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Upstream vs. downstream grants - The role of public contributions in improving railway efficiency in Europe

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Upstream vs. downstream grants - The role of public contributions in improving railway efficiency in Europe

Jan Thomas Schäfer*

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Abstract

The level of government support significantly influences the performance of European railways. However, prior analyses have largely focused on the sector as a whole, neglecting the distribution of public budget contributions between the upstream infrastructure manager and downstream service providers. This study employs a two-stage procedure involving Data Envelopment Analysis (DEA) in the first stage and a second-stage regression analysis to evaluate railway efficiency and analyze the relationship between funding structures and performance. Using a dataset covering eight European countries from 2001 to 2022, the results indicate that railways achieve higher efficiency when the upstream infrastructure manager receives a larger share of government funds, while downstream subsidies are relatively limited. Moreover, total operating contributions consistently enhance efficiency, whereas the impact of investment grants varies depending on the specification. These findings underscore the importance of balanced funding strategies that prioritize upstream contributions to foster competition and promote efficient use of public resources.

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1 Introduction

Research has shown that government support impacts the performance of European railways, explaining differences in productivity and efficiency between systems (e.g., Cantos et al., 1999; Friederiszick et al., 2003; Oum & Yu, 1994). However, existing studies primarily analyze the sector as a whole, neglecting the distribution of public budget contributions between upstream infrastructure managers and downstream transport operators.

European regulations permit different forms of government support, such as capital grants for infrastructure investment, revenue grants for infrastructure operation and maintenance, and public service compensation for transport operators. These funding schemes are interlinked through the vertical structure of the industry, in which track access charges connect the upstream infrastructure and downstream service levels. Adjustments in funding at one stage can influence the financial needs and incentives of the other, creating a trade-off in financing structures. For example, lower access charges resulting from upstream subsidies reduce public service compensation requirements and enhance competition. However, excessive reliance on tax-based financing can encourage inefficiencies, while user-based financing can undermine competitiveness. These considerations highlight the complexity of designing funding schemes that align with social, economic, and environmental goals.

This paper examines the impact of different funding structures on sector performance, with a focus on the trade-off between inefficiencies at the infrastructure level and those arising from public service subsidies. To explore this relationship, I use Data Envelopment Analysis (DEA) to measure efficiency and a second-stage truncated regression model (Simar & Wilson, 2007) to assess how funding structures influence performance. While DEA efficiency scores are calculated for a dataset covering nearly all European countries, the analysis of government grants' influence on performance is focused on eight countries: France, Germany, Italy, Norway, Spain, Sweden, Switzerland, and the United Kingdom. The study spans data from 2001 to 2022.

The results indicate that railway systems achieve higher efficiency when the upstream infrastructure manager receives a larger share of government funds, while downstream subsidies to service providers remain limited. These findings suggest that restructuring funding schemes could foster competition and more efficient use of public resources, provided that robust regulatory frameworks are in place.

This paper contributes to the extensive literature on the performance of European railways, which has been a focus of research for decades. Recent studies have examined the effects of competition and vertical separation on efficiency (e.g., Álvarez-SanJaime et al., 2024; Fitzová, 2022) and explored regional disparities (Fitzová & Nash, 2024). The role of direct government support in shaping sector performance has also been analyzed in several studies. However, only a few, such as Cantos et al. (1999), Friederiszick et al. (2003), and Oum and Yu (1994), have employed advanced performance measurement methods like Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). Other authors have relied on Partial Productivity Measures (PPM) to link performance indicators with sector financing.

Some recent analyses lack scientific rigor. For instance, the Boston Consulting

Group (2012) developed a weighted performance index (RPI) that combines indicators such as network utilization intensity, service quality, the share of high-speed rail, and safety aspects. Their findings indicate a positive correlation between public costs - defined as the sum of government contributions for operations, maintenance, and investments - and performance. By contrast, Friederiszick et al. (2003) used SFA to explore the impact of state aid on efficiency more comprehensively. They found that while state aid has a positive effect on efficiency, its intensity (state aid as a proportion of total operating costs) negatively influences efficiency scores. Similarly, Oum and Yu (1994) showed that higher levels of government support relative to operating costs adversely affect efficiency. Their DEA second-stage Tobit regression suggests that railways receiving significant subsidies tend to be less efficient than their counterparts. Likewise, Cantos et al. (1999) find that railways are more efficient when they are less dependent on public subsidies.

Panel data studies, such as Laabsch and Sanner (2012), have examined public contributions' effects on modal share in passenger rail transport. They concluded that higher public contributions do not significantly influence modal share but may correlate with higher sector costs, potentially negating the benefits of the subsidies. Other researchers, like Kyriacou et al. (2019), have incorporated investments (as a share of GDP) as input variables in DEA models to highlight the importance of government quality in ensuring efficient investments.

The trade-off between upstream and downstream subsidization has been addressed in a limited number of studies, most of which focus on climate or trade policy (Fischer et al., 2014; Hokari et al., 2003). While upstream subsidies are prevalent in network industries, downstream subsidies have been primarily examined in trade policy contexts (e.g., Bernhofen, 1997; Hamilton & Requate, 2004). Thus, this paper contributes to the literature on upstream and downstream subsidization by presenting evidence from the transport sector.

The remainder of the paper is organized as follows. Section 2 provides an overview of the organizational structure of railways in European countries and the principles of their financing. Section 3 details the methodology employed for the empirical analysis. Section 4 describes the data sources and presents descriptive statistics on government grants to European railways. The results of the first-stage DEA analysis are presented in Section 5.1, while Section 5.2 discusses the empirical assessment of the influence of government grants on performance. Finally, Section 6 concludes the paper.

2 Financing of Railways in Europe

Government support plays a major role in the financing of the European railway sector. Typically, infrastructure managers, regional transport operators, as well as some freight and long-distance passenger rail operators receive monetary contributions from public budgets to supply the market with services and to undertake investments in rolling stock and infrastructure. Figure 1 shows a simplified illustration of the organizational structure of railways in European countries, it also includes relevant directives and regulations that set out the framework for government support and track access charges.

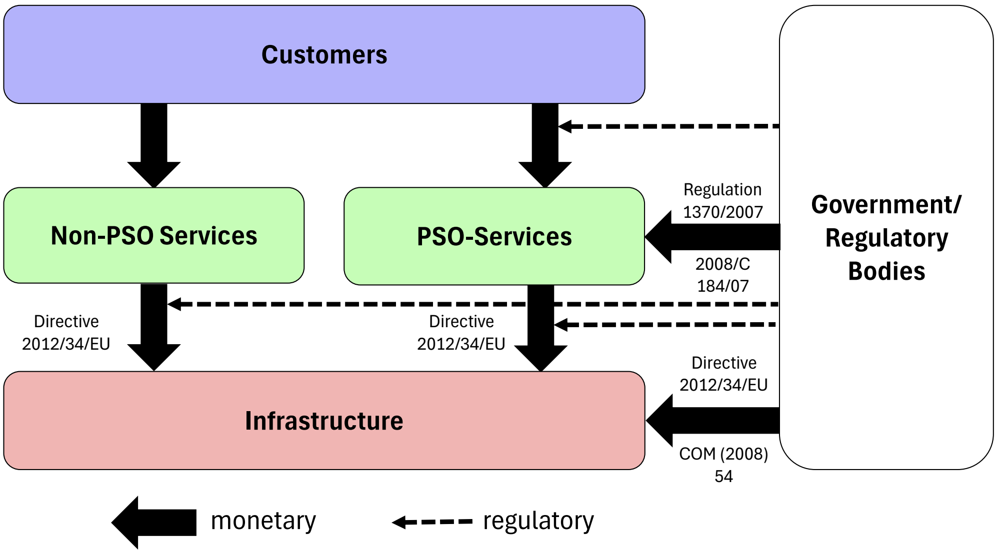

Figure 1: Overview of revenue sources and regulatory frameworks for European railway services, highlighting contributions from customers, non-PSO services, government PSO services, and infrastructure. Key regulations, including Directive 2012/34/EU and Regulation 1370/2007, are indicated as guiding frameworks.

Transport services are typically divided into two categories: services that are subject to a Public Service Obligation (PSO) and services that are operated on a commercial basis. The former usually refers to regional public passenger transport services. However, in some countries, long distance passenger transport services are subject to a Public Service Obligation. Non-PSO services include all other passenger transport services, i.e. services that are run on a commercial basis, as well as freight transport services. These services are run without government funding. However, as pointed out in the community guidelines on State aid for railway undertakings (2008/C 184/07), commercial operators might also receive funding, in particular for the purchase of rolling stock.

Public service operators, generally speaking, receive a compensation depending on the costs incurred, minus the receipts from tariff plus a reasonable profit (Regulation 1370/2007). I will refer to these payments using the term public service compensation (PSC). The level of necessary public service compensation is determined by the level of tariff receipts as well as the cost of services. In most cases, tariffs for PSO services are set by the competent authority. Costs of public services (and other operators) depend to a large extent on the level of payments for the use of the network, i.e. access charges. Access charges are regulated according to Directive 2012/34/EU and should be set on the level of direct costs plus a mark-up to obtain full cost recovery. The level of mark-ups crucially depends on the level of fixed costs as well as the amount of government financing that the infrastructure manager receives for the operation of the network. According to Communication COM (2008) 54 of the European Commission, payments for operating the network are likely to supplement user charges. Therefore, I will refer to them using the term revenue grants.

While public service compensation and revenue grants mainly substitute user-based financing, public funding of investments mainly impacts the necessary amount of loans to be raised by the infrastructure manager. While in some countries infrastructure investments are mainly financed from public funds, other countries let the infrastructure manager get into debt. This usually means that financing costs, i.e. interest expenses, are higher. Some governments compensate for the additional burden, while in other countries the market needs to bear the additional financing costs.

If revenue grants cover a large share of operating expenses of the infrastructure manager, mark-ups will be low. Thus, the overall level of access charges will be lower. Consequently, transport service providers need to pay less for the use of the infrastructure. In return, less public service compensation needs to be paid to compensate companies for the provision of services. Both services subject to a Public Service Obligation and those not subject to it might pass cost reductions through to consumers (Arrigo & Di Foggia, 2013). I will investigate the impact of this mechanism on the performance of the sector in the following chapters.

3 Methodology

3.1 Methods of Performance Measurement in the Railway Sector

The performance of railway systems has been extensively studied (Catalano et al., 2019; Oum et al., 1999). By comparing indicators across countries, sectors, or entities, these studies aim to identify best practices and opportunities for improvement. Economists use performance measures to analyze railway reforms, their impact on efficiency, and the influence of different operating environments.

Performance encompasses several interrelated dimensions: efficiency, productivity, and effectiveness. Efficiency assesses the optimal use of resources, focusing on input minimization or output maximization. Productivity measures the output produced relative to inputs used. Effectiveness evaluates goal achievement, often relative to resource utilization. Five primary methods of performance measurement have been applied in the railway sector: partial productivity measures, total factor productivity, data envelopment analysis (DEA), stochastic frontier analysis (SFA), and (corrected) ordinary least squares estimation (Catalano et al., 2019; Merkert et al., 2010; Oum et al., 1999).

