Measuring the Technical Efficiency of Railways in Developing Countries: A Two Stage- Bootstrap Data Envelopment Analysis

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Abstract:

This paper aims at measuring the technical efficiency of selected railways operating in developing countries over the period 2013-2018. We apply the Bootstrap Data Envelopment Analysis DEA to an Input-Output oriented model under Variable Return on Scale. In general, the findings suggest that the bootstrapping technique provides more consistent and realistic efficiency estimates, in contrast with the conventional DEA. In fact, the results show a technical efficiency score of 56,1 % for the sample which indicates that the observed railways could potentially reduce the usage of its inputs by 43,9 % on average and reach high levels of production at the same time. We also notice the existence of significant gaps in technical efficiency across the observed railways. Finally, the results show a performance decline in most of the railways during the period of analysis with shifts representing occasional back and forth developments for other railways in the middle periods.

Keywords : Railways ; Technical Efficiency ; DEA, Bootstrap ; Developing Countries .

JEL classification codes : D25 ; L92 ; R15.

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قياس الكفاءة الفنية لشركات النقل بالسكك الحديدية في البلدان النامية: باستعمال تقنية التحليل المغلف للبيانات على مرحلتين (مقاربة Bootstrap)

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الملخص:

تهدف هذه الدراسة الى تقييم مستوى الكفاءة الفنية لشركات النقل بالسكك الحديدية لعينة من البلدان النامية خلال الفترة الزمنية الممتدة من 2013 إلى 2018. نطبق تقنية التحليل المغلف للبيانات بمقاربة Bootstrap على نموذج ذو توجه مدخلي تحت فرضية عائد السلم المتغير. بصفة عامة، تشير نتائج الدراسة إلى ان تطبيق تقنية التحليل المغلف للبيانات بمقاربة Bootstrap تمكننا من تقدير مستويات اكثر اتساقا و واقعيتا للكفاءة الفنية مقارنة بالمقاربة التقليدية. بحيث أظهرت النتائج ان شركات النقل بالسكك الحديدية للعينة المدروسة تعتبر كفؤة في حدود 56,1 % على المتوسط، مما يعكس قدرة شركات النقل على تخفيض ما نسبته 43,9 % من مواردها المتاحة و في نفس الوقت تحقيق مستويات اعلى من الإنتاج. كما اشارت النتائج الى ان مستويات الكفاءة متفاوتة بين شركات النقل قيد الدراسة و ان معظمها شهد تدهورا في مستوى الأداء خلال الفترة المدروسة مع تسجيل تذبذب في تطور الكفاءة الفنية لبعض الشركات خلال الفترات الوسطى.

الكلمات المفتاحية: سكك حديدية ؛ كفاءة فنية ؛ تحليل مغلف بيانات ؛ بوستراب ؛ بلدان نامية.

رموز تصنيف JEL: D25 ; L92 ; R15.

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Introduction

For most of countries, railways have played a determinant role for long-term economic, social and environmental benefits. However, the railway industry is complex and costly demanding. In fact, Building and managing railway systems necessitate considerable investment in infrastructure, railway stations and rolling stocks. Hence, the concern for governments to emphasize on the efficient use of these invested capital assets by identifying the areas of improvement in production to ensure that performance and productivity are optimized. Another concern is to make the railways competitive with other modes of transport. In this regard, the last three decades witnessed substantial research studies on railways performance through the benchmark approach. The methodology suggests identifying the best practices and ways to grow by comparing the individual performances within a selected peer group. From a national perspective, an efficient railway minimizes the usage of its inputs while providing a maximum of desired services.

The literature on railways efficiency based on frontier analysis is still growing; the focus has been put on railway systems operating in developed countries particularly the European Railways. The efficiency of railways has been investigated either by applying the non-parametric Data Envelopment Analysis DEA or the Parametric Stochastic Frontier Analysis SFA. However, in developing economies, empirical studies on railways efficiency are quasi-inexistent so far. From this regard, we try in this paper to fill the gap by providing empirical evidence about how railways in the context of economies in development perform in terms of technical efficiency.

