Productivity Growth in European Railways: Technological Progress, Efficiency Change and Scale Effects

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February 27, 2009

This paper analyzes the performance of the European railway sector in the period of deregulation (1990-2005). Using a stochastic frontier panel data model that controls for unobserved heterogeneity a multiple-output multiple-input distance function model is estimated in order to evaluate the sources of productivity growth: technological progress, technical efficiency change and scale effects. The results indicate that technology improvements were by far the most important driver of productivity growth, followed by gains in technical efficiency, and to a lesser extent by exploitation of scale economies. Overall, we find an average productivity growth of 39 per cent within the sample period.

Keywords: European railways, Deregulation, Stochastic frontier analysis, Total factor productivity

JEL-Classification: D24, L51, L92

1 Introduction

In the last three decades of the 20th century the European railway sector faced severe losses of transportation market share. From 1970 to 1995 the modal split for rail passenger services and rail freight services within the EU-15 declined by more than 40 percent and almost 58 percent, respectively, compared to other transportation modes, like road, air or sea transport (European Commission, Directorate-General for Energy and Transport, 2003, 2007). This decline can be attributed to the poor performance of the national

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monopoly railway companies in terms of transportation times, service quality, and the lack of interoperability among the national railway systems. For these reasons and because of the high level of railway subsidies, the European national governments and the European Commission decided to introduce competitive elements into the European railway sector. Starting with Directive 91/440/ECC in 1991, several reforms have been introduced by the European Commission, with the last one, the so-called third railway package, implemented in 2007. The intention of the reforms has been to enhance competition by opening the market and to improve the efficiency and productivity of the European railway sector.

Several studies evaluating the efficiency and productivity of European railway companies can be found in the literature (for example, Oum and Yu, 1994; Gathon and Pestieau, 1995; Preston, 1996; Andrikopoulos and Loizides, 1998; Cantos et al., 1999; Cantos and Maudos, 2000; Coelli and Perelman, 2000; Loizides and Tsionas, 2002, 2004); however none of these studies evaluated productivity growth for the years 1990-2005, when the bulk of the deregulation of the European railway sector took place. In addition, none of the studies included railway companies from Eastern European countries, many of which started to reform their railway sector according to the EU deregulation policy well ahead of their EU accession.

The study which extends furthest into the main deregulation period is that of Cantos et al. (1999). Using a panel of 17 Western European state-owned railways covering the years 1970-1995 and applying a non-parametric estimation approach (data envelopment analysis), the authors evaluated technical change, efficiency change and productivity change in the European railway industry. The results indicated significant productivity gains, mainly based on technological progress between 1985 and 1995.

In order to fill the void in previous research and to determine the influence of regulatory changes upon the efficiency and productivity of Eastern and Western European railway industries, we apply a stochastic distance frontier approach for panel data, the so-called 'true' fixed effects model, developed by Greene (2004a,b, 2005). Compared to basic stochastic frontier fixed effects panel models this approach has the advantage of controlling for firm- and country-specific unobserved heterogeneity and to allow the inefficiency to vary over time. In addition, we use the generalized Malmquist productivity index approach proposed by Orea (2002) to decompose total factor productivity change into technological progress, efficiency change, and scale effects. The panel data set employed covers the years 1990-2005 and includes 31 railway companies from 22 Western and Eastern European countries. To our knowledge, this is the first productivity analysis of Eastern and Western European railway companies to include 16 of the last 18 years of deregulation and liberalization in the European railway sector and, more significantly, that accounts for unobserved heterogeneity.

The paper is organized as follows. Section 2 provides an overview on the European railway deregulation and presents the theoretical foundations of the decomposition of total factor productivity change. The methodology is discussed in Section 3. Section 4 introduces the modeling approach and describes the data. Estimation results are presented in Section 5. Section 6 summarizes and presents the main conclusions.

2 European Railway Deregulation and Productivity

Since the early 1990s the European railway sector has been subject to an incremental process of deregulation and liberalization. Starting with Directive 91/440/EEC in 1991, the deregulation policy of the European Commission has focused on:

- separation of infrastructure management from transport operations,
- implementation of interoperability among the national railway systems,
- assurance of third-party access to the infrastructure, and
- introduction of independent railway regulatory systems.

Overall, the deregulation policy consists of four major steps. The first step includes Directive 91/440/ECC, Directive 95/18/EC, and Directive 95/19/ EC, which were adopted by the European Commission in 1991 and 1995, respectively. Together these three directives implemented the first elements of separation and third-party access to the infrastructure. This entails accounting separation of infrastructure management and transport operations, access rights for third parties that provide international combined goods transport or international services between the states in which they are established, as well as common rules on the licensing of railway undertakings and allocation and charging of infrastructure capacity. Transposition of these directives into national law was compulsory for all member states not later than January 1993 and June 1997, respectively. The second step, the so-called first railway package, was implemented in 2001 and includes Directive 2001/12/EC, Directive 2001/13/EC, Directive 2001/14/EC, and Directive 2001/ 16/EC. The package amended the first directives and implemented the requirement for independent organizational entities for infrastructure and transport operations. The member states were free to decide between separate divisions within one company, that is, a holding structure, or complete institutional separation, with the infrastructure section managed by a separate entity from operations. Furthermore, it implemented accounting separation between passenger and freight transport services, extended the third-party access rights for international rail freights services operating on the Trans European Rail Freight Network (TERFN), required the establishment of independent regulatory bodies within the member states, and defined measures to enhance the interoperability between the national railway systems. The whole package had to be enacted into national law not later than March 2003. The third step, the so-called second railway package, was implemented in 2004 and includes Regulation (EC) No 881/2004, Directive 2004/49/EC, Directive 2004/50/EC, and Directive 2004/51/EC. The package amended several of the previous directives and extended the third-party access rights for international rail freights services to the whole European network beginning in January 2006, and for all kinds of rail freight services beginning in January 2007. Furthermore, it defined common safety standards, established a European Railway Agency responsible for safety and interoperability, and extended measures to enhance interoperability between the national railway systems to the trans-European high-speed rail system. The transposition deadlines for the directives were April and December 2005, respectively. The fourth step, the so-called third railway package, was implemented in 2007 and includes Regulation (EC) No 1371/2007, Directive 2007/58/EC, and Directive 2007/59/ EC. It is the first package which deals with rail passenger transport and defines the minimum quality standards for rail passenger services and introduces third-party access rights for international rail passenger services beginning in January 2010. The directives have to be enacted not later than June and December 2009.[1] In general, the intention of the reforms has been to enhance competition by opening the market and to improve the economic performance of the European railway sector. In addition, promoting a competitive rail transport market, which can be less polluting than other transport modes, is expected to reduce both congestion and pollution within the next decades.