DEA is the most widely used efficiency method in recent railway and transport studies, followed by SFA (Catalano et al., 2019; Cavaignac & Petiot, 2017). DEA, a non-parametric approach based on linear programming, compares the efficiency of decision-making units (DMUs) such as railway sectors, train operators, or infrastructure managers. Using input and output data, DEA constructs a piecewise linear production frontier. Efficiency is determined by measuring the distance of each DMU from this frontier. DEA can be input- or output-oriented, depending on whether the analysis minimizes input for a given output or maximizes output for a given input. When price data are available, cost or revenue frontiers can also be derived (e.g., Cantos et al., 2002).

SFA, in contrast, is a parametric approach that uses maximum likelihood estimation to model a stochastic production frontier. Like DEA, SFA can estimate cost frontiers reflecting the minimum cost of producing a given output at specific input prices (Holmgren, 2013). However, SFA requires assumptions about the functional form of the production function and the distribution of inefficiency, which can lead to biased estimates if incorrectly specified. DEA avoids these functional form assumptions but is sensitive to the choice of scale (constant vs. variable returns to scale). Additionally, DEA lacks inherent statistical tests for sensitivity, making SFA advantageous for some applications (e.g., Cantos et al., 2012; Fiorentino et al., 2006). Corrected ordinary least squares (COLS) is another approach occasionally used to estimate deterministic production frontiers, although DEA and SFA dominate the literature (Coelli & Perelman, 1996; Coelli et al., 2005).

Partial productivity measures (PPM), also known as partial factor productivity, are simpler tools that relate a single input to a single output, providing insights into sectoral productivity. Examples include the operating ratio (operating costs/operating revenue), revenue per traffic unit, traffic units per employee, and traffic density (traffic units per track-km) (Beck et al., 2013; NERA, 2004; Oum et al., 1999; World Bank, 2011). Efficient railway systems achieve higher asset utilization and output relative to costs under comparable conditions. In contrast to PPM, total factor productivity (TFP) aggregates inputs and outputs, offering a broader performance perspective (Tretheway et al., 1997).

This study uses DEA as the primary method for performance evaluation due to its flexibility and data-driven nature. Unlike parametric approaches such as SFA or COLS, DEA does not require assumptions about the functional form of the production function, making it particularly suitable for analyzing heterogeneous railway systems with varying operating environments. DEA's ability to accommodate multiple inputs and outputs simultaneously is advantageous when evaluating complex systems like railways, where performance depends on diverse factors. While SFA incorporates stochastic noise, the deterministic framework of DEA is sufficient for this analysis given the quality and consistency of the available data.

3.2 Two-Stage Procedure for Evaluating Railway Efficiency

I apply the two-stage procedure proposed by Simar and Wilson (2007) to analyze the impact of government funding on the performance of European railways. In the first stage, DEA efficiency scores are calculated. The second stage comprises a bootstrap-based two-stage estimation that yields estimated standard errors and confidence intervals that do not suffer from bias due to estimated efficiency scores being correlated. It also overcomes issues of sample selection (efficiency scores are calculated from a common sample of data).

First-Stage: DEA

First, efficiency scores are estimated. The output-oriented DEA with constant returns to scale, can be formalized as follows (see Charnes et al. 1978). Given n decision-making units (DMUs), each using m inputs $\mathbf{x} = (x_1, \ldots, x_m) \in \mathbb{R}_+^m$ to produce s outputs $\mathbf{y} = (y_1, \ldots, y_s) \in \mathbb{R}_+^s$, the output-oriented DEA with constant returns to scale (CRS) is obtained by solving the following linear programming problem, for each DMU i:

$$\max \quad \phi_i$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{k,j} \leq x_{k,i} \quad k = 1, \ldots, m,$$

$$\sum_{j=1}^{n} \lambda_j y_{r,j} \geq \phi_i \cdot y_{r,i} \quad r = 1, \ldots, s,$$

$$\lambda_j \geq 0 \quad j = 1, \ldots, n,$$

where ϕ is the scalar that reflects the proportional increase in outputs achievable by DMU i without changing the input levels, and $\lambda = (\lambda_1, \ldots, \lambda_n)$ are the intensity variables (weights for other DMUs in the reference set). A score of $\phi = 1$ indicates that the DMU is on the efficient frontier, while $\phi > 1$ suggests inefficiency. In the case of variable returns to scale (VRS), an additional constraint $\sum_{j=1}^{n} \lambda_j = 1$ is added, which ensures that each DMU is compared only to convex combinations of other DMUs, thus allowing for VRS.

For the orientation and assumption of returns to scale, I adopt an output-oriented model with constant returns to scale (CRS). This choice is appropriate because the railway network length, one of the inputs, is relatively fixed and cannot be significantly adjusted between periods. Therefore, it is more plausible to assume that inputs remain constant while outputs adjust. Previous research indicates that the choice of orientation is generally not critical for railways (e.g., Coelli & Perelman, 2000). The assumption regarding returns to scale appears to be more critical. However, repeating the analysis under the assumption of variable returns to scale (VRS) produces similar, yet less robust, results (see Table B.4 for the second-stage results).[1]

[1] Note that the VRS model can only be estimated for DEA efficiency scores calculated using a pooled frontier, as countries in the smaller subset are on the yearly frontiers in many

Since the data used in this study has a panel structure, different approaches for the computation of DEA efficiency scores are employed in the literature. Some authors, such as Oum and Yu (1994), Coelli and Perelman (1999), and Kleinová (2016), treat each observation, i.e., each combination of time and country, as an independent decision-making unit (DMU). Thus, they measure the efficiency of each DMU against a pooled frontier. The resulting efficiency scores capture both technical progress and catching-up effects (see Growitsch and Wetzel 2007). Other studies run separate DEA models for each period, while some apply the Malmquist Index to decompose productivity changes over time into efficiency change (catching-up) and technical change (frontier shift) components (see Färe et al. 2011 for technical details). Additionally, some authors model dynamic DEA frameworks, for example, by accounting for the fact that today's (quasi-fixed) inputs are yesterday's outputs (see Lim et al. 2022).

As the main specification, I calculate an independent efficiency frontier for each year, rather than relying on a pooled frontier across the entire period. This approach ensures that efficiency scores are measured relative to contemporaneous peers, accounting for temporal variations in economic conditions, regulatory changes, and external shocks. For example, the COVID-19 pandemic likely disrupted productivity and operating conditions, making it inappropriate to compare pandemic-era performance with other years. Year-specific frontiers provide a fairer assessment of efficiency by isolating performance within comparable periods.

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years. Since these observations are dropped from the regression due to truncation, there are too few observations for the maximum likelihood estimation to converge. Therefore, these results cannot be directly compared to those of the main specification.

Although year-specific frontiers reduce the sample size for each year's estimation, this limitation is outweighed by their advantages. A pooled frontier assumes stable production technology and environmental conditions over time, which may not hold in dynamic contexts. By adopting yearly frontiers, I avoid the potential biases of pooling data across periods with differing production environments, ensuring a more accurate comparison of efficiency scores across countries. However, repeating the analysis for a pooled frontier, yields similar results (see Table B.2 for the DEA efficiency scores and Table B.3 for the second-stage results).

Second-Stage: Two-stage estimation

In the second-stage of the analysis, DEA efficiency scores are regressed on several explanatory variables. Standard OLS is unsuitable here due to boundary constraints and potential serial correlation among the efficiency estimates. These boundary issues arise because DEA scores are bounded - typically, efficiency scores lie between zero and one, depending on whether inefficiency is defined from above or below. Simar and Wilson (2007) address these challenges by proposing two algorithms that account for both, the bounded nature of DEA scores and the complex correlation structure among them. Both algorithms involve bootstrapping to enhance the accuracy and reliability of efficiency estimates. In this study, I will use what Simar and Wilson (2007) call *Algorithm 1*.

The steps in this approach involve: (a) conducting a truncated regression of the DEA scores on the explanatory variables, which respects the bounded nature of the efficiency estimates; (b) generating artificial efficiency scores through bootstrapping to account for sampling variability; and (c) calculating bias-corrected efficiency scores, along with bootstrap standard errors and confidence intervals. This multi-step process improves the reliability of inference by adjusting for both truncation and potential bias, making it a robust approach for second-stage DEA analysis. The feasibility and effectiveness of this method are further supported in Simar and Wilson (2011).

The structural equation of the second-stage model has the following form:

$$\phi_i = \mathbf{X}'_{i,t}\beta + \epsilon_{i,t} \tag{1}$$

where $\phi_{i,t}$ represents the technical efficiency score of DMU i in year t, $\mathbf{X}_{i,t}$ is a vector of exogenous (environmental) variables, β is a vector of coefficients, and $\epsilon_{i,t}$ is the error term.

To estimate the structural Equation (1), *Algorithm 1* from Simar and Wilson (2007) follows a structured bootstrapping process. First, the initial DEA efficiency scores $\phi_{i,t}$ for which $\phi_{i,t} > 1$ holds are included in a truncated regression (left-truncated at 1) of $\phi_{i,i}$ on the exogenous variables $\mathbf{X}_{i,t}$. This step provides initial estimates for the coefficients, β, and the variance parameter, σ, through maximum likelihood estimation.

Next, a bootstrap procedure is applied, consisting of the following steps, repeated B times to obtain a set of B bootstrap estimates $(\beta^{(b)}, \sigma^{(b)})$ for $b = 1, \ldots, B$:

1. For each observation (i, t), an artificial error term $\epsilon_{i,t}^{(e)}$ is drawn from a truncated normal distribution $N(0, \sigma)$, truncated at $1 - \mathbf{X}'_{i,t}\beta$.

2. Artificial efficiency scores $\phi_{i,t}^{(e)}$ are then generated as $\phi_{i,t}^{(e)} = \mathbf{X}'_{i,t}\beta + \epsilon_{i,t}^{(e)}$ for each observation (i, t).

3. A truncated regression (left-truncated at 1) of $\phi_{i,t}^{(e)}$ on $\mathbf{X}_{i,t}$ is conducted to obtain maximum likelihood estimates $\beta^{(b)}$ and $\sigma^{(b)}$ for each bootstrap iteration.

After completing B iterations, the bootstrap distributions of β and σ are used to compute confidence intervals and standard errors, providing robust inference for the second-stage DEA model.

4 Data Sources and Descriptive Statistics

The variables used as input or output measures in the first-stage vary across existing studies and are influenced by the data sources employed. Some researchers utilize data from the UIC, available at the company level (see Fitzová and Nash 2024 and Álvarez-SanJaime et al. 2024). However, UIC data primarily includes major (incumbent) railway undertakings, potentially limiting the scope of analyses. Other authors rely on country-level data, which can be obtained from sources such as Eurostat, the International Transport Forum, or the World Bank (see Kleinová 2016 for an application using country-level data). It is not always clear, however, to what extent the country-level data includes smaller undertakings.[2] Some authors combine information from the UIC with country-level data (see, for example, Niu et al.

[2]In Germany, for example, only freight companies with a transport volume exceeding 10 million tonne-kilometers are legally required to report data to the national statistical service.

2023). In the following analyses, I will mainly use country-level data from the Statistical Pocketbook (see European Commission and Directorate-General for Mobility and Transport 2024).