In this paper, we conduct a DEA multi-variable analysis to assess the technical efficiency of railways operating in developing countries. The analysis uses a balance panel data of twenty railways that provide both passenger and freight transportation services, spread over the period from 2013 to 2018. The DEA method constructs an efficiency frontier using linear programming techniques, and measures the efficiency scores of each Decision-Making Unit DMU in relation to which inputs are minimized or outputs are maximized. The use of this optimization method is highly recommended when the analyst is concerned with providing an objective benchmark of any complex production units such as railways operations where the interaction between inputs and outputs is not clear in the first instance. We apply the bootstrap-technique to a DEA model, with an input-output orientation under the Variable Return on Scale VRS. The Bootstrap-DEA in contrast with the so-called naïve or traditional DEA accounts for statistical inference of error measurement and thus provide more consistent efficiency estimates.

To sum up, this paper aims to answer the following main question: How do railways in developing countries perform in terms of technical efficiency and how does the railways efficiency evolve over the time?. To provide answers to these questions, we formulate the following hypotheses:

Hypothesis 1: The bootstrap-DEA analysis provide more consistent and realistic efficiency estimates than traditional DEA analysis

Hypothesis 2: The technical efficiency varies across the observed railways: Large-sized railways are not necessarily the most technical efficient firms.

Hypothesis 3: In the short run, the dynamic changes in technical efficiency of railways are not obvious.

We believe that two other mains aspects made the originality of this study: First, using the most recent data on railways in a balanced panel structure, we establish annual frontiers instead of just one frontier if using a single time point. This enables us to observe the dynamic changes in technical efficiency of our observed railways. Second, we apply one of the most recent developments in DEA (Bootstrap-DEA). The method has received many positive considerations in the last decade and has begun to be widely adopted by researchers when dealing with non-parametric frontier analysis.

The study has many policy implications for railways managers and policy makers as well. The findings would help the managers of railways to objectively identify the best practices amongst the different railways transportation systems. A determination not always possible when relying on the traditional key performance indicators. Thus, overused inputs can be easily detected, and then reduced which leads to improvements in the overall performance. On other side, most of railways are state-owned companies and governments engage a lot of money to build railways infrastructures. With this regard, the governments may gain insight into whether the capitals invested and the subsidies are efficiently used. And therefore, readjust their policies.

This study is structured as follows: The section 2 presents a brief literature review. In section 3, we describe the methodology of the bootstrap-DEA analysis and the specified model. Data and variables are explained in section 4. Section 5 presents and discusses the empirical findings. Finally, section 6 concludes where new avenues of research are proposed.

Literature Review

Many research studies based on frontier techniques fuel the literature on railway efficiency and productivity in developed countries particularly in the context of Western European Railways as stated above. Most of studies have favored the use of the non-parametric approach rather than the parametric approach for the benefits it offers to the analysis in the context of the railways transportation industry. Some of few researches involving the parametric analysis namely the Stochastic Frontier Analysis SFA we can find (Coelli & Perelman, 2000) ; (De jorge & Suarez, 2003) and (Wetzel, 2008). Since the non-parametric techniques are the most popular methods used in studies involving the efficiency and productivity analysis and for sake of brevity, this section only discusses the DEA-based literature on railways efficiency.

For instance, we can find the study of (De Jorge Moreno & Garcia-Cebrian, 1999) who applied the nonparametric DEA to assess the technical efficiency of 21 European railways during the period 1984-1995 in the context of the new environmental changes that mandates the split of the organizational structure of railways in operations and infrastructure. The main results of this study showed that small-sized railways are the most technically efficient which demonstrated how mistakes regarding the choice of the appropriate size can affect the performance of the railways leading to scale inefficiencies.

(Hilmola, 2007) Investigated the efficiency and the productivity of 31 European railways between 1980 to 2003 using DEA and Partial Productivity analysis. The research focused only on freight transportation mode. The authors' findings suggest that railway freight transportation show significant differences between the European counties and the Baltic states have the most efficient freight transportation system. Also, a significant decline in technical efficiency is particularly observed for railways that showed the highest efficiency score in the 1980s. The productivity analysis results state that improvements should be made in the productivity of locomotives and railways tracks.

In another study, (Hilmola, 2008) analyzed the efficiency of 30 European railways for both freight and passenger transportation modes in the timeframe of 1994-2003 with different inputs-outputs combinations. The results indicated that very few railways perform better in both transportation modes. Most of investigated railways are efficient either in passenger or in freight operations. The authors' results also showed that Central and Eastern European (CEE) railways experienced a technical efficiency collapse during the period and considerable inputs restructuring or outputs increase should be implemented to improve the overall railways performance.