Given this concise review of the elements and aims of the deregulation policy, an analysis of the efficiency and productivity development of the companies in this sector is of great interest. Evaluating the development can provide valuable results on how the companies reacted to the several reforms and how effective the first deregulation measures have been in the sense of enhancing efficiency and productivity in the sector.

Taking a closer look on technical efficiency and productivity change in a multiple-output multiple-input industry allows the decomposition of total factor productivity (TFP) change into three factors: technical change (a production frontier shift), technical efficiency change (a catch-up to the industry's production frontier), and scale effects (an alteration of the scale of operations). Figure 1 displays a graphical illustration of these three factors for a production technology that uses a single input to produce a single output.

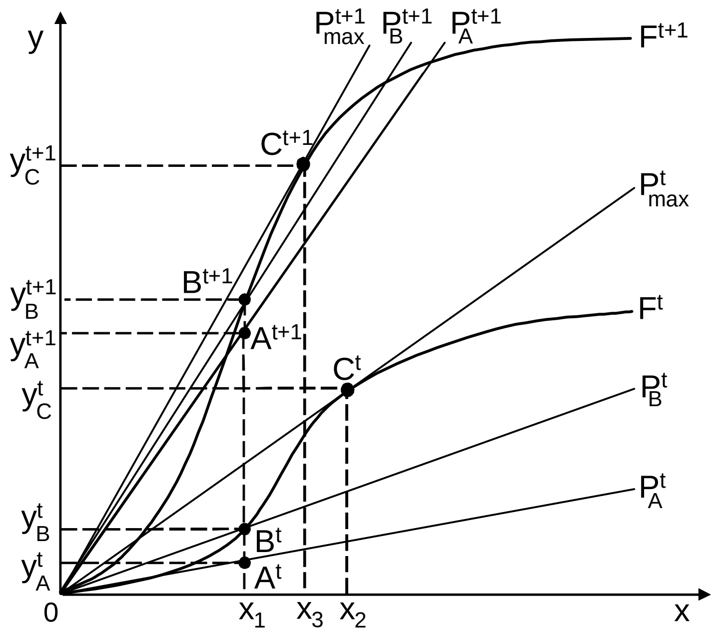

Figure 1: Technical Efficiency and the Decomposition of Productivity Change

[1] For a detailed overview on the European railway deregulation see, for example, Holvard (2006) or visit the website of the European Commission, Directorate-General for Energy and Transport (http://ec.europa.eu/transport/rail/countries/es/admin_en.htm).

First, focussing on period t the curve labeled F^t represents a variable returns to scale production frontier, that is, the maximum achievable output at each input, given a specific technology; and A^t, B^t, and C^t represent different production points. Since productivity is defined as the ratio of the outputs to the inputs, productivity at each production point can be measured by the slope of a ray through the origin and the relevant production point. For example, if a firm is operating at point B^t on the frontier it is technically efficient, whereas a firm operating at point A^t under the frontier is technically inefficient. Hence, the level of technical inefficiency can be measured by comparison of point A^t with point B^t. Furthermore, the slope of the ray at point B^t is greater than at point A^t, indicating a higher productivity at point B^t. However, the maximum possible productivity in period t is marked by point C^t, where the ray from the origin is a tangent to the production frontier F^t. Since the production frontier exhibits increasing returns to scale at any production point left of C^t and decreasing returns to scale at any production point right of C^t, a firm operating at point C^t is both technically and scale efficient. Hence, the level of scale inefficiency of a firm operating at point B^t can be measured by comparison of point C^t with point B^t. The closer a production point on the frontier is to point C^t the lower is the scale inefficiency and the higher is the productivity.

Considering the second period $t+1$, the upward shift of the production frontier F^t to the new production frontier F^{t+1} represents technical change or, in other words, technological progress. As before, A^{t+1}, B^{t+1}, and C^{t+1} mark technically inefficient, technically efficient, and both technically and scale efficient production points, respectively, with increasing productivity from the first to the last.

In terms of productivity change from one year to the next, an improvement of productivity can be the result of a single factor or a combination of three factors. For example, a firm operating in point A^t in period t moving to point A^{t+1} in period $t+1$ increased its productivity solely by technical change. Neither the scale of operations nor the distance to the respective frontier changed. If the production point of that firm moves to point B^{t+1} in period $t+1$ the productivity change is a combination of technical change and technical efficiency change. Finally, if the production point of that firm is C^{t+1} in period $t+1$ the productivity change is due to a combination of technical change, technical efficiency change, and scale effects. To summarize, firm-specific productivity change can be a result of technical change, technical efficiency change, scale effects, or a combination of all three.

Combining these theoretical aspects of decomposing TFP change with the aims of the deregulation and liberalization of the European railway sector, several hypotheses on the development and sources of productivity growth can be derived:

Hypothesis 1 Technical efficiency significantly increased in the European railway sector.

This hypothesis is supported by the fact that during the first years of deregulation most of the former state-controlled national railways gained more management independence from the state and started to developed more competitive and, hence, more efficient management structures. Furthermore, the development of employment and transportation services during the observed period shows that most railway firms significantly reduced their labor force while increasing their output level or at least keeping it constant.

Hypothesis 2 Technological progress was the main driver of productivity growth in the European railway sector.

On the one hand, this hypothesis is based on the assumption that more competition and managerial independence created incentives to develop advanced, more competitive technologies, such as high-speed railway systems, and on the other hand by developments in information technology. In particular, in infrastructure management and traffic coordination the introduction of modern computer systems should have created significant time- and labor-savings potentials.