Regarding the data on revenue grants and public service compensation for the second-stage, I will use country-level data from an updated version of the dataset compiled by Schäfer and Götz (2017). Data sources include annual reports from infrastructure managers, railway undertakings, and public budget reports. However, the scope of the data limits the analyses in the second-stage because detailed data on revenue grants and public service compensation for European railways are not centrally collected by European or transnational institutions. The updated version of the dataset from Schäfer and Götz (2017) covers eight European countries, namely France, Germany, Italy, Norway, Spain, Sweden, Switzerland, and the United Kingdom, spanning the period from 2001 to 2022.[3]

Figure 2 shows a map with the countries for which data is available. Countries that enter the first-stage are colored grey. Countries for which financing data is available, and that thus enter the second-stage truncated regression, are marked with a white hatch.

Table 1 contains summary statistics for the variables used in the DEA and the second-stage regression. The smallest network in the sample has a length of 204.2 kilometers, while the largest network has a total length of 41 531 kilometers. On average, 13.6 billion passenger-kilometers (*rail_pkm*) and 18.41 billion tonne-kilometers (*rail_tkm*) are produced. The average share of freight

[3]Data for Italy and Sweden is available only for certain years.

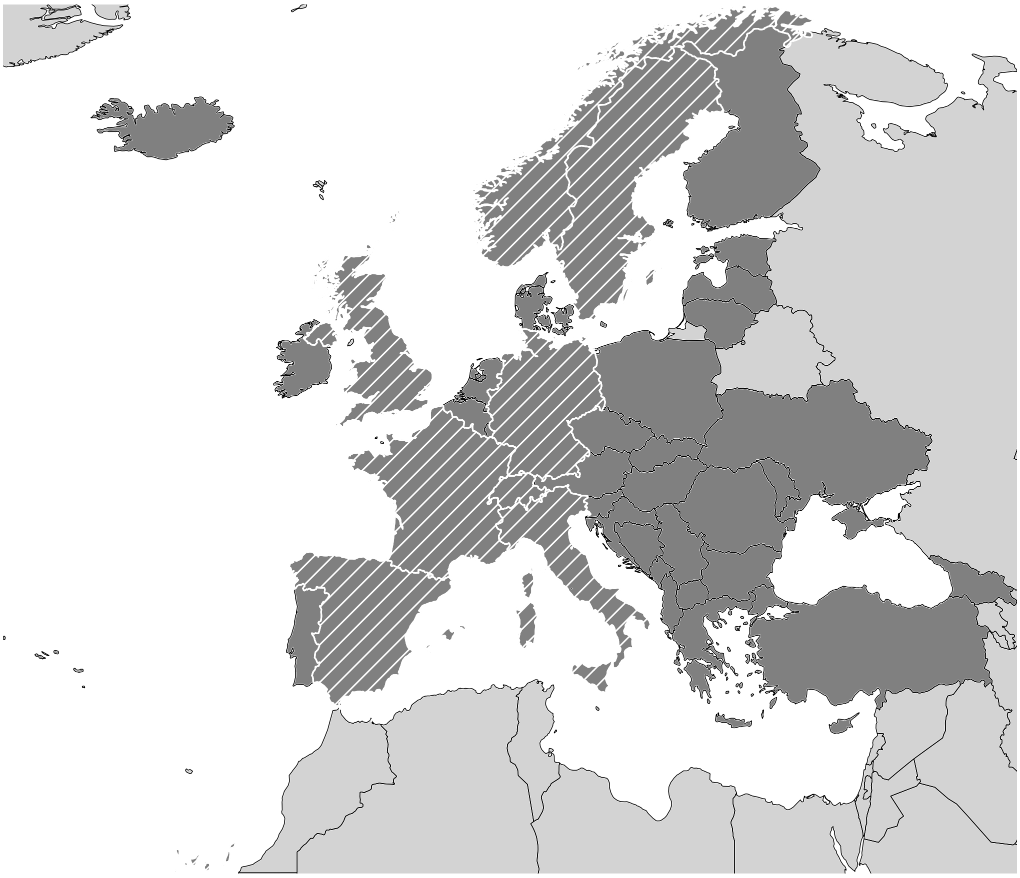

Figure 2: Countries in the sample

transport (*share_freight*), i.e., *rail_tkm* divided by the sum of *rail_pkm* and *rail_tkm* (*rail_ptkm*), is 59.83 %.

On average, an annual investment grant (*infra_inv_grant_pps_capita*) of € 71.01 per capita is granted to the infrastructure manager. The average revenue grant to the infrastructure manager (*infra_rev_grant_pps_ptkm*) is € 0.023 per passenger-tonne-kilometer, while the average public service compensation amounts to € 0.025 per passenger-tonne-kilometer (*psc_pps_ptkm*). All monetary values are expressed in terms of Purchasing Power Standards (PPS),

Table 1: Summary statistics

	N	Mean	SD	Min	Median	Max
Inputs						
rail_length	763	7 303	8 584	204.2	3 631	41 531
rolling_stock_pocketbook	801	26 190	41 487	62	10 551	266 002
staff_uic	718	44 057	70 758	360	18 109	377 511
Outputs						
rail_pkm	769	13.6	22.61	0.000437	3.957	108.7
rail_tkm	778	18.41	38.02	0.009	8.526	262.5
Non-financial control variables						
pop_density	780	157.6	233.7	2.8	100.2	1 693
gdp_pps_capita	805	24 869	13 424	3 600	23 500	90 600
share_freight	762	0.5983	0.2456	0.02914	0.6431	0.9866
share_passenger	762	0.4017	0.2456	0.01341	0.3569	0.9709
Fincancial control variables						
infra_rev_grant_pps_ptkm	171	0.02297	0.02572	-2.3e-06	0.01355	0.1541
infra_rev_grant_pps_capita	171	34.28	29.75	-0.001926	22.2	115.7
infra_inv_grant_pps_ptkm	171	0.03956	0.03485	0	0.02666	0.1778
infra_inv_grant_pps_capita	171	71.01	63.13	0	51.79	246.3
psc_pps_ptkm	167	0.02531	0.02412	-0.007626	0.0229	0.236
psc_pps_capita	167	43.78	31.61	-10.09	35.1	139.8

with the EU27 average price level, based on actual individual consumption, serving as the constant reference (EU27 = € 1).[4]

The evolution of financial control variables over time, expressed on a per capita basis, is shown in Figure 3. These figures reveal notable differences across countries both in terms of levels and trends. Across all countries, infrastructure investment grants (*infra_inv_grant_pps_capita*) have steadily increased over the observed period. However, Spain exhibits a contrasting trend in investment grants, which show a significant decline over time, particularly after the onset of the financial crisis.

[4]Figures expressed in nominal values are presented in the appendix (Figure A.1 and Figure A.2).

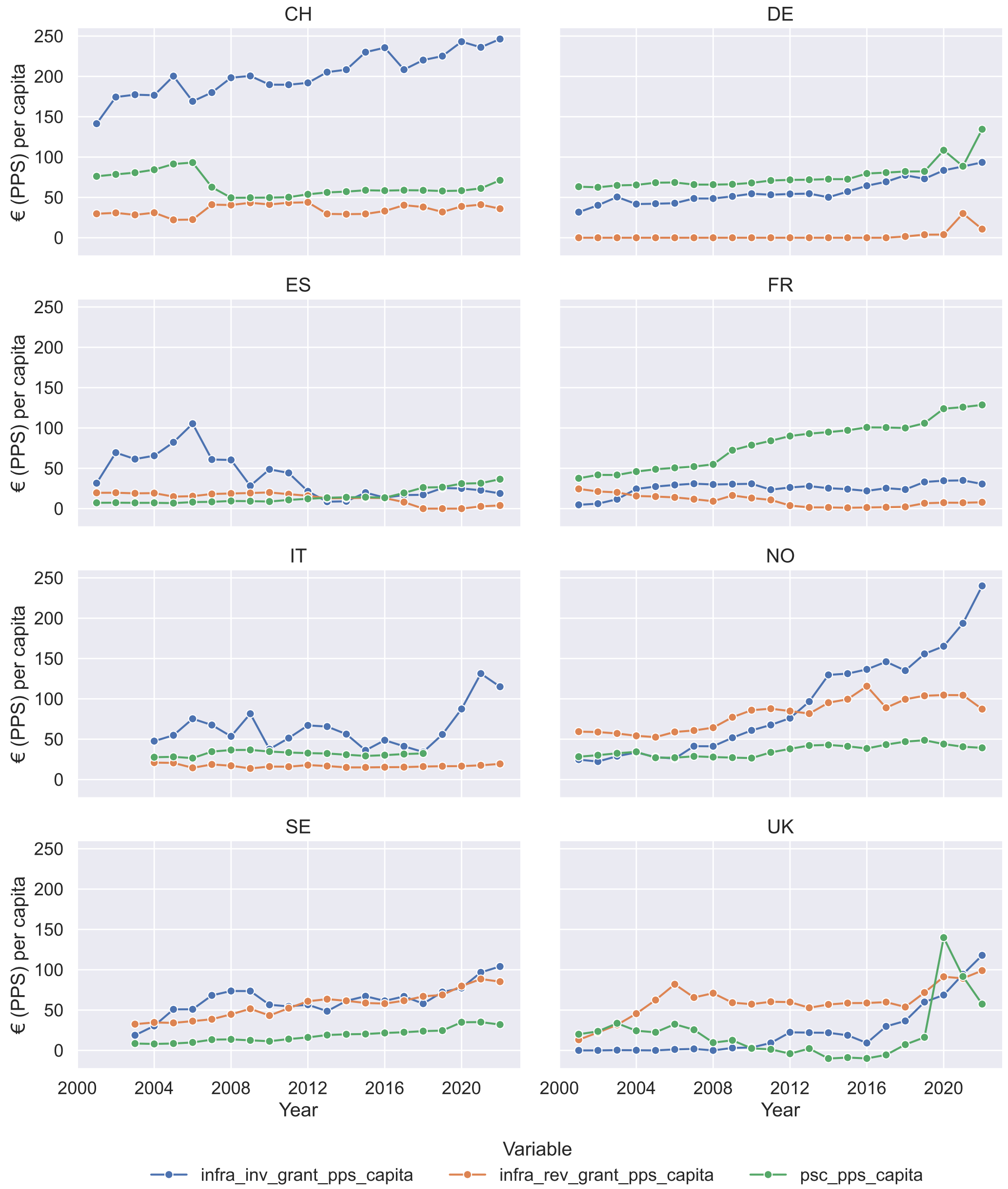

Figure 3: Grants for infrastructure investment, the operation of the infrastructure, and the provision of public services in € (PPS) per capita.

In 2022, there were notable differences in per capita grants for infrastructure investments across countries. Switzerland (CH) and Norway (NO) had the highest levels, with € 246.3 and € 240.1 per capita, respectively. These amounts were markedly higher than those of other countries in the sample. Italy (IT) followed with € 115.0 per capita, while the United Kingdom (UK) recorded € 117.9 per capita. Sweden (SE) had a slightly lower level of € 104.0 per capita, and Germany (DE) reached € 93.4 per capita. France (FR) had a lower level of € 30.5 per capita, and Spain (ES) recorded the lowest grants for investments in infrastructure at € 18.8 per capita.

