.000).

$$\hat{\gamma}_{it} = \hat{\beta}_1 + 2 \cdot \hat{\beta}_2 lnTgtden_{it} + 3 \cdot \hat{\beta}_3 (lnTgtden)^2_{it} + \hat{\beta}_4 lnIron_{it} + \hat{\beta}_5 lnTrack\_l_{it} + \hat{\beta}_6 lnRatio\_tlro_{it} + \hat{\beta}_7 lnRail\_age_{it} + \hat{\beta}_8 lnQual\_ave_{it} + \hat{\beta}_9 lnSwitch\_tl_{it} + \hat{\beta}_{10} lnSwitch\_age_{it} + \hat{\beta}_{11} lnMax.axle\_load_{it} + \hat{\beta}_{12} lnSnow_{it}, \quad (6)$$

[8] exp(-0.1060)-1 = -0.1006

To calculate the marginal cost, we use a fitted cost, $\hat{C}_{it}$, as specified in equation (7), which derives from the double-log specification of our model that assumes normally distributed residuals (see Munduch et al. 2002 and Wheat and Smith 2008).

$$\hat{C}_{it} = \exp\left(\ln(C_{it}) - \hat{v}_{it} + 0.5\hat{\sigma}^2\right) \tag{7}$$

From a charging perspective, a distance unit is required for the marginal cost estimate, where ton kilometre is the preferred charging unit in Europe. The marginal cost per gross ton kilometre is calculated by multiplying the average cost by the cost elasticity from eq. (6). In eq. (8), the predicted average cost is used. This is the cost from eq. (7) divided by gross ton-kilometres (eq. 9):

$$MC_{it} = \widehat{AC}_{it} \cdot \hat{\gamma}_{it} \tag{8}$$

$$\widehat{AC}_{it} = \hat{C}_{it}/GTKM_{it} \tag{9}$$

Similar to previous studies a weighted marginal cost is calculated for the entire railway network included in this study. In this calculation, the traffic share on each track section is used in order to derive a marginal cost for all track sections that generates the same income for the infrastructure manager as if each track section's marginal cost would be used:

$$MC_{it}^{W} = MC_{it} \cdot \frac{GTKM_{it}}{(\sum_{it} GTKM_{it})/N} \tag{10}$$

The average and marginal costs are summarized in Table 3.[9] The lower value of costs deriving from the weighting procedure indicates that track sections with relatively more traffic have lower marginal costs than average.

[9] Note that the mean value of the weighted marginal cost in equation (10) is equal to the weighted sum of marginal costs ($MC^{W} = \sum MC_{it} \cdot \frac{GTKM_{it}}{(\sum_{it} GTKM_{it})}$), which is the expression used in for example Munduch et al. (2002) and Andersson (2008).

Table 3 - Estimated costs in SEK, 2014 prices (2802 obs.), Model 1

	Mean	Std. Err.	[95 % Conf.	Interval]
Average cost	0.3163	0.0329	0.2517	0.3808
Marginal cost	0.1192	0.0198	0.0804	0.1580
Weighted marginal cost	0.0065	0.0002	0.0062	0.0068

4.2 Estimation results: dynamic model

Two dynamic models are estimated - the system GMM and the difference GMM model - in order to assess how the level of maintenance cost during one year affects the level of maintenance cost in the next. We also estimate the system GMM on a panel data set over the period 1999-2002 for comparison between a shorter data set (as in Andersson 2008) and our extended data set. The output table is presented in the appendix (Table 9), where *Model 2a* and *2b* refer to model estimations using observations over the period 1999-2014 and 1999-2002, respectively. We use the Windmeijer (2005) correction of the variance-covariance matrix of the estimators, and we therefore only report the two-step results.[10] Dummy variables for regions are included in the system GMM model to control for heterogeneity. Region West is the baseline in the model.

To examine the validity of the lagged instruments, we test for autocorrelation in the differences of the idiosyncratic errors. 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, the presence of a second-order autoregressive process – AR(2) – would indicate 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 in both models (see Table 10). The other test results presented in Table 10 also indicate valid

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

instruments: the null hypothesis of the Sargan test (not robust) and the Hansen test (robust) of overidentifying restrictions is that we have valid instruments (not correlated with the error term), which we maintain in both models (except for the Sargan test, which however is not robust). Moreover, the tests of the subsets of instruments also show that these are valid; we maintain the null hypothesis of the Hansen test of excluding groups (excluded instruments are not correlated with independent variables) as well as the null hypothesis of the difference-in-Hansen test (C-test) that the instruments used are exogenous.