Hypothesis 3 Scale effects only had a slight influence on productivity growth in the European railway sector.

This hypothesis is driven by the finding of most European railway studies (see, for example, Kumbhakar et al., 2007; Loizides and Tsionas, 2004) that European railways show only slight increasing or constant returns to scale. Hence, the potential for the exploitation of scale economies should have been relatively limited.

Hypothesis 4 Productivity significantly increased in the European railway sector.

The assumed positive development of technical efficiency change and technological progress should have had a positive influence on productivity growth.

3 Methodology

To model the multiple-output multiple-input production technology and to measure the technical efficiency of European railway firms, we apply an input distance function approach introduced by Shephard (1953, 1970). Compared to other representations of technologies, such as cost or revenue functions, this approach requires no specific behavioral objectives, such as cost minimization or profit maximization, which are likely to be violated in the case of partly state-owned and highly regulated industries like European railways (Coelli and Perelman, 2000).

Distance functions can be input- or output-oriented. Depending on whether the input set or the output set is assumed to be determined by exogenous factors, the output or the input orientation is appropriate. In this study, the input orientation is favored over an output orientation because we assume that railway firms have a higher influence on the usage of inputs than on outputs. This assumption is supported by the substantial proportion of state-controlled public transport requirements within rail passenger transportation and by the decreasing market share of rail transportation within both the passenger and freight transport sector over the last decades (Coelli and Perelman, 2000).[2]

An input distance function measures how much the input usage can be proportionally reduced given a fixed output vector. Assuming that the technology satisfies the standard properties of economic theory (see, for example, Färe and Primont, 1995) the distance function can be defined as:

$$D_I\left(x, y, t\right) = \max\{\theta : (x/\theta) \in L\left(y\right)\}, \tag{1}$$

where the input set $L(y)$ represents the set of all input vectors x that can produce the output vector y; t is a time trend introduced to account for technical change; and θ measures the proportional reduction of the input vector x. The function is non-decreasing, linearly homogeneous and concave in x, and non-increasing and quasi-concave in y (Coelli et al., 2005). From $x \in L(y)$ follows $D_I(x, y, t) \geq 1$.

Figure 2 illustrates an input distance function for the case of two inputs x_1 and x_2.[3] $L(y)$ represents the area of all feasible input vectors x that can produce the output vector y. The area is bounded below by the isoquant Isoq-$L(y)$, which reflects all minimum inputs combinations that can produce the output vector y. That means, the isoquant is the best-practice production frontier. Input vectors that belong to the frontier have an input distance function value equal to unity while all other feasible input vectors located above the frontier have an input distance function value greater than unity. For example, the input vector x (marked as B in Figure 2) can produce the output vector y, but y can also be produced with the smaller input vector x/θ (marked as A). Thus, the value of the input distance function at point B is $D_I(x, y, t) = 0B/0A = \theta > 1$. In other words, the input distance function measures how efficient a firm uses a vector of inputs to produce a fixed vector of outputs.

This concept is closely related to Farell's (1957) measure of input technical efficiency, which defines technical efficiency at point B as:

$$TE(x, y, t) = 0A/0B = 1/\theta = \left[D_I\left(x, y, t\right)\right]^{-1} < 1. \tag{2}$$

The input-oriented technical efficiency measure is the reciprocal of the input distance function. Technical efficiency values equal to unity identify efficient firms using an input vector located on the production frontier. Technical efficiency values between zero and unity belong to inefficient firms using an input vector above the frontier.

To estimate the input distance function we adopt a translog (transcendental-logarithmic) function form. Unlike a Cobb-Douglas form, which assumes the same production elasticities, the same scale elasticities, and a substitution elasticity equal to unity for all firms, the translog does not impose such restrictions and, hence, is more flexible (Coelli et al., 2005).

[2] Estimating both an input- and an output-oriented distance function for European railways, Coelli and Perelman (2000) found similar results for both orientations and concluded that the choice of orientation in this industry is not as important for efficiency measurement as it is in other industries.

[3] Figure 2 and its description follow Coelli et al. (2005) and Kumbhakar and Lovell (2000).

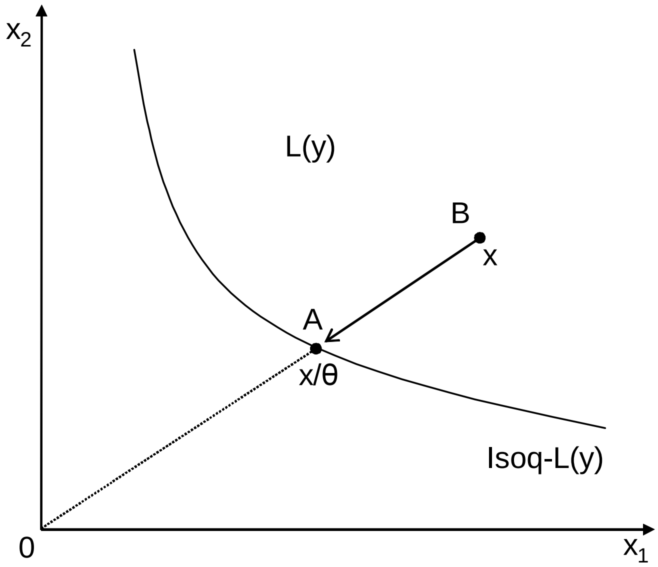

Figure 2: Technical Efficiency and the Input Distance Function

The translog input distance function for K (k=1,...,K) inputs and M (m=1,...,M) outputs can be written as:

$$\begin{aligned} ln\, D^I_{it} \;=\; & \alpha_0 + \sum_{m=1}^{M} \alpha_m \, ln\, y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn}\, ln\, y_{mit}\, ln\, y_{nit} + \sum_{k=1}^{K} \beta_k \, ln\, x_{kit} \\ & + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl}\, ln\, x_{kit}\, ln\, x_{lit} + \sum_{k=1}^{K}\sum_{m=1}^{M} \theta_{km}\, ln\, x_{kit}\, ln\, y_{mit} \\ & + \phi_t\, t + \frac{1}{2}\phi_{tt}\, t^2 + \sum_{m=1}^{M} \psi_{mt}\, ln\, y_{mit}\, t + \sum_{k=1}^{K} \lambda_{kt}\, ln\, x_{kit}\, t + \delta_z\, z_{it}, \end{aligned} \tag{3}$$

where D^I_{it} is the input distance term; $i = 1, 2, ..., I$ denotes firms; $t = 1, 2, ..., T$ is a time trend; x_{kit} and y_{mit} denote the input and output quantity, respectively; z_{it} is a network characteristic; and $\alpha, \beta, \theta, \phi, \psi, \lambda$, and δ are unknown parameters to be estimated.