The development of grants for the operation of infrastructure (*infra_rev_grant_pps_capita*) and for the provision of public services (*psc_pps_capita*) confirms the findings of Schäfer and Götz (2017) and Götz and Schäfer (2020). In general, two financing models are applied: either focusing on grants to upstream or downstream undertakings. Germany focuses government contributions on the operation of transport services, while the UK emphasizes revenue grants to the infrastructure manager. Other countries apply a hybrid model, where both public service compensation and revenue grants are granted - i.e., upstream and downstream undertakings receive almost equal shares of government grants.

However, with the onset of the pandemic, changes in the funding schemes of Germany and the UK can be observed. To support specific transport services, the German government allocated funds to reduce access charges. At the same time, the UK suspended rail franchising to maintain service as passenger demand fell due to the COVID-19 pandemic. Subsequently, it was decided to permanently abolish the rail franchising policy, effectively converting the franchises into concessions. This change had a notable effect on the level of public service compensations. Note that the UK publishes figures in terms of financial years, ranging from April to March. I attribute the figures to the year in which most months are situated; for example, the financial year 2020–2021 (ranging from April 2020 to March 2021) is shown as 2020 in the figures.

In the course of the war in Ukraine, Germany heavily subsidized public transport by introducing a nationwide flat-fee ticket (€ 9 per month) in 2022. To compensate for the forgone revenue, public service compensations were increased. In 2022, Germany's public service compensations amounted to € 134.5 per capita, representing one of the highest levels among the countries analyzed. France followed closely with € 128.6 per capita. Switzerland and the United Kingdom had notably lower levels of public service compensations, at € 71.2 and € 57.4 per capita, respectively. In contrast, Spain, Norway, and Sweden allocated even less, with € 36.5, € 39.3, and € 32.0 per capita, respectively. Data for Italy were not available for 2022, as Trenitalia stopped publishing annual reports.

At the same time, revenue grants for infrastructure in Germany were among the lowest in 2022, amounting to € 10.7 per capita. This level was significantly lower compared to most other countries in the sample. For instance, Norway and Sweden had the highest levels of revenue grants for infrastructure, at € 87.3 and € 85.2 per capita, respectively. The United Kingdom followed with € 99.0 per capita, reflecting its emphasis on revenue grants to the infrastructure manager. Switzerland also reported a higher level, at € 36.0 per capita. France and Spain had relatively low levels, at € 7.9 and € 3.9

per capita, respectively, while Italy recorded € 19.4 per capita.

Figure 4 shows the evolution of financial control variables over time, expressed per passenger-tonne-kilometer (ptkm). Investment grants, revenue grants for infrastructure, and public service compensations exhibit similar trends to those presented on a per capita basis. However, the reduction in transport volumes during the pandemic accentuates the effects of increased grants aimed at mitigating the crisis. In some cases, grants that declined between 2019 and 2020 on a per capita basis increased when measured per passenger-tonne-kilometer, due to the sharp decline in transport volumes. Since transport volumes had not returned to pre-crisis levels by the end of 2022 in all of the studied countries, the level of grants may still reflect the ongoing impact of the pandemic.

In 2022, revenue grants for infrastructure in France amounted to € 0.0037 per ptkm, among the lowest in the sample. Germany followed with € 0.004 per ptkm, while Spain recorded slightly higher levels at € 0.0049 per ptkm. Italy exhibited a more substantial level of revenue grants for infrastructure at € 0.016 per ptkm, whereas Sweden and Norway had significantly higher levels at € 0.025 and € 0.065 per ptkm, respectively. The United Kingdom reported the highest value in the sample, with revenue grants for infrastructure reaching € 0.099 per ptkm. Switzerland, despite its high overall infrastructure investment, recorded € 0.010 per ptkm.

Grants for the provision of public services were € 0.051 per ptkm in Germany in 2022. France recorded the highest level in the sample, with € 0.061 per ptkm, followed closely by the United Kingdom at € 0.058 per ptkm. Spain

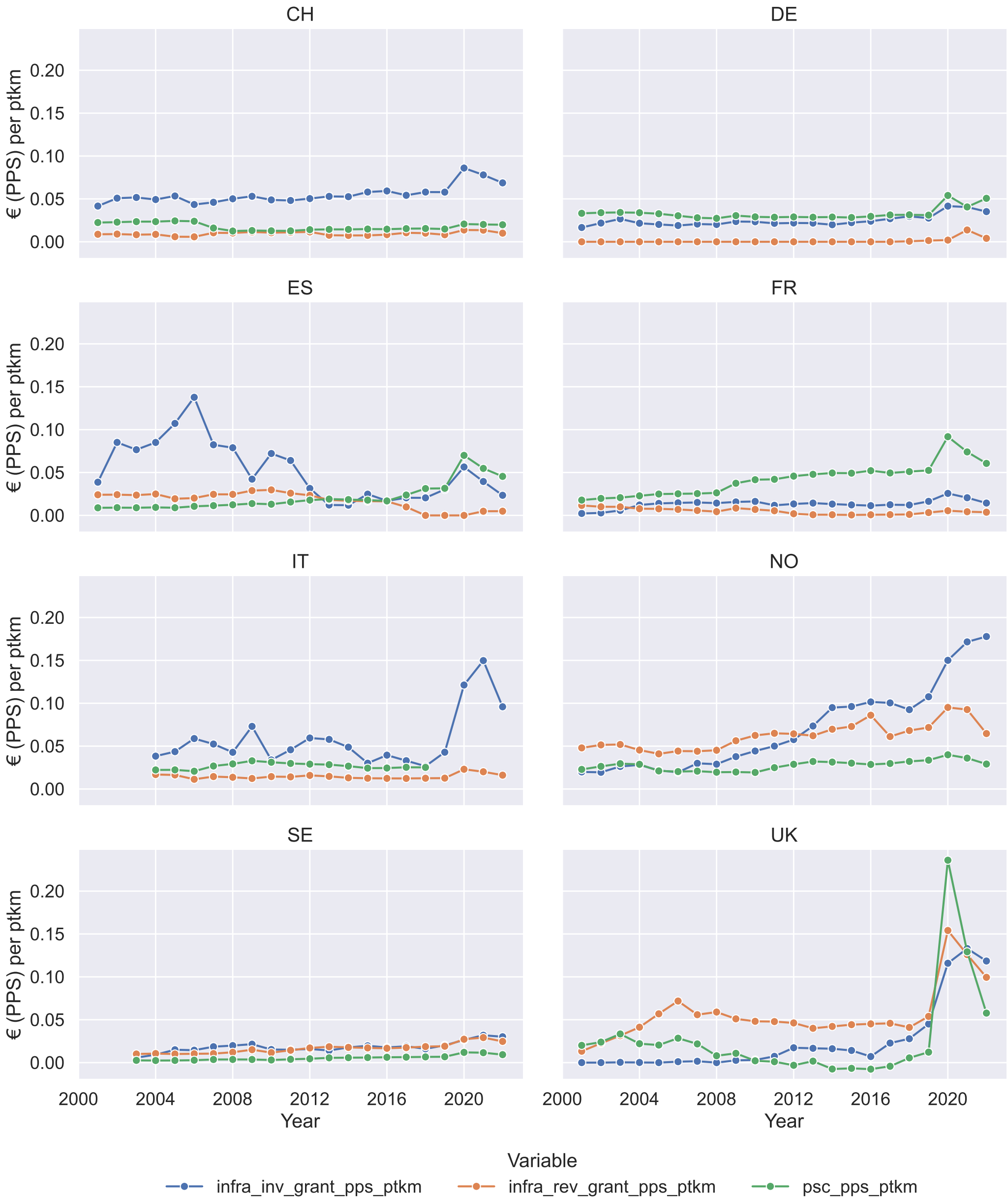

Figure 4: Grants for infrastructure investment, the operation of the infrastructure and for the provision of public services in € (PPS) per passenger-tonne-kilometer

also demonstrated significant expenditure in this category, reaching € 0.045 per ptkm. In contrast, Norway and Switzerland allocated € 0.029 and € 0.020

per ptkm, respectively, while Sweden reported the lowest value at € 0.009 per ptkm.

As described before, countries with lower revenue grants for infrastructure, such as Germany, France, and Spain, tended to allocate more funds per ptkm toward public service compensations. In contrast, Sweden had relatively higher revenue grants for infrastructure but low public service compensations. In order to systematically compare these differences across countries, the ratio of revenue grants for infrastructure to public service compensations is used as a metric. In 2022 Germany, France, and Spain had ratios of 0.08, 0.06, and 0.11, respectively, reflecting a stronger reliance on public service compensations. In contrast, Sweden and Norway had significantly higher ratios, at 2.66 and 2.22, indicating a greater emphasis on revenue grants for infrastructure. The United Kingdom exhibited a ratio of 1.72, whereas Switzerland had a ratio of 0.50, indicating that public service compensations were about twice as high as revenue grants for infrastructure.

In the following section, I will first compute DEA efficiency scores and then, in a subsequent second-stage regression, use the ratio of revenue grants for infrastructure to grants for the provision of public services to explain differences in the efficiency scores.

5 Results

5.1 First-Stage: DEA Efficiency Scores

Table 2 presents the DEA efficiency scores for the output-oriented model with constant returns to scale, using the length of the rail infrastructure (*rail_length*), the size of the rolling stock (*rolling_stock_pocketbook*), and the average annual staff size (*staff_uic*) as input variables. Passenger-kilometers (*rail_pkm*) and tonne-kilometers (*rail_tkm*) are used as output variables. Values close to or equal to one indicate efficient decision-making units.

Several countries achieved efficient outcomes in one or more years, including Estonia, Latvia, the Netherlands, Norway, Sweden and Ukraine, which consistently exhibited efficiency scores of 1 over multiple years. These countries often have a high share of freight transport on their networks, a factor that may contribute to their efficiency. Switzerland and Denmark also reached efficient outcomes in specific years, particularly in 2020 and 2021, respectively. In contrast, countries such as Germany and France exhibited scores close to, but not at, full efficiency over most of the observed period, reflecting their relatively stable, albeit slightly suboptimal, performance. Meanwhile, missing data (NA) for several countries underscore the challenges of consistent data collection. Notably, some countries experienced significant inefficiencies, with scores well above 1, suggesting room for substantial improvement in their operations.