The results from the difference GMM are unsatisfactory with respect to significance levels and the coefficients for track length, rail age and length of structures (tunnels and bridges) have unexpected negative signs. As mentioned in Section 2.3, Alonso-Borrego and Arellano (1999) and Blundell and Bond (1998) show that the GMM estimator based on first differences can produce imprecise and biased estimates.

We therefore focus on the system GMM results. The coefficient for lagged maintenance costs (MaintC t-1) is 0.2140, with a standard error at 0.0548, indicating that an increase in maintenance costs in year $t-1$ increase costs in year t. The cost elasticity with respect to gross ton is 0.3058 with a standard error at 0.1415 (p-value=0.032). 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:

$$\hat{\gamma}_{it} = \frac{\hat{\beta}_1}{(1-\hat{\beta}_0)} \tag{11}$$

$\hat{\beta}_0$ is the estimated coefficient for the lagged dependent variable and $\hat{\beta}_1$ is the cost elasticity for gross ton.[11] The cost elasticity with respect to output and lagged costs is 0.3891 with standard

[11] In equilibrium $lnC_{it} = lnC_{it-1}$ which implies that equilibrium cost $lnC_i^e = \mu_i + \beta_0 lnC_i^e + \beta_1 lnTGTDEN_i$ (only considering track section specific effect and tonnage for simplicity) and rearranging gives $lnC_i^e = \frac{\mu_i}{1-\beta_0} + \frac{\beta_1}{1-\beta_0} lnTGTDEN_i$.

error at 0.1701 (p-value=0.023). This may be referred to as the equilibrium cost elasticity[12] since it shows how an increase in traffic (picked up by MaintC t-1) affects maintenance costs that have adjusted into equilibrium. This elasticity is significantly different from the direct cost elasticity (0.3058) at the 5 per cent level (F(1, 197)=5.26 and Prob>F= 0.023).

Similar to equations (7)-(10), we use the predicted cost to estimate average cost and marginal costs, which are summarized in Table 4. The weighted marginal cost is 0.0094 SEK, while the equilibrium weighted marginal cost (0.0120 SEK).

Table 4 - Estimated costs, SEK in 2014 prices: Model 2a (2578 obs.)

Variable	Mean	Std. Err.	[95% Conf.	Interval]
Average cost	0.1144	0.0043	0.1060	0.1228
Marginal cost	0.0350	0.0013	0.0324	0.0375
Weighted marginal cost	0.0094	0.0002	0.0091	0.0098
Equilibr. marginal cost	0.0445	0.0017	0.0413	0.0478
Equilibr. weighted marginal cost	0.0120	0.0002	0.0116	0.0124

The positive coefficient for lagged maintenance costs might to some extent seem counterintuitive, since an increase in maintenance costs in one year could be expected to reduce the need to maintain the track the following year. In this, however, it is important to note that the coefficient for lagged maintenance costs shows how a change in traffic (and/or in other cost drivers) affects costs in subsequent period(s) – that is; the estimate is an indication of the response taken by the IM. To make this clearer, we consider two main scenarios in Table 5. An increase in (planned) preventive maintenance can be expected to reduce the need for both (unplanned) corrective and preventive maintenance the following year; this is *scenario 1* in Table 5. On the other hand, an increase in corrective maintenance is typically triggered by acute, un-foreseen problems and will not necessarily reduce the level of maintenance the following year. This is so since an increase in the number of corrective maintenance activities can be a

[12] We thank Phill Wheat (Institute for Transport Studies, University of Leeds) for suggesting this term.

sign of a track with quality problems, and may signal the need for additional corrective maintenance the following year. If this is correct, the following year might even require more maintenance compared to the previous year since the line has now been used another year by another millions of gross tons (*scenario 2b*). Preventive maintenance may slow down this downward circle, and it is likely that a welfare optimising IM allocates additional resources to a track section with high corrective maintenance the previous year (*scenario 2a*), or decides to renew the tracks.

Table 5 - 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

We also note that a large coefficient for lagged maintenance costs (and hence a large equilibrium cost) may reflect an inability of the IM to give the appropriate response to past changes, indicating that the IM has not done enough - or the right type of activities - to cope with these changes. Whether that is the case or not for the Swedish IM is beyond the scope of this paper, and would also require information on delay costs caused by poor infrastructure quality.