In accordance with economic theory the input distance function must be symmetric and homogenous of degree +1 in inputs. Symmetry requires the restrictions

$$\alpha_{mn} = \alpha_{nm}, \quad (m, n = 1, 2, ..., M) \quad \text{and} \quad \beta_{kl} = \beta_{lk}, \quad (k, l = 1, 2, ..., K), \tag{4}$$

and homogeneity of degree +1 in inputs is given if

$$\sum_{k=1}^{K} \beta_k = 1, \quad \sum_{l=1}^{K} \beta_{kl} = 0, \quad \sum_{k=1}^{K} \theta_{km} = 0, \quad \text{and} \quad \sum_{k=1}^{K} \lambda_{kt} = 0. \tag{5}$$

The estimation method used in this paper is stochastic frontier analysis (SFA), simultaneously introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977).

SFA is a parametric method which estimates a production or distance function with a 'composed error term' that includes a standard error term v_{it}, accounting for measurement errors and other random factors, as well as a non-negative random error term u_{it}, representing technical inefficiency. In contrast to models, which incorporate only one error term and, hence, account firm-specific deviations from the best-practice frontier to technical inefficiency only, SFA decomposes the deviations into two parts: firm-specific technical inefficiency and random noise.

In order to account for the panel structure of our data and unobserved firm-specific heterogeneity we apply the 'true' fixed effects (TFE) model recently proposed by Greene (2004a,b, 2005). In contrast to the basic fixed effect SFA model (Schmidt and Sickles, 1984) the TFE model allows the inefficiency to vary over time and controls for firm-specific unobserved heterogeneity that is unrelated to inefficiency. Basically, the model adds a full set of firm dummy variables to the SFA model that, if included in a loglinear production function, cause a firm-specific neutral shift of the function (Greene, 2004b).

One limitation of this model is that any time-invariant inefficiency is absorbed by the firm-specific fixed effects. Hence, for short panels with presumably constant efficiency over time, the model estimates unreliable inefficiency terms and, thus, its application would be inappropriate (Saal et al., 2007). Furthermore, as the number of estimated parameters increases with the sample size the 'incidental parameter' problem arises in short panels, yielding inconsistent estimates of the firm-specific fixed effects and therefore of the inefficiency component (Greene, 2004a, 2005).[4]

However, since our panel set covers a relatively long time period of 16 years in which the European railway sector was subject to a substantial restructuring process and a variety of regulatory reforms, we follow Saal et al. (2007) and assume time-variant inefficiency. In this case the firm-specific fixed effects capture time-invariant firm-specific characteristics not specifically controlled for in the model rather than time-invariant inefficiency. Furthermore, the sample size of 31 railways companies form 22 countries, observed over 16 years should overcome the 'incidental parameter' problem, and therefore provide consistent estimators.[5]

[4] In his 2005 paper Greene considers a panel set of five years as small.

[5] An alternative estimation approach could have been the 'true' random effects model, also proposed by Greene (2004a,b, 2005). However, a conducted hausman test strongly rejects the hypothesis that the firm-specific effects are uncorrelated with the regressors. In this case random effects models produce biased estimators and the use of a fixed effects model is more appropriate.

Altogether, imposing the homogeneity restrictions in Equation 5 by normalizing the translog input distance function in Equation 3 by one of the inputs (Lovell et al., 1994), the TFE model is defined as:[6]

$$
\begin{aligned}
-\ln x_{Kit} \quad = \quad & \alpha_i + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K-1} \beta_k \ln x^*_{kit} \\
& + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1} \beta_{kl} \ln x^*_{kit} \ln x^*_{lit} + \sum_{k=1}^{K-1}\sum_{m=1}^{M} \theta_{km} \ln x^*_{kit} \ln y_{mit} \\
& + \phi_t \, t + \frac{1}{2}\phi_{tt}\, t^2 + \sum_{n=1}^{M} \psi_{mt} \ln y_{mit}\, t + \sum_{k=1}^{K-1} \lambda_{kt} \ln x^*_{kit}\, t + \delta_z \, z_{it} - \ln D^I_{it},
\end{aligned}
\tag{6}
$$

where $x^*_{kit} = (x_{kit}/x_{Kit})$. Replacing the negative log of the distance term $-\ln D^I_{it}$ with a composed error term $\varepsilon_{it} = v_{it} - u_{it}$ yields a standard normal-half normal SFA model. That is, v_{it} is the i.i.d. normally distributed random error term that captures measurement error ($v_{it} \sim iidN(0, \sigma_v^2)$), and u_{it} is the i.i.d. half-normally distributed non-negative time-varying inefficiency term ($u_{it} \sim iidN^+(0, \sigma_u^2)$). Furthermore, the error terms are assumed to be independently distributed from each other. Finally, replacing the single intercept parameter α_0 in Equation 3 with the firm-specific parameters α_i extents the standard SFA model to the TFE model that accounts for unobserved firm-specific heterogeneity.