Table 2: Efficiency scores (yearly frontiers) - output oriented model, constant returns to scale

country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
AL	1	1.55	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
AT	1.83	1.79	1.7	1.73	1.76	1.52	1.58	1.52	1.81	1.65	1.71	1.85	1.79	1.68	1.56	1.51	1.43	1.4	1	1.31	1.24	1
BA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	6.94	7.24	5.03	6.83	8.17	4.7	4.51	3.85	3.27
BE	1.66	1.67	1.67	1.65	1.74	1.66	1.61	1.53	1.72	1.58	NA	NA	1	1.25	1.1	1.24	1.27	1.27	1.14	1	1.08	1.14
BG	4.11	4.68	4.24	4.58	4.68	4.27	4.59	5.09	6.85	6.65	7.22	8.44	4.35	4.02	3.6	5.95	3.48	3.77	3.68	2.97	2.84	2.21
CH	1.27	1.2	1.18	1.25	1.43	1.4	1.46	1.41	1.41	1.32	1.38	1.46	1.48	1.45	1.33	1.34	1.36	1.21	1.15	1	1	1.18
CZ	3.14	3.63	3.37	3.71	3.83	3.42	3.5	3.73	4.12	3.66	4.38	4.36	4	3.76	3.45	2.93	2.63	2.64	2.52	2.07	2.1	2.04
DE	1.34	1.57	1.74	1.84	1.83	1.67	1.66	1.62	1.81	1.68	1.8	1.86	1.79	1.79	1.64	1.63	1.54	1.56	1.49	1.38	1.38	1.06
DK	1.28	1.3	1	1.48	1.93	2.12	2.16	1.35	1.58	1.47	1.53	1.51	1.61	1.86	1.79	1.59	1.43	1.37	1.39	1	1	1
EE	1	1	1	1	1	1	1	1	1	1	1	1	NA	NA	1.54	1.75	1.74	NA	NA	NA	NA	NA
ES	1.67	1.61	1.69	1.92	2.04	1.96	1.92	1.66	1.69	1.87	2.53	2.86	3	2.82	2.08	1.85	1.79	1.73	1.66	1.67	1.31	1.25
FI	1.65	1.56	1.55	1.59	1.61	1.42	1.64	1.45	1.66	1.82	2.04	2.09	2.15	1.82	1.79	1.56	1.39	1.5	1.81	1.47	1.43	1.88
FR	1.47	1.4	1.43	1.52	1.93	1.96	2.02	1.89	1.91	1.86	1.86	1.9	2.01	2.03	1.77	1.79	1.72	1.37	1.31	1	1	1
HR	5.57	5.11	4.87	5.18	5.4	4.25	4.17	4.27	4.39	4.63	5.42	6.07	6.21	5.69	5.46	5.45	3.08	3.59	4.36	2.53	2.57	2.14
HU	2.97	2.64	2.73	2.87	3.24	3.25	3.38	2.95	3.22	2.82	3.26	3.11	2.68	2.46	2.4	3.22	1.96	2.37	2.31	2	2.04	1.87
IE	2.71	2.47	3.2	3.67	3.96	3.99	3.25	3.08	2.73	3.23	3.04	2.5	2.66	2.36	2.15	NA	1.82	1.5	1.47	1.9	1.96	NA
IT	1.38	1.28	1.3	1.39	1.69	1.75	1.83	1.83	1.94	1.94	2.02	2.05	2.1	1.99	1.83	1.81	1.54	1.32	1.31	1.39	1.08	1.02
LT	1.81	1.67	1.3	1.34	1.29	1.08	1	1.04	1.38	1.14	1.29	1.35	1.31	1.18	1.16	1.01	NA	1	1	1	1	NA
LU	2.28	2.78	2.89	3.07	3.57	3.11	2.61	3.65	4.11	3.32	3.75	3.96	NA	NA	NA	3.67	3.5	3.55	3.63	3.05	3.18	3.88
LV	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1.04	1.68	1.68	NA
MD	NA	NA	NA	NA	NA	NA	NA	NA	7.18	7.39	7.71	10.02	8.2	8.66	10.29	11.61	9.17	10.23	9.96	NA	NA	3.82
ME	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	4.61	6.59	7.21	6.26	5.85	NA
MK	1	1.47	1.85	8.02	6.68	5.19	4.38	4.82	5.89	4.65	5.4	7.02	6.33	NA	NA	13.34	10.25	10.5	8.92	8.86	7.82	7.12
NL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NO	1.41	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NA	NA	NA	NA	NA
PL	2.38	2.58	2.31	2.36	2.59	2.27	2.3	2.43	2.95	2.57	2.88	3.1	2.77	2.64	1.67	1.51	1.37	1.8	1.88	1.53	1.43	1.31
PT	2.05	1.92	2.27	2.44	2.6	2.62	2.46	2.14	1.47	2.35	2.66	2.78	2.92	2.65	1.58	2.04	1.76	1.77	1.76	1.44	1.55	1.61
RO	3.11	3.78	3.63	3.37	3.85	3.72	3.93	4.2	5.58	5.06	5.38	5.72	5.7	5.55	4.68	2.5	3.87	3.63	3.96	1.27	2.63	3.19
RS	NA	NA	NA	NA	NA	NA	NA	1	1.38	1	6.02	8.09	6.62	6.69	6.12	6.62	4.75	5.62	5.3	4.72	4.33	3.45
SE	1.09	1.05	1	1.03	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SI	2.82	2.64	2.53	2.62	2.72	2.37	2.4	2.54	2.89	2.01	2.24	2.45	2	1.84	1.76	1.97	1.32	1.49	1.37	1.52	1.39	1
SK	2.22	2.51	2.45	2.71	2.84	2.48	2.61	2.75	3.67	3.09	3.62	3.99	3.45	3.24	2.95	2.8	2.61	2.65	2.51	2.38	2.48	1.83
TR	2.89	3.02	3.27	3.54	3.69	3.29	3.55	3.24	3.16	2.97	3.53	4.26	4.08	3.79	4.22	3.56	2.99	3.37	2.85	2.88	2.82	1.97
UA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1	1	1	1	1	1	1	1	1	NA	NA
UK	1	1	1	1	1	1.15	1.83	1.69	1.51	1.31	1.15	1.25	1.33	1.27	1.12	1.01	1	1	1	1.03	1	1

Note:
Output oriented model with constant returns to scale. Inputs are: rail_length, rolling_stock_pocketbook, staff_uic. Outputs are: rail_pkm, rail_tkm.

Figure 5 shows the average efficiency scores by country. On average, countries in the Balkans exhibit lower efficiency scores compared to other European countries.

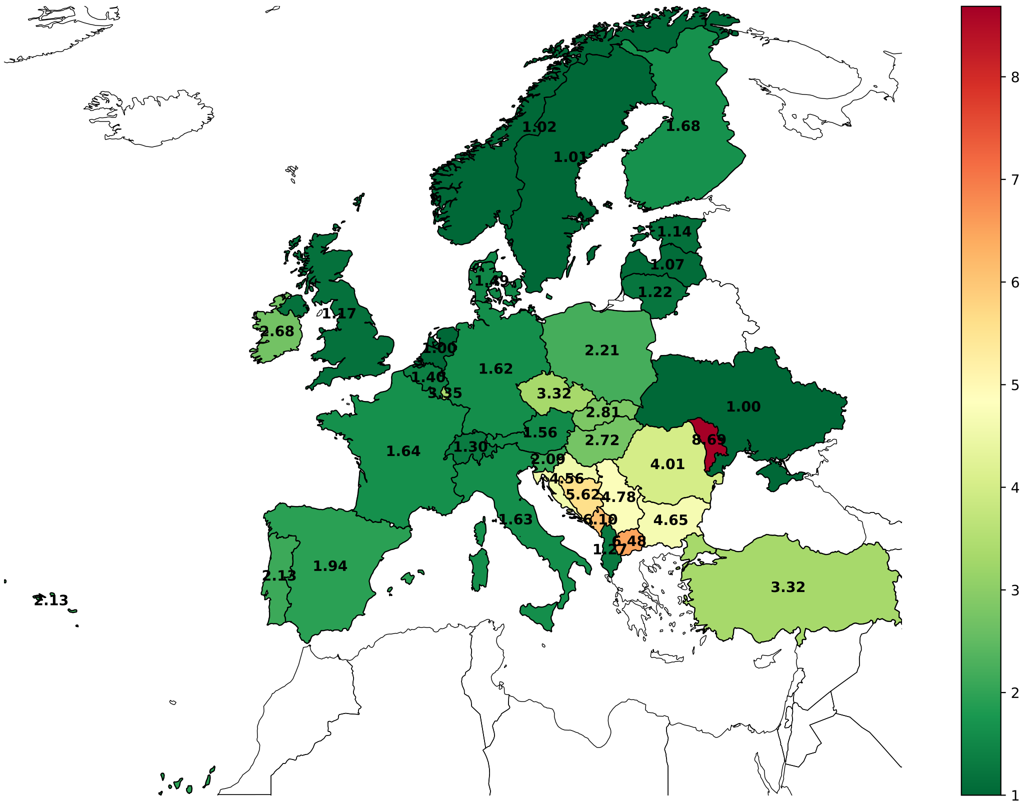

Figure 5: Average efficiency scores. Output oriented model with constant returns to scale. Inputs are: rail_length, rolling_stock_pocketbook, staff_uic. Outputs are: rail_pkm, rail_tkm.

5.2 Second-Stage: Efficiency and Government Grants

This chapter estimates the model (see Equation 1) using the approach proposed by Simar and Wilson (2007) across four different specifications. All models are estimated in logarithms, with specifications (1) and (2) including fixed effects for each country and year.

To assess the impact of different funding structures - i.e., upstream vs. downstream grants - on efficiency, two new variables are constructed: total operating grants (*infra_rev_grant_pps + psc_pps*) and the ratio of upstream to downstream grants, $\left(\frac{infra\_rev\_grant}{psc}\right)$. The latter variable examines whether countries focusing more heavily on either upstream or downstream grants achieve higher performance scores. A higher ratio indicates that a greater share of funding comes from revenue grants for infrastructure (e.g., subsidies for maintaining tracks) rather than public service compensations (compensation for running trains).

Specifications (1) and (3) examine grants per passenger-tonne-kilometer, while Specifications (2) and (4) focus on grants per capita. Both approaches have their advantages and disadvantages. Specifications (1) and (3) offer a performance-based perspective by linking funding to transport demand. However, it is highly sensitive to external shocks, such as the COVID-19 pandemic, which caused significant reductions in transport activity and potentially biased the measure. In contrast, Specifications (2) and (4) provide a more stable and consistent metric that is less influenced by short-term fluctuations in transport volumes. However, to account for potential structural breaks caused by the COVID-19 pandemic, interaction terms are included. Specifically, the ratio variable is interacted with a binary indicator for the pre-pandemic period (*covid0*) and the pandemic/post-pandemic period (*covid1*), resulting in the terms $\left(\frac{infra\_rev\_grant}{psc}\right)$ *:covid0* and $\left(\frac{infra\_rev\_grant}{psc}\right)$ *:covid1*. These interaction terms enable an investigation of whether the relationship between funding structures and efficiency differs across these two distinct periods.

As shown in Table 3, the ratio of operating grants has a statistically significant negative effect on the efficiency scores in the pre-pandemic period, suggesting that higher revenue grants to the infrastructure manager relative to public service compensation are associated with greater efficiency (as lower efficiency scores indicate higher efficiency). The coefficient is -0.035 in specification (1) and -0.034 in specification (2). This implies that a one percent increase in the ratio of infrastructure grants to public service compensation corresponds to an efficiency improvement of 0.035 % and 0.034 %, respectively. Specifications (3) and (4), estimated without year- or country-specific fixed effects, yield slightly larger coefficients of -0.037 and -0.067, respectively.