The positive dependence between current and future maintenance costs is opposite to previous results in Andersson (2008), who used a difference GMM model. To make sure that it is not the model choice that generate the difference in signs of the intertemporal effect, we consider the system GMM estimator on the 1999-2002 sample, which yields similar (yet not significant) results to Andersson (2008) with a negative coefficient for lagged maintenance costs. The results from this model (2b) are provided in Table 9 in the appendix. The short sample period results may be caused by a temporary response in maintenance towards wear and tear, such as an increase in preventive maintenance rather than corrective maintenance. Information on the amount of corrective and preventive maintenance performed over the years is unfortunately not available.

5. Discussion and conclusion

With access to considerably more data than previous studies, this paper uses econometric techniques for estimating the relationship between maintenance costs and traffic. The first observation is that our new (static) estimate is lower than before; using Swedish data and the fixed effects estimator, it is 0.17 rather than 0.26. The second result is that adding a dynamic component to the model estimation increases the elasticity to 0.39. These values are all within the range of what we use as our benchmark. Using much data and modern econometric techniques, it is therefore fair to say that research is converging towards consensus. The results from the dynamic model are, however, contrasting previous estimation results on a shorter panel data set. Our paper has therefore shown that a longer panel can be critical for the conclusions drawn from an analysis on maintenance costs in a dynamic context.

A change in results of the static elasticity 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. An additional difference is that our modelling includes more infrastructure characteristics. These were assumed to be constant in previous model estimations on Swedish data, which can be a reasonable assumption using a fixed effects model on a short panel.

The introduction of factor prices has not made a visible imprint on results. This outcome is not very surprising, bearing in mind the homogeneity of Sweden's labour market with small wage differences at large, as well as the fact that much input to the maintenance activity –

notably rails and sleepers – is tendered separately by the IM and made available to maintenance contractors.

The transfer from in-house production to competitive tendering has reduced costs by about 10 percent. This further motivates a comparison of our marginal cost estimates with previous estimates presented in Table 1. Considering that previous estimates on Swedish data do not include snow removal costs, we delete these costs in Model 1 in order to make a fair comparison of new versus previous marginal costs. The weighted marginal cost is then 0.0060 SEK, which is about 26-29 per cent lower than previous estimates in Andersson (2007 and 2008).

Table 6 summarises the outcome of both the static *Model 1* estimate and a dynamic aspect of maintenance (*Model 2a*). The results show that an increase in maintenance costs in year $t-1$ predicts an increase in maintenance costs in year t. While the tests are done in a dynamic setting, the results are fully consistent with the standard definition of short run marginal costs: an exogenous change in traffic triggers not only immediate but also subsequent maintenance activities.

Table 6 - Cost elasticities and marginal costs with standard errors in parentheses

Model	Method	Cost elasticity (std. err)	Weighted marginal cost, SEK
1	Fixed eff.	0.1729 (0.0421)	0.0065
2a	System GMM	0.3058 (0.1415)	0.0094
		0.3891[a] (0.1701)	0.0120[b]

[a] Equilibrium cost elasticity. [b] Equilibrium weighted marginal cost.

Future research should aim at examining the dynamic costs more in depth. Budget restrictions and maintenance strategies governed by contract design will affect the amount and type of maintenance activities that will be implemented one year, which will have an effect on the required maintenance in future years. Moreover, modelling the interdependence between maintenance and renewals is an important area of research, for example in order to perform a cost benefit comparison of the significance of these two activities. This includes a study of the consequences of using accumulated rather than annual tonnage in order to understand whether time and aggregate use offer complementary explanations of track decay.

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Appendix

Table 7 – Definitions of variables

Variable	*Definition*
Mixtend	Dummy for years when mix between tendered and not tendered in competition, which is the year when tendering starts
Ctend	Dummy when tendered in competition
Year00-Year14	Year dummy variables, 2000-2014
Tgtden	ln(total ton density)
Track_l	ln(track length)
Ratio_tlro	[ln(track length/route length)]
Rail_age	ln(average rail age)
Qual_ave	ln(average quality class)
Switch_l	ln(track length of switches)
Switch_age	ln(average age of switches)
Struct_l	ln(track length of structures (tunnels and bridges))
Max.axle_lo	ln(maximum axle load allowed)
Snow	ln(average mm of precipitation (liquid water) when temperature < 0˚Celcius)
MaintC t-1	ln(Maintenance $costs_{t-1}$)
Qual_ave t-1	ln($Qualave_{t-1}$)
D.eas	Dummy for region East
D.nth	Dummy for region North
D.ctr	Dummy for region Central
D.sth	Dummy for region South