The same findings were identified by (Kapetanović, Milenković, Bojović, & Avramović, 2017) in a more recent study. The authors conducted a two–stage analysis to examine the determinants of 34 European railways and found that few companies outperform their peers in both transportation services. Most of investigated firms are oriented either in freight or in passenger transport services.

In a novel study, (Yu, 2008) proposed a Network DEA model to assess the technical efficiency, service effectiveness and technical effectiveness of 40 railways in the year 2002 and compared the results with those obtained from the Traditional DEA model. The author found that the two applied models provide the same results for the performance ranking. However, the magnitude of both the technical efficiency and service effectiveness scores varies significantly between the two used models. It was found that Western Europe railways outperform the other region's railways in terms of technical efficiency whilst the African railways tend to have a higher technical and service effectiveness.

The study of (Doomernik, 2015) was the first attempt that tackles the performance and the productivity of 8 high-speed rail systems (four from Asia and four from Europe) between 2007 and 2012 using a combined Network DEA and Malmquist Productivity Index. The benchmark of the railways was considered in terms of two distinct approaches (production efficiency and service effectiveness). The author found that Asian high-speed railways perform better that Europe with regard to the two approaches, even more reaching a fully efficient score of unity in variable return scale DEA model. In terms of productivity, it was found that Asia achieved positive productivity growth due to improvements in technical efficiency and technological change while Europe did witness any productivity growth during the period of the analysis

(Kutlar, Kabasakal, & Sarikaya, 2012) expand the efficiency analysis to railways operating in other continents. The study assessed the determinants of technical and allocative efficiency of 31 companies around the world from 2000 to 2009 using two DEA models based on different return on scale assumptions. The authors noticed a slight improvement in the number of efficient railways between the first and the last observed years depending on the adopted DEA model. In fact, the constant return scale DEA model (So called: CCR model) suggested 17 firms being efficient in the first year while the variable return scale DEA model (BCC) identified 20 efficient firms. In the last year the number of the efficient firm reached only 18 for the CCR model and 24 for the BCC model.

We can also mention the seminal work of (Li & Hilmola, 2019) where the authors focused on the efficiency of railways operating in countries members of the Belt and Road Initiative from 2000 to 2016. The authors performed different DEA model configurations and noticed a slight improvement in the analyzed railways whether they are oriented for freight or passenger transportation operations. Railways operating in China, Estonia and Latvia were found to be the best benchmark for their similar sized peers.

Research Methodology

Bootstrapped Data Envelopment Analysis

Since its introduction by Charnes, Cooper and Rhodes in 1978. The Data Envelopment Analysis DEA has gained great popularity in studies that tackle performance and productivity issues based on frontier techniques. DEA constructs a non-parametric peace wise frontier that envelops all the data of DMUs of the sample relative to which inputs are minimized or outputs are maximized. Efficiency scores are then calculated from the frontier generated by a sequence of linear programs. Each DMU is assigned an efficiency score between zero and one with higher score indicating the most efficient DMU (Charnes, Cooper, & Rhodes, 1978, p. 431).

DEA has two main advantages for the analysis: First, it does not require any assumptions regarding the form of the production function, particularly when assessing the organizational performance where interactions among the variables are not explicitly modeled (Coelli, Rao, O'Donnell, & Battese, 2005, p. 162) . Second, DEA is suitable to use when dealing with small samples (Besstremyannaya, 2013, p. 341). However, the so-called conventional or naive DEA is sensitive to outliers and does not account for measurement error beside the fact firms on the constructed frontier are assigned an efficiency score equal to unity (Besstremyannaya, 2013, p. 341). To overcome these drawbacks, (Simar & Wilson, 1998) introduced the bootstrap DEA that allows to examine the statistical properties (bias, adjusted scores and confidence intervals) which result from the distribution of efficiency scores generated by the conventional DEA in the sample. The key assumption is that the known bootstrap distribution will mimic the original unknown distribution, if the known Data Generating Process (DGP) is a consistent estimator of the unknown DGP. The bootstrap process will therefore generate values that mimic the distributions, which would be generated from the unobserved and unknown DGP (Aggelopoulos & Georgopoulos, 2017, p. 1176) .

The Model Specification

Under the assumption that managers of railways companies have higher control over the inputs rather than outputs which are influenced by different macroeconomic factors exogenously determined by public transport institutions (Merkert, Smith, & Nash, 2010, p. 7), we opt for an input-output orientation model in estimating the technical efficiency. The input-output oriented model measures improve in efficiency through proportional reduction of input quantities without altering produced output quantities.