In other words: countries that grant a relatively higher share of operating grants to the infrastructure manager reach higher efficiency scores, while countries that focus their operating contributions on the compensation of transport undertakings seem to be less efficient. This can be explained as follows: It seems like the positive effect of revenue grants, which typically lower access charges and thus stimulate intermodal and intramodal competition (e.g, Álvarez-SanJaime et al., 2016; Arrigo & Di Foggia, 2013), outweighs possible inefficiencies due to distorted cost structures (e.g., Obeng & Sakano, 2020; Oum & Yu, 1994; Pucher et al., 1983). In addition, as a major part of compensation for public services is used to cover access charges, paying grants directly to the infrastructure manager can avoid double marginalization problems (e.g., Gutiérrez-Hita et al., 2022) and thus allow for a more efficient use of resources. However, the marginal effect of shifting funding to infrastructure on efficiency remains below proportionality, with estimated effects between 0.034 % and 0.067 %, since (high) access charges are not the sole factor influencing competition (Crozet & Chassagne, 2013).

To illustrate the practical magnitude of this effect, consider the case of Germany in 2022. That year, the ratio of revenue grants for infrastructure to public service compensation amounted to approximately 0.08. With total rail transport volumes reaching 220.95 billion passenger-tonne-kilometers (ptkm), a 1 % increase in this ratio - equivalent to a relative shift in the funding structure - would correspond to an estimated efficiency improvement of about 0.035 %. Applied to the observed output, this translates into roughly 77 million additional ptkm, assuming constant inputs and a linear approximation.[5] Achieving this 1 % increase in the ratio while keeping the total operating subsidies constant would require reallocating approximately 8.07 million euro PPS from public service compensation to revenue grants for infrastructure. While modest in scale, this calculation quantifies the tangible efficiency gains that can result from rebalancing operating grants in favor of upstream infrastructure support. These estimates should, however, be interpreted with caution, as they are based on average marginal effects from a regression model and assume linearity, constant inputs, and no endogenous behavioral response from railway operators or users. Larger changes in the grant ratio may yield diminishing or nonlinear effects.

In contrast, the direction of the impact reverses in the post-COVID period. The coefficients for the interaction term are positive and statistically significant

[5]For the output-oriented DEA model, efficiency gains can be interpreted as potential increases in output (ptkm, pkm, etc.) for the same level of inputs.

in specifications (1) and (2), with values of 0.124 and 0.123, respectively. In specifications (3) and (4), the coefficients are 0.021 and 0.064, which are smaller and not statistically significant. These results suggest that in the post-pandemic period, a higher ratio of revenue grants for infrastructure to public service compensation is associated with a decline in efficiency. One possible explanation is that the disruption caused by the pandemic may have shifted priorities or led to inefficiencies in the allocation and utilization of operating grants, diminishing the benefits of stimulating competition through lower access charges. Furthermore, the pandemic likely exacerbated challenges in cost recovery for transport undertakings, making public service compensation a more critical factor for sustaining operational efficiency.

The analysis also reveals that infrastructure investment grants - whether measured per capita or per passenger-tonne-kilometer (ptkm) - have a significant and variable impact on efficiency. When measured in passenger-tonne-kilometers, the coefficients are -0.038 in specification (1) and 0.048 in specification (3), indicating differing effects across model specifications. Similarly, when measured per capita, the coefficients are -0.042 in specification (2) and -0.004 in specification (4), with the latter being statistically insignificant. These mixed results suggest that while infrastructure investment grants can positively influence efficiency under certain measurement and specification conditions, their effect is not consistent and may depend on contextual factors. One potential explanation for this variability is the strong correlation between costs and grants, as highlighted by Laabsch and Sanner (2012), which could obscure or complicate the interpretation of the grants' true impact on

Table 3: Results of the truncated regression - output oriented model, constant returns to scale (yearly frontier)

	(1)	(2)	(3)	(4)
log(infra_rev_grant/psc):covid0	−0.035**	−0.034**	−0.037***	−0.067***
	(0.016)	(0.015)	(0.013)	(0.014)
log(infra_rev_grant/psc):covid1	0.124***	0.123***	0.021	0.064
	(0.039)	(0.038)	(0.049)	(0.040)
log(infra_inv_grant_pps_ptkm)	−0.038**		0.048**	
	(0.017)		(0.020)	
log(infra_inv_grant_pps_capita)		−0.042**		−0.004
		(0.017)		(0.021)
log(infra_rev_grant_pps_ptkm + psc_pps_ptkm)	−0.137*		−0.116*	
	(0.070)		(0.066)	
log(infra_rev_grant_pps_capita + psc_pps_capita)		−0.186**		−0.284***
		(0.078)		(0.057)
log(gdp_pps_capita)	−1.236***	−1.111***	−0.550***	−0.123
	(0.268)	(0.255)	(0.120)	(0.135)
log(pop_density)	1.297**	0.952	−0.019	0.029
	(0.593)	(0.591)	(0.049)	(0.045)
log(share_freight)	0.166	0.114	−0.392***	−0.198**
	(0.196)	(0.191)	(0.106)	(0.098)
(Intercept)	5.738*	7.877**	5.574***	2.525**
	(3.208)	(3.281)	(1.108)	(1.194)
/sigma	0.071***	0.071***	0.163***	0.147***
	(0.005)	(0.005)	(0.013)	(0.012)
N	87	87	87	87
FE: country	yes	yes	no	no
FE: year	yes	yes	no	no

Note:
The dependent variable is log(efficiency_scores_out_crs_yearly). Negative coefficients indicate a positive effect on efficiency. Bootstrapped standard errors (2000 replications) are reported in parentheses. Coefficients are significant at the * 10%, ** 5%, and *** 1% level.

efficiency. On the other hand, the results in specifications (3) and (4) could also be driven by unobserved heterogeneity, which might be absorbed by the year- or country-specific fixed effects included in specifications (1) and (2). The coefficients for the country and year fixed effects are provided in Table B.1.

Moreover, the results demonstrate that total operating contributions (the sum of revenue grants for infrastructure and public service compensation), measured either per capita (*infra_inv_grant_pps_capita*) or per passenger-tonne-kilometer (*infra_inv_grant_pps_ptkm*), can improve efficiency. The coefficients are -0.137 in specification (1) and -0.116 in specification (3) when measured per passenger-tonne-kilometer, and -0.186 in specification (2) and -0.284 in specification (4) when measured per capita. These findings indicate that higher operating contributions, regardless of the measurement approach, are associated with increased efficiency.

Finally, the non-financial control variables, namely GDP per capita (*gdp_pps_capita*), population density (*pop_density*), and the share of freight transport (*share_freight*), exhibit notable effects on efficiency. However, the size and significance of these effects vary significantly across the models. GDP per capita positively impacts efficiency in specifications (1)–(4), with coefficients of -1.236, -0.111, -0.550, and -0.123, although the latter is not statistically significant. As in other studies (e.g., Lerida-Navarro et al. 2019), the results suggest that wealthier economies tend to operate more efficiently. This finding can be attributed to several factors: higher GDP per capita is often associated with better-developed infrastructure, which reduces costs and enhances the reliability of transport operations. Moreover, wealthier countries are more likely to invest in advanced technology and innovation, fostering greater efficiency in transport systems. The availability of financial resources also supports higher operational standards and improved system management.

Population density has a negative effect on efficiency, as indicated by the coefficients in specifications (1), (2), and (4). In specification (3), population density shows a positive effect on efficiency. However, the coefficients are only statistically significant in specification (1). The negative relationship between population density and efficiency may reflect the challenges associated with densely populated areas. Higher population density often correlates with increased infrastructure congestion, leading to delays, overcrowding, and inefficient allocation of resources. These issues arise because the capacity of transport infrastructure may not keep pace with the high and diverse demand. Furthermore, the complexity of transportation networks in densely populated areas - encompassing urban, suburban, and intercity services - requires sophisticated coordination and incurs higher operational costs. While densely populated areas may benefit from economies of scale in transport services, these gains are often outweighed by the administrative and operational burdens tied to congestion and network complexity, ultimately reducing efficiency.

The influence of differences in the mix of freight and passenger transport on each country's network is not clear. In specifications (1) and (2), a higher share of freight transport is associated with a loss of efficiency. However, the coefficients are not statistically significant. In contrast, specifications (3) and (4), which were estimated without year- and/or country-specific fixed effects, suggest that a higher share of freight transport positively affects efficiency. This aligns with findings in the literature, which highlight that freight transport can have both positive and negative effects on efficiency. Fitzová and Nash (2024) argue that in countries with high freight volumes (e.g., bulk commodities), freight transport may benefit from economies of scale and standardized operations. However, a high share of wagonload traffic can reduce efficiency. Similarly, Lerida-Navarro et al. (2019) find that countries with a high modal share of rail freight transport tend to be more efficient.

It is important to note that these results may be influenced by the sample selection used in the second-stage regression. While the first-stage analysis includes a broad sample of countries, only eight countries are included in the second-stage regression due to data availability constraints. This limited sample may not fully represent the diversity of infrastructure quality, regulatory environments, and service mixes observed in the broader dataset. Consequently, the relationships identified in the second-stage regression should be interpreted with caution, as they may reflect the specific characteristics of the smaller sample rather than generalizable trends across all countries.

6 Conclusion

This study examines the effects of government funding structures on the efficiency of European railways, focusing on the allocation of grants to upstream infrastructure managers versus downstream service providers. Using a two-stage procedure involving Data Envelopment Analysis (DEA), I calculate efficiency scores and investigate their relationship with funding structures through a truncated regression model. The findings provide key insights into the implications of railway financing choices.

The results indicate that railways achieve higher efficiency when a larger share of government funds is allocated to upstream infrastructure managers. Specifically, a higher ratio of revenue grants for infrastructure relative to public service compensation correlates with increased efficiency. This is attributed to lower access charges for downstream operators, which foster competition and enhance network utilization. Conversely, a reliance on downstream grants appears less effective, potentially due to inefficiencies linked to duplicated subsidies or insufficient incentives for cost containment.

Infrastructure investment grants exhibit mixed effects on efficiency. While these grants play a essential role in expanding capacity, improving network quality, and maintaining reliable operations, their impact varies depending on the model specification. In contrast, total operating contributions (the combined funding for infrastructure and public services) consistently demonstrate positive effects on efficiency.

In addition, non-financial variables such as GDP per capita and population density show varied effects on efficiency, underscoring the complexity of railway performance drivers. Wealthier countries benefit from advanced infrastructure and innovation, while densely populated areas face challenges from congestion and complex network coordination.

These findings underscore the importance of balanced, upstream-oriented funding structures to enhance railway efficiency. Policymakers should aim to optimize the allocation of public funds by emphasizing infrastructure support and fostering competitive, efficient rail networks aligned with broader environmental and economic goals.