The model estimates are obtained by maximum likelihood estimation. Since only the composed error term $\epsilon_{it} = v_{it} - u_{it}$ is observed, the method of Jondrow et al. (1982) is used, to obtain point estimates of u_{it} (Greene, 2004b):

$$
E(u_{it}|\varepsilon_{it}) = \frac{\sigma\lambda}{1+\lambda^2}\left[a_{it} + \frac{\phi(a_{it})}{\Phi(a_{it})}\right], \tag{7}
$$

where $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$; $\lambda = \sigma_u/\sigma_v$; $a_{it} = -\lambda\varepsilon_{it}/\sigma$; and $\phi(a_{it})$ and $\Phi(a_{it})$ represent the standard normal density and cumulative distribution evaluated at a_{it}, respectively. Measures of technical efficiency (TE_{it}) for each firm in each time period can then be calculated as:

$$
TE_{it} = exp\{-E(u_{it}|\varepsilon_{it})\}. \tag{8}
$$

The calculated efficiency scores range between zero and one. A score of one defines an efficient firm operating on the best-practice frontier, while a score lower than one represents the degree of a firm's inefficiency. The λ-parameter represents the relative contribution of the inefficiency and noise component to the total error term. If $\lambda \to 0$ all deviations from the best-practice frontier are due to noise, and if $\lambda \to +\infty$ all deviations from the best-practice frontier are due to inefficiency. In the former case using a standard estimation model (for example, ordinary least squares) with no technical inefficiency

[6] The symmetry restrictions in Equation 4 are imposed in estimation.

would be appropriate, whereas in the latter case a deterministic frontier with no noise results (Kumbhakar and Lovell, 2000).

Once the input distance function has been estimated, the parameter estimates can be used to calculate the TFP change. Furthermore, following the generalized Malmquist productivity index approach proposed by Orea (2002), TFP change can be decomposed into a technical efficiency change component, a technical change component and a scale effect component.

According to Coelli et al. (2003), who illustrate this approach for an input distance function, TFP change for the i-th firm between the periods t and $t+1$ is calculated as:

$$\begin{aligned} ln\,(TFP_{it+1}/TFP_{it}) &= [ln\,(TE_{it+1}/TE_{it})] \\ &+\frac{1}{2}\left[(\delta\, lnD_{it+1}/\delta\, t) + (\delta\, lnD_{it}/\delta\, t)\right] \\ &+\frac{1}{2}\sum_{m=1}^{M}\left[(SF_{it+1}\,\varepsilon_{mit+1} + SF_{it}\,\varepsilon_{mit})\,(ln\,y_{mit+1} - ln\,y_{mit})\right], \end{aligned} \tag{9}$$

where the three terms on the right indicate the technical efficiency change, the technical change, and the scale effect, respectively. As shown, technical efficiency change is simply calculated by the log of the ratio of the technical efficiency scores for the i-th firm in the periods $t+1$ and t.

Technical change is measured by the mean of the partial derivatives of the input distance function with respect to time evaluated at the period $t+1$ and t data points. Given Equation 3 the partial derivative with respect to time for the i-th firm in the t-th period is:

$$\delta\, lnD_{it}/\delta\, t \;=\; \phi_t + \phi_{tt}\, t + \sum_{m=1}^{M}\psi_{mt}\, ln\, y_{mit} + \sum_{k=1}^{K}\lambda_{kt}\, ln\, x_{kit}. \tag{10}$$

The scale effect measure requires the calculation of output elasticities at the period $t+1$ and t data points. Given Equation 3 the output elasticity for each output for the i-th firm in the t-th period is:

$$\varepsilon_{mit} \;=\; \delta\, lnD_{it}/\delta\, ln\, y_{mit} = \alpha_m + \sum_{m=1}^{M}\alpha_{mn}\, ln\, y_{mit} + \sum_{k=1}^{K}\theta_{km}\, ln\, x_{kit} + \psi_{mt}\, t. \tag{11}$$

Furthermore, the input distance scale factor (SF_{it}) for the i-th firm in the t-th period is calculated as:

$$SF_{it} = \left(\sum_{m=1}^{M}\varepsilon_{mit} + 1\right)\Bigg/\sum_{m=1}^{M}\varepsilon_{mit} = 1 - RTS_{it}, \tag{12}$$

where RTS_{it} is the scale elasticity for the i-th firm in the t-th period. For an input distance function RTS_{it} is equal to the negative of the inverse of the sum of the output elasticities (Färe and Primont, 1995):

$$RTS_{it} = -\left(1\Bigg/\sum_{m=1}^{M}\varepsilon_{mit}\right). \tag{13}$$

Thus, if constant returns to scale are given, $RTS = 1$, the SF as well as the scale effect will equal 0. In this case the generalized Malmquist productivity index in Equation 9 is reduced to the standard Malmquist productivity index, decomposing TFP change into technical efficiency change and technical change only. In contrast, if increasing (decreasing) returns to scale, $RTS > 1$ ($RTS < 1$), are given, the SF is negative (positive), and the scale effect evaluates the contribution of scale changes on TFP change (Saal et al., 2007).

4 Modeling Approach and Data Description

The data set used in this paper consists of 31 railway firms from 22 European countries observed from 1990 to 2005 and was primarily taken from the railway statistics published by the Union Internationale des Chemins de Fer (UIC) (2004, 2005, 2006, 2007). In addition, since the UIC data reveal inconsistent and incomplete time-series for several countries, we also used other data sources, including companies' annual reports, and in particular a data collection provided by NERA Economic Consulting. Within this data collection, great effort was made to fill the gaps of the UIC data and secure consistent and comparable time-series over time (NERA Economic Consulting, 2004).

The sample is limited to the incumbent railway firms or their legal successors. Some countries separated the infrastructure from transport operations. For example, in the Netherlands, the infrastructure is managed by Prorail while freight and passenger transportation is provided by Nederlandse Spoorwegen (NS).[7] For the purpose of comparison, observations for these countries are generated by combining the data of the separated firms. Unfortunately, we had to exclude the United Kingdom and Estonia from our analysis due to poor data. Consequently, our sample altogether covers 21 of the EU-25 member states plus Switzerland. This creates an unbalanced panel, with the difference between 352 observations having full data coverage and the lower number of 318 de facto observations resulting from missing data.

To estimate the multiple-output multiple-input production technology, we use two input variables and two output variables. The *number of employees* (emp) (annual mean) and the *number of rolling stock* (roll) are used as physical measures for labor and capital input.[8] Since revenues for passenger transportation depend on the number of passengers and the distance traveled, we measure the passenger service output using the variable *passenger-km (pkm)*. Accordingly, freight transportation revenues depend on the amount and distance of tonnes transported. Hence, we measure the freight service output by the variable *freight tonne-km (tkm)*. As noted by Oum and Yu (1994)

[7] In 2000, NS passenger and freight service were split into two entities, with Railion NL (a subsidiary company of DB) taking over the freight service section. Due to missing data from Railion NL, our data set does not include observations for the Netherlands since 2000. The same applies for Denmark and Sweden since 2001, where the freight section was taken over by Railion DK (another subsidiary company of DB) and GreenCargo, respectively.