Table 8 – Estimation results: Model 1, Static panel data model

	Coef.	Drisc/Kraay Std. Err.		Coef.	Drisc/Kraay Std. Err.
Cons.	15.5319***	0.1141	TgtdenSwitch_tl	0.0102	0.0217
Tgtden	0.1437***	0.0401	TgtdenSwitch_age	-0.0077	0.0319
Track_l	0.5550***	0.1545	TgtdenMax.axle_load	-0.2347	0.2158
Ratio_tlro	0.0410	0.1921	TgtdenSnowmm	-0.0077	0.0209
Rail_age	0.1023**	0.0475	Track_l^2	0.5707***	0.1062
Qual_ave	0.0285	0.1908	Track_lRatio_tlro	-0.2130	0.1820
Switch_tl	0.1123	0.0740	Track_lRail_age	0.1473**	0.0590
Switch_age	0.0245	0.0426	Track_lQual_ave	-0.1962	0.2370
Max.axle_load	0.3244	0.3742	Track_lSwitch_tl	-0.0292	0.0619
Snowmm	0.0492	0.0329	Track_lSwitch_age	-0.0826**	0.0389
Mixtend	-0.0272	0.0398	Track_lMax.axle_load	-0.4127*	0.2451
Ctend	-0.1060**	0.0372	Track_lSnowmm	-0.0524	0.0402
Year00	0.0400	0.0426	Ratio_tlro^2	-0.3325	0.2845
Year01	0.0018	0.0263	Ratio_tlroRail_age	0.2501***	0.0458
Year02	0.2231***	0.0330	Ratio_tlroQual_ave	-0.4226	0.3362
Year03	0.2166***	0.0420	Ratio_tlroSwitch_tl	0.0113	0.1294
Year04	0.2580***	0.0362	Ratio_tlroSwitch_age	0.0677	0.0836
Year05	0.2803***	0.0463	Ratio_tlroMax.axle_load	-0.2685	0.7719
Year06	0.2081***	0.0548	Ratio_tlroSnowmm	-0.0185	0.0468
Year07	0.2857***	0.0637	Rail_age^2	0.0632	0.0660
Year08	0.2778***	0.0710	Rail_ageQual_ave	-0.0660	0.1698
Year09	0.3146***	0.0607	Rail_ageSwitch_tl	-0.0978***	0.0237
Year10	0.3273***	0.0609	Rail_ageSwitch_age	0.0154	0.0616
Year11	0.4227***	0.0702	Rail_ageMax.axle_load	0.9280	0.6136
Year12	0.4881***	0.0660	Rail_ageSnowmm	-0.0342	0.0247
Year13	0.6111***	0.0667	Qual_ave^2	0.3241	0.5042
Year14	0.7676***	0.0707	Qual_aveSwitch_tl	0.0155	0.1439
IronTgtden	0.0710**	0.0317	Qual_aveSwitch_age	-0.0119	0.0483
IronTrack_l	0.0184	0.0382	Qual_aveMax.axle_load	0.1831	0.8838
IronRatio_tlro	0.0771	0.0701	Qual_aveSnowmm	-0.0690	0.0810
IronRail_age	0.0959	0.0650	Switch_tl^2	0.0360	0.0591
IronQual_ave	0.2190	0.1697	Switch_tlSwitch_age	-0.0412	0.0351
IronSwitch_tl	-0.0277	0.0310	Switch_tlMax.axle_load	-0.1404	0.3532
IronSwitch_age	-0.0120	0.0539	Switch_tlSnowmm	0.0445**	0.0201
IronMax.axle_load	-1.0525***	0.2491	Switch_age^2	-0.0283	0.0884
Tgtden^2	0.0425	0.0390	Switch_ageMax.axle_load	-0.8663	0.7138
Tgtden^3	0.0271**	0.0131	Switch_ageSnowmm	0.0017	0.0353

TgtdenTrack_l	0.0428	0.0267	Max.axle_load^2	1.1700	1.4623
TgtdenRatio_tlro	-0.0116	0.0544	Max.axle_loadSnowmm	0.2600	0.3151
TgtdenRail_age	0.0066	0.0373	Snowmm^2	-0.0005	0.0387
TgtdenQual_ave	0.1605***	0.0548			

No. Obs.	2802		
Mean VIF	6.02		
Pesaran's test[a]	-1.983	p-value=	0.048
Breusch-Pagan (1980) LM-test	Chi2bar2(1)=985.1	p-value=	0.000
Hausman's test statistic[b]	Chi2(65)=187.6	p-value=	0.000
Cobb-Douglas restriction test	F(15, 202)=190.64	p-value=	0.000

[a] Test is made on a balanced panel of 2176 obs. The null hypothesis is cross sectional independence.