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Appendix

A Descriptive Statistics

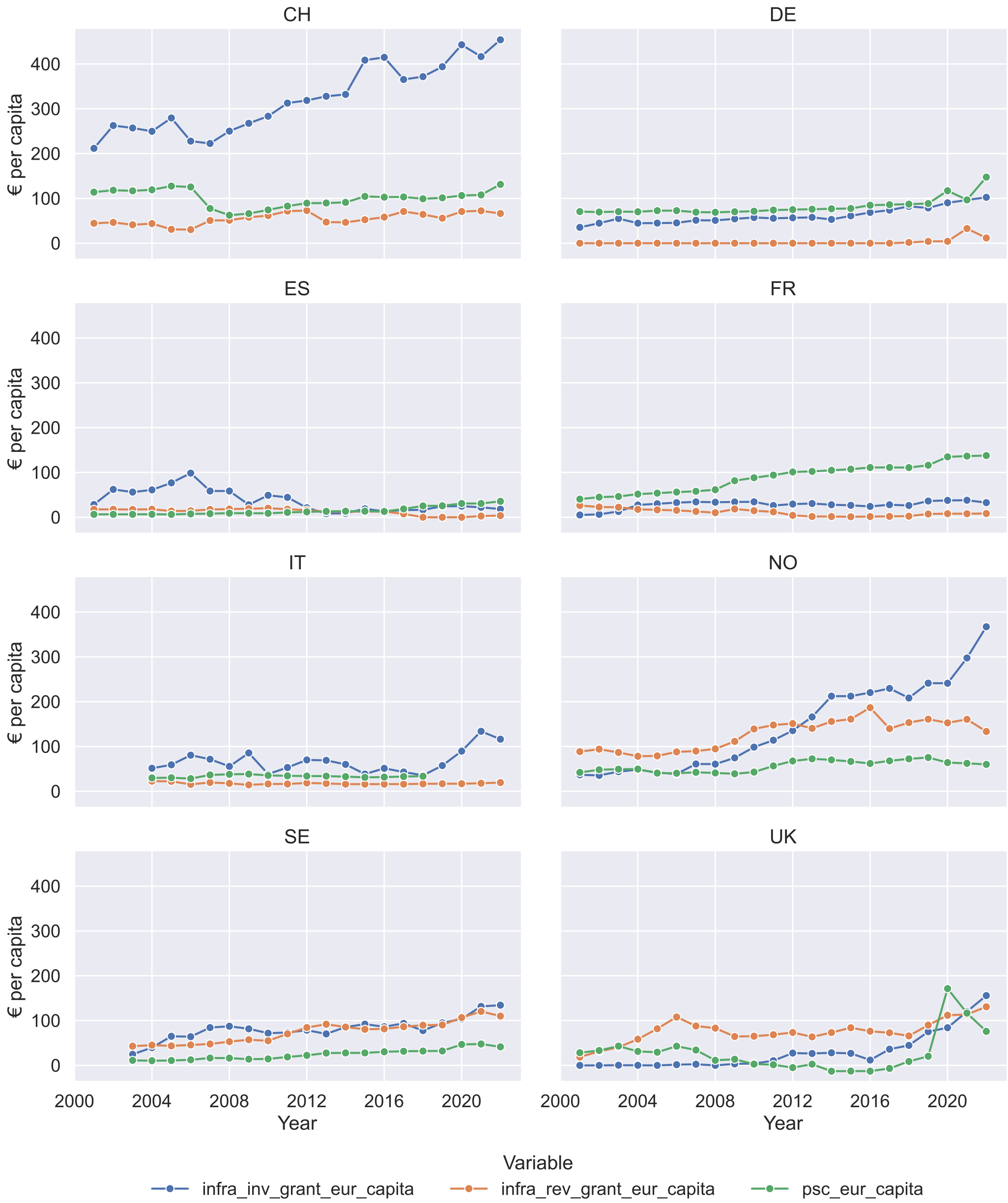

Figure A.1: Grants for infrastructure investment, the operation of the infrastructure, and the provision of public services in € per capita.

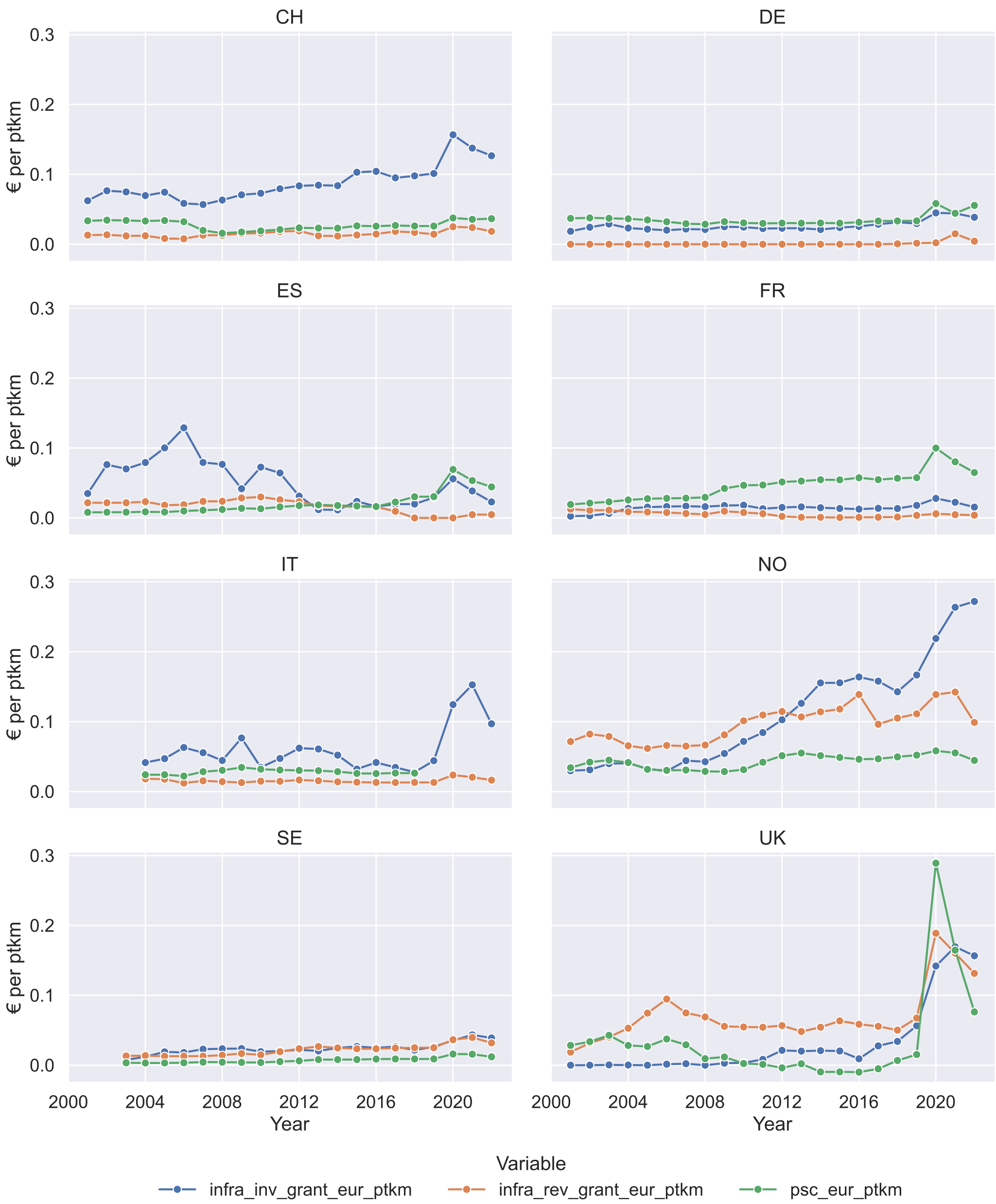

Figure A.2: Grants for infrastructure investment, the operation of the infrastructure and for the provision of public services in € per passenger-tonne-kilometer

B Robustness Checks

Table B.1: Results of the truncated regression - output oriented model, constant returns to scale (yearly frontier)

	(1)	(2)	(3)	(4)
log(infra_rev_grant/psc):covid0	−0.035**	−0.034**	−0.037***	−0.067***
	(0.016)	(0.015)	(0.013)	(0.014)
log(infra_rev_grant/psc):covid1	0.124***	0.123***	0.021	0.064
	(0.039)	(0.038)	(0.049)	(0.040)
log(infra_inv_grant_pps_ptkm)	−0.038**		0.048**	
	(0.017)		(0.020)	
log(infra_inv_grant_pps_capita)		−0.042**		−0.004
		(0.017)		(0.021)
log(infra_rev_grant_pps_ptkm + psc_pps_ptkm)	−0.137*		−0.116*	
	(0.070)		(0.066)	
log(infra_rev_grant_pps_capita + psc_pps_capita)		−0.186**		−0.284***
		(0.078)		(0.057)
countryDE	−0.214	−0.192		
	(0.147)	(0.140)		
countryES	0.858**	0.289		
	(0.430)	(0.471)		
countryFR	0.603*	0.284		
	(0.359)	(0.377)		
countryIT	−0.227*	−0.420***		
	(0.127)	(0.138)		
countryNO	3.539**	2.475*		
	(1.495)	(1.487)		
countrySE	1.968	1.210		
	(1.274)	(1.279)		
countryUK	−0.763***	−0.867***		
	(0.236)	(0.220)		
year2002	−0.001	0.001		
	(0.060)	(0.060)		
year2003	0.018	0.017		
	(0.061)	(0.060)		
year2004	0.119*	0.121*		
	(0.065)	(0.065)		
year2005	0.316***	0.312***		
	(0.073)	(0.070)		
year2006	0.350***	0.346***		
	(0.081)	(0.077)		
year2007	0.514***	0.508***		
	(0.089)	(0.087)		
year2008	0.405***	0.399***		
	(0.098)	(0.092)		
year2009	0.427***	0.409***		
	(0.107)	(0.103)		

year2010	0.424***	0.405***		
	(0.109)	(0.104)		
year2011	0.485***	0.475***		
	(0.108)	(0.103)		
year2012	0.554***	0.543***		
	(0.108)	(0.107)		
year2013	0.556***	0.545***		
	(0.113)	(0.109)		
year2014	0.525***	0.519***		
	(0.116)	(0.114)		
year2015	0.396***	0.394***		
	(0.121)	(0.114)		
year2016	0.399***	0.396***		
	(0.122)	(0.118)		
year2017	0.379***	0.377***		
	(0.128)	(0.125)		
year2018	0.249*	0.241*		
	(0.135)	(0.129)		
year2019	0.272*	0.266*		
	(0.144)	(0.141)		
year2020	0.606***	0.565***		
	(0.204)	(0.188)		
year2021	0.416**	0.384**		
	(0.163)	(0.156)		
year2022	0.477***	0.477***		
	(0.181)	(0.176)		
log(gdp_pps_capita)	−1.236***	−1.111***	−0.550***	−0.123
	(0.268)	(0.255)	(0.120)	(0.135)
log(pop_density)	1.297**	0.952	−0.019	0.029
	(0.593)	(0.591)	(0.049)	(0.045)
log(share_freight)	0.166	0.114	−0.392***	−0.198**
	(0.196)	(0.191)	(0.106)	(0.098)
(Intercept)	5.738*	7.877**	5.574***	2.525**
	(3.208)	(3.281)	(1.108)	(1.194)
/sigma	0.071***	0.071***	0.163***	0.147***
	(0.005)	(0.005)	(0.013)	(0.012)
N	87	87	87	87
FE: country	yes	yes	no	no
FE: year	yes	yes	no	no

Note:
The dependent variable is log(efficiency_scores_out_crs_yearly). Negative coefficients indicate a positive effect on efficiency. Bootstrapped standard errors (2000 replications) are reported in parentheses. Coefficients are significant at the * 10%, ** 5%, and *** 1% level.