[8] Data on energy, another primary input of railway services, were not available. However, as stated by Coelli and Perelman (1999), this should not be a serious problem for our estimation results as it can be assumed that energy is closely related to rolling stock.

these output measures, compared to other measures like passenger train-km and freight train-km, also take the potential influence of government and regulatory restrictions on allocation into account.

In addition, we use *network density* (netden) (network length in km/area km^2) as a network characteristic. High density networks have a more complex shape than less dense networks and are usually located in areas with higher population density (Farsi et al., 2005). Therefore, this variable should reflect the impact of differences in network structure and density on the production process and, hence, on the input requirements.[9] Following Saal et al. (2007), the network density variable is introduced in a linear non-interactive way into the input distance function. By this specification it influences the input distance function estimates, but does not appear in the TFP calculation and the TFP decomposition.

As can be seen in Table 1, all variables show a significant amount of variation. This is because our sample covers a wide range of firm sizes and firms with different key activities. For example, the network length of the largest railway company in Europe, Germany's Deutsche Bahn (DB), is more than 130 times longer than that of the smallest railway company, Chemins de Fer Luxembourgeois (CFL) in Luxembourg. Furthermore, while some railway firms mainly provide freight services, others concentrate on passenger services, and still others have an equal relation between freight and passenger services. In addition, a significant part of the variation is a function of time. For example, from 1990 to 2005 the average number of employees decreased by almost 14 percent, while in the same time the average amount of passenger-km increased by more than 15 percent.

The last column in Table 1 presents the fraction of within variation of the overall variation for the main variables used in the estimations. The figures indicate that most variables show a significant fraction of within variation. Only for network density the fraction of within variation is relatively low. Altogether, the descriptive statistics indicate that the used variables show a reasonable between and within variation, supporting the use of panel data models and in particular the use of a TFE model.[10]

[9] We tried other model specifications, for example, including network length as a third input variable or using additional network characteristics, such as percentage of electrified lines of the total network length. However, the estimated coefficients of the input distance function revealed some unexpected signs and statistical significance as well as wrong curvature characteristics, probably caused by multicollinearity problems due to the strong correlation between some inputs and the included network characteristics.

[10] As stated by Kuenzle (2005), the TFE estimator is not a within estimator as in the basic FE model. Therefore, it does not solely rely on within variation. Nevertheless, Farsi and Filippini (2006) note that from their experience models that separate time-variant inefficiency from time-invariant heterogeneity, such as the TFE model, are numerically unstable or not feasible in cases with low within variation.

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Variable	Fraction of within variation[a]
Number of rolling stock (10^3)	45.92	60.47	1.69	306.29	$-\ln roll$	0.17
Number of employees (10^3)	60.31	72.78	3.03	355.69	$\ln(emp/roll)$	0.42
Passenger-km (10^9)	13.93	19.79	0.21	76.16	$\ln pkm$	0.16
Tonne-km (10^9)	15.67	19.33	0.29	83.98	$\ln pkm$	0.11
Network density (10^{-1})	0.59	0.31	0.17	1.21	$netden$	0.08

[a]Within variation represents the standard deviation of firm observations from the firm's average ($X_{it} - \bar{X}_i$). The fraction of within variation is defined as the ratio of within to overall standard deviation (Farsi et al., 2005). Source: Union Internationale des Chemins de Fer (UIC) (2004, 2005, 2006), annual reports, company statistics.

5 Results

The estimated parameters for the translog input distance function defined in Equation 6 are presented in Table 2. First, focussing on the functional form, the conducted likelihood-ratio tests reject the hypotheses – that the Cobb-Douglas functional form is a better representation of the data, that no technical change occurs, and that a Hicks neutral technical change occurs – at the 1 percent level of significance. Hence, the translog stochastic production frontier with non-neutral technical change defined in Equation 6 is an adequate representation of the data. Furthermore, the statistically significant coefficient of λ indicates that inefficiency effects are present in the model. This confirms the assumption that a standard estimation model with no technical inefficiency would not be appropriate.

As each variable is normalized by its sample mean, the first-order coefficients can be interpreted as distance elasticities at the sample mean. All first-order coefficients are statistically significant at the 1 percent level and have the expected signs. In other words, the estimated input distance function is decreasing in outputs and increasing in inputs. Furthermore, the negative of the inverse of the sum of the first-order output coefficients is 1.088, indicating slight increasing returns to scale at the sample average firm, as observed in the majority of railway studies. Evaluating the returns to scale on the firm-specific level provides similar results. The average and median value of returns to scale are 1.178 and 1.112, respectively, and 73 percent of all observations reveal increasing returns to scale.

The input elasticities reflect the relative importance of each input in the production process. The estimated coefficient of labor (employees) elasticity (β_1) is used to calculate the capital (rolling stock) elasticity via the homogeneity restriction presented in Equation 5. The coefficients of labor and capital elasticities are found to be equal to 0.199 and 0.801, respectively, implying a high capital intensity of the European railway sector. The first-order coefficient of time (t) is 0.025 and indicates a rate of technical change of

Table 2: Estimation Results of the Input Distance Function[a,b]