[b] Year dummies are excluded in the test (see Imbens and Wooldridge 2007).

We have transformed all data by dividing by the sample median prior to taking logs.

See Table 7 for definition of variables.

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

Table 9 – Estimation results: Model 2a (years 1999-2014) and Model 2b (years 1999-2002)

	Model 2a		*Model 2b*	
	Coef.	Corr. Std. Err.	Coef.	Corr. Std. Err.
Cons.	4.1174**	2.0144	38.4547	63.7508
MaintCt-1	0.2140***	0.0548	-0.3388	0.9666
Tgtden	0.3058**	0.1415	0.4890	0.3201
Track_l	0.3842***	0.0749	-0.5364	1.7634
Ratio_tlro	-0.1531	0.1480	-1.8262	2.7499
Rail_age	0.0606	0.0418	0.2180	0.4997
Qual_avet-1	0.1204	0.2708	-6.5761	12.8970
Switch_tl	0.1546***	0.0563	0.6725	0.7738
Switch_age	0.0680	0.0945	2.0418	3.4254
Struct_tl	0.0422	0.0342	-0.3132	0.5862
Max.axle_lo	-0.8031	0.9147	-7.2321	10.7404
Snowmm	0.0439*	0.0249	0.1103	0.1776
Mixtend	-0.0012	0.0379	-	-
Ctend	-0.1286***	0.0444	-	-
Year01	0.0099	0.0425	0.0000	0.1069
Year02	0.2163***	0.0407	0.1239	0.2346
Year03	0.1537***	0.0434	-	-
Year04	0.1967***	0.0469	-	-
Year05	0.2231***	0.0472	-	-
Year06	0.1983***	0.0570	-	-
Year07	0.2370***	0.0505	-	-
Year08	0.2221***	0.0578	-	-
Year09	0.2860***	0.0602	-	-
Year10	0.3071***	0.0705	-	-
Year11	0.3984***	0.0665	-	-
Year12	0.4806***	0.0695	-	-
Year13	0.5696***	0.0667	-	-
Year14	0.6768***	0.0757	-	-
D.eas	-0.1500	0.1562	1.4950	2.6475
D.nth	0.0458	0.1319	4.2988	7.7234
D.ctr	-0.1367	0.1205	2.0658	3.9842
D.sth	-0.0975	0.0840	1.4463	2.6754
No. obs.	2578		508	
No. instruments	68		20	
See Table 7 for definition of variables.				

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

Table 10 – Diagnosis tests: Models 2a and 2b

Model 2a		*Model 2b*	
A-B test AR(2) in first diff.			
z=1.28	Pr>z=0.202	-	-
Sargan test of overidentifying restrictions:			
Chi2(36)=81.06	Pr>Chi2=0.000	Chi2(2)=16.62	Pr>Chi2=0.000
Hansen test of overid. restrictions:			
Chi2(36)=44.40	Pr>Chi2=0.159	Chi2(2)=7.71	Pr>Chi2=0.021
GMM instruments for levels			
Hansen test excl. group			
Chi2(33)=40.96	Pr>Chi2=0.161	-	-
Diff.-in-Hansen test (null H = exogenous):			
Chi2(3)=3.43	Pr>Chi2=0.330	Chi2(2)=2.44	Pr>Chi2=0.295
gmm($MaintC_{t-1}$ lag(1 14))		*gmm($MaintC_{t-1}$ lag(1 14))*	
Hansen test excl. group:			
Chi2(21)=25.50	Pr>Chi2=0.226	-	-
Diff.-in-Hansen test (null H = exogenous)			
Chi2(15)=18.90	Pr>Chi2=0.218	-	-
gmm(tgtden. lag(4 14))		*gmm(tgtden. lag(3 4))*	
Hansen test excl. group			
Chi2(24)=25.12	Pr>Chi2=0.399	-	-
Diff.-in-Hansen test (null H = exogenous)			
Chi2(12)=19.28	Pr>Chi2=0.082	Chi2(2)=7.71	Pr>Chi2=0.021
gmm($Qualave_{t-1}$ lag(3 13))		*gmm($Qualave_{t-1}$ lag(3 13))*	
Hansen test excl. group			
Chi2(24)=27.28	Pr>Chi2=0.292	-	-
Diff.-in-Hansen test (null H = exogenous)			
Chi2(12)=17.12	Pr>Chi2=0.145	-	-