Table B.2: Efficiency scores (pooled frontier) - output oriented model, constant returns to scale

country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
AL	4.15	5.07	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
AT	2.56	2.4	2.43	2.32	2.28	2.06	2.03	1.94	2.23	2.09	1.93	1.94	1.9	1.81	1.79	1.73	1.7	1.67	1.03	2.21	2.03	1
BA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	8.85	9.04	5.08	9.57	8.85	5.46	6.65	5.71	5.26
BE	2.29	2.26	2.27	2.07	2.16	2.06	1.95	1.84	2.04	1.93	NA	NA	1	1.41	1.37	1.37	1.54	1.53	1.38	1.79	1.86	1.63
BG	5.9	6.49	6.05	6.1	6.02	5.85	5.81	6.32	8.17	8.18	7.97	8.84	6.94	6.61	6.19	6.58	5.87	5.92	5.79	5.25	4.96	4.27
CH	2.02	1.97	1.93	1.86	1.75	1.68	1.66	1.65	1.66	1.58	1.55	1.58	1.55	1.5	1.48	1.47	1.5	1.51	1.46	2.09	1.94	1.58
CZ	4.46	4.85	4.83	4.93	4.87	4.57	4.45	4.62	5.2	4.86	4.63	4.49	4.42	4.2	3.98	3.8	3.6	3.4	3.36	3.92	3.59	3.32
DE	2.26	2.39	2.7	2.56	2.26	2.12	2	1.98	2.17	2.07	2.01	1.99	1.95	1.94	1.89	1.79	1.84	1.82	1.79	2.43	2.26	1.8
DK	3.07	3.1	2.24	2.19	2.15	2.21	2.17	2.17	2.36	2.24	2.13	1.99	1.97	2.15	2.14	2.09	2.01	2.01	1.99	2.64	2.72	1.79
EE	1.21	1.02	1.09	1	1	1.04	1.25	1.43	1.35	1.2	1.3	1.62	NA	NA	2.94	3.64	3.65	NA	NA	NA	NA	NA
ES	3.3	3.24	3.29	3.33	3.33	2.9	3.02	2.87	3.08	3.27	3.14	3.06	3.08	2.83	2.41	2.34	2.29	2.23	2.13	4.29	3.37	2.2
FI	2.9	2.88	2.73	2.68	2.68	2.4	2.46	2.38	2.77	2.53	2.57	2.48	2.36	2.28	2.34	2.15	1.93	1.79	1.89	1.98	1.87	2.12
FR	2.36	2.32	2.37	2.31	2.31	2.23	2.19	2.1	2.19	2.17	2.07	2.09	2.09	2.04	1.96	1.96	1.87	1.9	1.82	2.86	2.19	1.68
HR	8.62	8.36	7.77	7.59	6.64	5.58	5.01	5.13	5.73	6	6.38	6.87	7.38	6.81	6.55	6.7	4.47	4.17	5.08	3.4	3.35	2.8
HU	4.24	4.06	4.16	3.97	3.96	3.95	4.03	3.68	4.5	4.3	4.24	4.14	3.88	3.66	3.69	3.61	3.06	3.46	3.44	3.61	3.62	3.29
IE	6.9	6.55	6.27	5.35	4.99	4.92	4.22	4.47	3.82	4.45	4.16	3.67	3.67	3.33	3.01	NA	2.72	2.53	2.44	7.18	6.84	NA
IT	2.01	2.04	2.07	2.01	2.01	2	2	2.05	2.23	2.25	2.25	2.23	2.18	2.11	2.02	1.99	1.95	1.87	1.84	3.42	2.77	2.06
LT	2.54	2.12	1.82	1.79	1.66	1.59	1.38	1.36	1.67	1.46	1.31	1.4	1.5	1.39	1.4	1.4	NA	1	1.11	1.11	1.15	NA
LU	3.31	3.9	4.05	3.98	4.57	4.08	3.52	4.35	4.85	4.15	4.27	4.3	NA	NA	NA	4.06	3.8	3.73	3.7	5.93	5.28	4.37
LV	1.65	1.51	1.26	1.28	1.2	1.38	1.26	1.16	1.17	1.24	1	1	1.11	1.13	1.16	1.34	1.38	1.08	1.21	1.99	2.01	NA
MD	NA	NA	NA	NA	NA	NA	NA	NA	9.26	9.71	8.74	10.26	8.73	9.54	11.89	14.89	12.59	12.25	12.22	NA	NA	8.83
ME	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	6.59	8.78	8.07	9.19	9.05	NA
MK	7.43	10	8.9	11.61	8.78	7.62	6.07	6.17	8.32	7.58	7.92	7.19	7.28	NA	NA	15.95	13.5	11.8	10.41	10.38	9.34	9.82
NL	1.29	1.3	1.32	1.13	1.08	1	1	1.09	1.11	1.14	1.09	1.04	1	1	1.07	1.09	1.07	1.03	1.01	1.8	1.57	1.12
NO	4.22	2.53	1.55	1.29	1.29	1.07	1.01	1	1	1	1.47	1.14	1.27	1.65	1.27	1.23	1.22	NA	NA	NA	NA	NA
PL	3.31	3.41	3.27	3.16	3.27	3.08	2.97	3.04	3.51	3.27	3.03	3.21	3.04	3.06	2.48	2.42	2.26	2.27	2.4	2.88	2.58	2.17
PT	4.17	4.16	4.33	3.89	3.62	3.4	3.17	3.13	2.08	3.29	3.15	2.94	3.03	2.85	2.11	2.53	2.47	2.42	2.34	3.56	3.72	2.75
RO	4.46	5.07	5.06	4.58	4.77	4.81	4.97	5.22	6.59	6.42	5.81	6.28	6.35	6.26	5.51	4.08	5.31	4.59	4.77	3.72	4.96	4.81
RS	NA	NA	NA	NA	NA	NA	NA	3.87	5.46	4.46	7.67	9.72	8.82	8.96	8.93	8.02	6.47	6.4	6.56	6.23	5.33	5.82
SE	2.15	2.13	2.01	1.95	1.86	1.79	1.62	1.74	1.84	1.39	1.4	1	1.03	1.02	1	1	1.01	1	1	1.05	1	1.08
SI	3.98	3.69	3.63	3.6	3.48	3.37	3.12	3.16	3.75	2.97	2.98	3.17	2.85	2.66	2.56	2.41	2.02	2.01	1.94	2.13	2	1.95
SK	3.32	3.47	3.64	3.75	3.8	3.6	3.68	3.71	4.45	3.98	3.98	4.09	3.75	3.58	3.39	3.38	3.25	3.23	3.22	4.38	3.93	3.49
TR	6.03	6.1	5.01	4.78	4.88	4.6	4.49	4.27	4.42	4.06	4.24	4.55	4.67	4.36	4.84	4.44	3.73	3.73	3.23	3.29	3.36	2.86
UA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1	1.03	1.11	1.18	1	1.1	1.13	1.15	1.29	NA	NA
UK	1.48	1.41	1.13	1	1.3	1.36	1.9	1.88	1.85	1.76	1.43	1.33	1.34	1.27	1.28	1.28	1.27	1.26	1.22	2.92	2.53	1.78

Note:
Output oriented model with constant returns to scale. Inputs are: rail_length, rolling_stock_pocketbook, staff_uic. Outputs are: rail_pkm, rail_tkm.

Table B.3: Results of the truncated regression - output oriented model, constant returns to scale (pooled frontier)

	(1)	(2)	(3)	(4)
log(infra_rev_grant/psc):covid0	−0.046*	−0.057**	−0.030**	−0.034**
	(0.024)	(0.023)	(0.013)	(0.014)
log(infra_rev_grant/psc):covid1	−0.093**	−0.099**	−0.128***	−0.153***
	(0.041)	(0.039)	(0.028)	(0.028)
log(infra_inv_grant_pps_ptkm)	0.077***		0.120***	
	(0.025)		(0.018)	
log(infra_inv_grant_pps_capita)		0.080***		0.090***
		(0.023)		(0.022)
log(infra_rev_grant_pps_ptkm + psc_pps_ptkm)	−0.148*		−0.004	
	(0.083)		(0.038)	
log(infra_rev_grant_pps_capita + psc_pps_capita)		−0.277***		−0.140**
		(0.090)		(0.055)
log(gdp_pps_capita)	−1.661***	−1.677***	−1.105***	−0.958***
	(0.359)	(0.341)	(0.089)	(0.141)
log(pop_density)	1.584	1.501	0.038	0.024
	(0.966)	(0.940)	(0.026)	(0.026)
log(share_freight)	0.114	0.164	0.034	−0.040
	(0.228)	(0.219)	(0.086)	(0.084)
(Intercept)	9.691*	11.474**	12.332***	10.617***
	(5.322)	(5.298)	(0.995)	(1.286)
/sigma	0.136***	0.134***	0.182***	0.190***
	(0.009)	(0.009)	(0.012)	(0.014)
N	122	122	122	122
FE: country	yes	yes	no	no
FE: year	yes	yes	no	no

Note:
The dependent variable is log(efficiency_scores_out_crs). Negative coefficients indicate a positive effect on efficiency. Bootstrapped standard errors (2000 replications) are reported in parentheses. Coefficients are significant at the * 10%, ** 5%, and *** 1% level.

Table B.4: Results of the truncated regression - output oriented model, variable returns to scale (pooled frontier)

	(1)	(2)	(3)	(4)
log(infra_rev_grant/psc):covid0	−0.038	−0.056**	0.047*	0.046
	(0.025)	(0.024)	(0.027)	(0.032)
log(infra_rev_grant/psc):covid1	−0.082**	−0.092**	−0.086*	−0.146***
	(0.040)	(0.038)	(0.052)	(0.054)
log(infra_inv_grant_pps_ptkm)	0.046*		0.237***	
	(0.024)		(0.042)	
log(infra_inv_grant_pps_capita)		0.055**		0.192***
		(0.024)		(0.053)
log(infra_rev_grant_pps_ptkm + psc_pps_ptkm)	−0.093		−0.001	
	(0.088)		(0.069)	
log(infra_rev_grant_pps_capita + psc_pps_capita)		−0.247***		−0.272**
		(0.093)		(0.111)
log(gdp_pps_capita)	−1.535***	−1.582***	−0.852***	−0.592**
	(0.343)	(0.314)	(0.165)	(0.269)
log(pop_density)	2.191**	2.218**	−0.042	−0.082
	(0.939)	(0.893)	(0.049)	(0.060)
log(share_freight)	0.058	0.132	−0.034	−0.241
	(0.227)	(0.222)	(0.166)	(0.181)
(Intercept)	5.153	6.582	10.077***	6.895***
	(5.213)	(4.897)	(1.851)	(2.421)
/sigma	0.124***	0.121***	0.258***	0.278***
	(0.009)	(0.009)	(0.026)	(0.028)
N	118	118	118	118
FE: country	yes	yes	no	no
FE: year	yes	yes	no	no

Note:
The dependent variable is log(efficiency_scores_out_vrs). Negative coefficients indicate a positive effect on efficiency. Bootstrapped standard errors (2000 replications) are reported in parentheses. Coefficients are significant at the * 10%, ** 5%, and *** 1% level.