Variable	Parameter	Coef.	T-ratio	Variable Parameter	Coef.	T-ratio
$ln\,pkm$	α_1	-0.317	-20.48	*Sigma* σ	0.466	34.61
$ln\,tkm$	α_2	-0.602	-25.49	*Lambda* λ	2.681	11.53
$0.5 \cdot (ln\,pkm)^2$	α_{11}	0.004	0.25			
$0.5 \cdot (ln\,tkm)^2$	α_{22}	-0.290	-18.25	Log-likelihood function	90.65	
$ln\,pkm \cdot ln\,tkm$	α_{12}	0.101	7.67			
$ln(emp/roll)$	β_1	0.199	3.95	RTS (sample average firm)	1.088	
$0.5 \cdot (ln(emp/roll))^2$	β_{11}	2.277	8.72			
$ln(emp/roll) \cdot ln\,pkm$	θ_{11}	-0.252	-5.73			
$ln(emp/roll) \cdot ln\,tkm$	θ_{12}	0.021	0.51			
t	ϕ_t	0.025	10.51	Likelihood-ratio tests	Value	
$0.5 \cdot t^2$	ϕ_{tt}	-0.000	-0.47			
$ln\,pkm \cdot t$	ψ_{1t}	0.007	3.08	H_0: Cobb Douglas	49.29	Reject
$ln\,tkm \cdot t$	ψ_{2t}	-0.004	-1.60	H_0: No technical change	54.43	Reject
$ln(emp/roll) \cdot t$	λ_{1t}	-0.023	-2.91	H_0: Neutral technical change	168.56	Reject
$netden$	δ_1	-0.375	-32.17			

[a]The number of rolling stock has been used as the numeraire; therefore, the dependent variable is $-\,ln\,roll$. [b]All estimates are obtained by using 'Limdep 8.0'.

2.5 percent for the sample average firm in the mid year of the sample.[11] Referring to the cross term of employees and time, the statistically significant and negative coefficient of λ_{1t} suggests a decline in the labor elasticity over time and, hence, implies non-neutral labor-saving technical change. Finally, the statistically significant and negative coefficient of network density (δ_1) indicates that an increase in network density leads to an increase in input requirements.

The development of technical efficiency over time derived from the input distance function estimates is illustrated in Figure 3. Average and median technical efficiency scores show a relatively continuous increase, with average efficiency increasing by 10.8 percent from 0.74 in 1990 to 0.82 in 2005. Moreover, the development of minimum efficiency scores reveals significant catch-up effects, in particular within the early and mid-1990s. From 1990 to 2005 minimum efficiency increased by almost 70 percent form 0.39 to 0.66, while maximum efficiency decreased by around 4 percent from 0.93 to 0.89 in the same period. Overall, the difference between the minimum and maximum technical efficiency scores significantly decreased from 0.54 in 1990 to 0.23 in 2005, suggesting a convergence of technical efficiency levels within the European railways sector over time.

The results of the TFP change decomposition calculated from the estimates of the input distance function by employing the generalized Malmquist productivity index approach described in Equation 9 are reported in Table 3 and Figure 4. Table 3 displays the average growth rates of TFP and its components per year, whereas Figure 4 illus-

[11] As noted by Saal et al. (2007), these technical change estimates are for a nonexistent hypothetical sample average firm with unchanging characteristics. Hence, they do not account for changes in inputs and outputs and should be interpreted with caution.

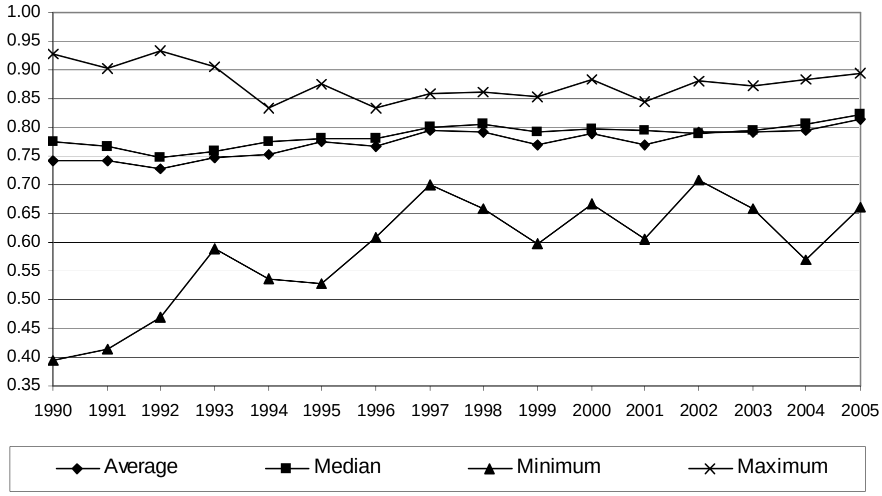

Figure 3: Development of Technical Efficiency Scores, 1990-2002

trates cumulative indices of average TFP growth, technical efficiency change, technical change, and scale effects, relative to the base year of 1990.

Table 3: Average Growth Rates of TFP and its Components (in %)

	Efficiency change	Technical change	Scale effect	TFP growth
1990-1991	0.58	2.16	0.71	3.44
1991-1992	-3.24	2.18	0.45	-0.60
1992-1993	1.94	2.17	-0.73	3.39
1993-1994	0.72	2.13	1.01	3.86
1994-1995	3.00	2.14	0.34	5.48
1995-1996	-0.79	2.09	-0.15	1.15
1996-1997	3.74	2.03	0.54	6.31
1997-1998	-0.42	1.98	0.42	1.98
1998-1999	-2.97	1.89	0.22	-0.87
1999-2000	1.36	1.78	0.38	3.53
2000-2001	-2.34	1.78	0.16	-0.40
2001-2002	3.10	1.74	0.05	4.89
2002-2003	-0.07	1.68	-1.33	0.28
2003-2004	-0.20	1.61	0.15	1.56
2004-2005	2.54	1.62	0.81	4.98

First, focussing on average technical efficiency change, it can be seen, that the development from one year to the next is quite volatile. Only between 1992 and 1995 is a persistent positive development shown. However, the cumulative average efficiency change index indicates an overall positive impact of technical efficiency change on average TFP growth. In the 1992-1997 period, right after the adoption of the first railway deregulation directive, the index shows an average TFP growth of 6 percent due to effi-

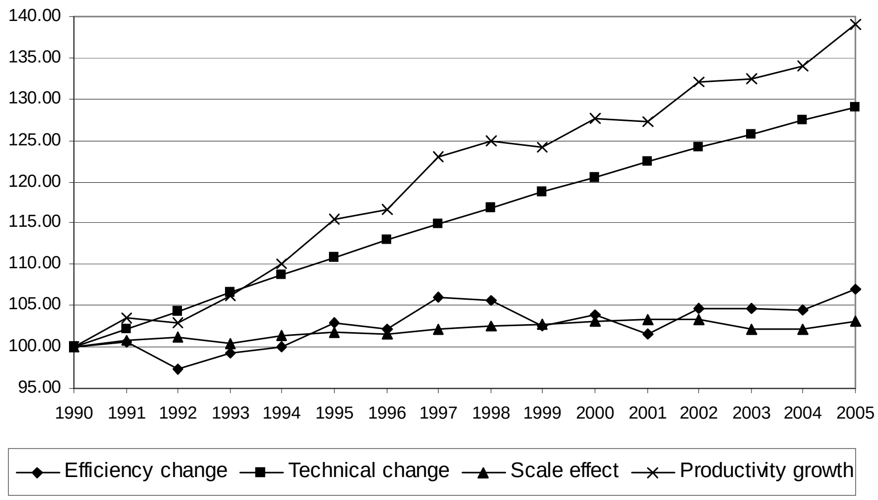

Figure 4: Cumulative Indices of Average TFP Growth and its Components

ciency gains, compared to the base year of 1990. After that, the index fell to 102 in 2001 and finally increased again to 107 in 2005. Thus, our first hypotheses that technical efficiency significantly increased within the European railway sector is confirmed.

In contrast to the uneven development of average technical efficiency change, average technical change was always positive, though with a declining growth rate. The cumulative average technical change index shows an average TFP growth of 29 percent due to technological progress over the whole observed period. This value is more than four times higher than the average TFP growth due to efficiency gains and confirms our second hypotheses, that technological progress was the main driver of productivity growth within the European railway sector in the observed period.

Our third hypothesis, that scale effects only had a slight influence on productivity growth, is likewise confirmed. The cumulative average scale effect index indicates a small positive influence of scale effects on average TFP growth of about 3 percent over the whole observed period. Given the estimated slight increasing returns to scale at the sample average firm, this result was to be expected.

Finally, due to the significant improvement of technological development and technical efficiency, average productivity significantly increased in the European railway sector. Considering the per year development, negative values of TFP growth are only shown for three periods, provoked by a negative development of average technical efficiency in the respective periods. The cumulative average TFP growth index indicates an average productivity growth of 39 percent over the whole observed period. Thus, our fourth and final hypothesis is confirmed.

6 Summary and Conclusions

In this study we analyzed the performance of the European railway sector for the years 1990-2005. In this period numerous deregulation and liberalization steps were introduced with the aim to enhance competition by opening the market and to improve the sector's efficiency and productivity. Based on a stochastic frontier model for panel data that accounts for firm-specific heterogeneity (TFE model) we estimated a translog input distance function to investigate technical efficiency and TFP change. Furthermore, we used a generalized Malmquist index approach to decompose TFP change into different components: technological progress, efficiency change, and scale effects.

In terms of efficiency comparison, our results indicate a convergence of the firm-specific technical efficiency levels over time. The difference between the minimum and maximum technical efficiency scores almost halved from 1990 to 2005. This effect primarily was a result of significant catch-up effects of the low performers in the early and mid-1990s. Our results for TFP change indicate that improvements in technology were by far the most important driver of productivity growth, though this declined over time. Over the observed period, average TFP grew by 29 percent due to technological progress. In comparison, technical efficiency change and scale effects, respectively, only contributed 7 percent and 3 percent to the evolution of average TFP. Taken as a whole, our results imply a 39 percent increase of average TFP for the European railway sector in the 1990-2005 period. Thus, the aim of the European railway deregulation and liberalization seems to have been met.

Due to different methodological approaches, sample periods, and variable definitions, the possibility of comparing our results with previous research is quite limited. Gathon and Pestieau (1995) analyzed efficiency and productivity of 19 European railways covering the years 1961-1988. By applying a stochastic production frontier model that includes cross-effects between time and inputs in a translog production function they decomposed productivity change into a technical efficiency change and a technical change component. Consistent with our results, their findings suggested that an increase of railway companies' productivity is mainly driven by technological progress and only to a lesser extent by technical efficiency change. However, one drawback of their study is that they used an aggregated output measure for freight and passenger transport services, neglecting the multiple-output production technology of railway services.

Similar results were obtained by Cantos and Maudos (2000), who estimated a stochastic cost frontier model for a sample of 15 European railways covering the years 1970-1990. Decomposing TFP change into a cost efficiency change, scale change, and technical change component, they found technical changes to be the main source of railway companies' productivity gains, followed by cost efficiency changes and, to a lesser extent, scale changes. However, as opposed to our output definition they used passenger train-km and freight train-km as output measures.

Probably, the most comparable study to our own in terms of methodology, sample period, and variable definition is that of Cantos et al. (1999). Using a sample of 17 European railways covering the years 1970-1995, the authors applied a non-parametric estimation approach (data envelopment analysis) to estimate and decompose TFP change into technical efficiency change and technical change by the means of the Malmquist productivity index. Consistent with our results, the authors found significant TFP gains, which are mainly based on technological progress and occur between 1985 and 1995.

The contribution of our study is twofold. First, the sample period covers 16 of the last 18 years of deregulation and liberalization in the European railway sector. Furthermore, for the first time, railways companies of Eastern European countries are included in a productivity growth analysis of European railways. To our knowledge this is the most up-to-date data base used in this kind of study.

Second, we account for presumably high unobserved firm- and country-specific heterogeneity within a cross-country sample by using an innovative TFE estimation approach recently proposed by Greene (2004a,b, 2005). In addition, the usage of a distance function approach in combination with the generalized Malmquist index approach proposed by Orea (2002) allows to account for the multiple-output multiple-input technology of railways services and to calculate productivity influencing scale effects.

Finally, some limitations of our study and aspects for further research should be noted. Due to data problems, we were not able to include the United Kingdom or the last years of Denmark, the Netherlands, and Sweden in our estimations. Since railway deregulation in these countries is far advanced in several areas, it would be of great interest to examine the development of these railway sectors compared to others. Similar problems apply to the incorporation of quality and safety aspects. At least on a cross-country basis there is as yet no consistent data available. Since both quality and safety are important issues for the development of railway services over time, they should be considered in future data collection and research.

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