The DEA model is applied by assuming either a Constant Return on Scale CRS or a Variable Return on Scale VRS. The CRS-DEA model assumes that all observed firms are operating at the optimal scale (Banker, Charnes, & Cooper, 1984, p. 1078). However, it is a common knowledge that railway industry is subject to imperfect competition, budgetary restrictions as well as regulatory constraints on entries and mergers, which may lead to firms not operating at optimal scales (Merkert, Smith, & Nash, 2010, p. 40) . Accordingly, and given the heterogeneity across size and development level of the investigated railways, in this paper we favor the VRS-DEA model proposed by (Banker, Charnes, & Cooper, 1984) known as BCC-DEA.

We proceed in two distinct stages, in the first stage we apply the traditional DEA to estimate the VRS pure technical efficiency of the sample observations assuming *n* railway observations that use multiple inputs to produce multiple outputs. In the second stage, we follow the methodology of (Simar & Wilson, 1998) and (Simar & Wilson, 2002) to generate the bootstrap estimates from the traditional DEA :

- Stage 1 (Traditional DEA): We run a traditional DEA model for each railway observation $\{(x_i, y_i), i = 1, \dots n)\}$. The technical efficiency $\hat{\theta}_k$ is computed as solution to the linear program formula based on the following BCC-DEA model (Coelli, Rao, O'Donnell, & Battese, 2005, p. 172) :

$$\theta^*_{k,} = \min\{\ \theta \text{ subject to } \theta x_k \ \geq\ \textstyle\sum_{i=1}^{n} z_i\ x_i\ ;\ y_k\ \leq\ \sum_{i=1}^{n} z_i y_i\ ;\ \sum_{i=1}^{n} z_i = 1\,;\, z_i\ \geq 1\ \}.$$

Where $\hat{\theta}_k$ denotes efficiency of *k*-th DMU, *k=1,..,n* ; *y* and *x* are the outputs and inputs respectively and *z* represents weighting coefficients of inputs and outputs which are to be determined.

- Stage 2 (Bootstrapped DEA) : in the first step , we generate the smoothed bootstrap sample $\hat{\theta}_1,\dots,\hat{\theta}_n$ to obtain a bootstrap replica $\theta^*_1, \dots, \theta^*_n$. . This is implemented as follows (Simar & Wilson, 1998) :

a- We draw with replacement (bootstrap) from $\hat{\theta}_1,\dots,\hat{\theta}_n$ to generate $\beta^*_1, \dots, \beta^*_n$.

b- We smooth the sampled estimates using the following formula: F

$$\grave{\theta}^*_n = \begin{cases} \beta^*_i + h\varepsilon^*_i & \text{if } \ \beta^*_i + h\varepsilon^*_i \ \leq 1 \\ 2 - \beta^*_i + h\varepsilon^*_i & ,\text{otherwise} \end{cases}$$

Where h is the bandwidth of a standard normal kernel density and ε_i^* is a random error drawn randomly from the standard normal distribution. The cross-validation method (Silverman, 1986) can be used to determine the bandwidth parameter as detailed by (Simar & Wilson, 1998).

We correct the variance of the bootstrap estimates by computing:

$$\theta_i^* = \grave{\beta}^* + \frac{\theta_i^* - \grave{\beta}^*}{\sqrt{1 + \sigma^2/\widehat{\sigma}_{\widehat{\theta}}^2}}$$

Where $\grave{\beta}^*$ is the average of $\beta_1^*, \dots, \beta_n^*$ and $\widehat{\sigma}_{\widehat{\theta}}^2$ is the sample variance of $\widehat{\theta}_1,\dots,\widehat{\theta}_n$

-Step 2: We generate a pseudo-data set $\eta_b^* = \{\{x_{ib}^*,\ y_i\}\ i = 1, \dots, n\}$, given $x_{ib}^* = \frac{\widehat{\theta}_i}{\theta_{ib}^*} x_i$(i.e., the calculated bootstrapped input based on bootstrap efficiency).

-Step 3: We solve the DEA program to estimate $\theta_{k,b}^*$. i.e., the bootstrap replica b estimate based on the replica technologyT^b. (Simar & Wilson, 2002)

$\theta_{k,b}^*$ = min $\{\theta \text{ subject to } \theta x_k \ \geq \sum_{i=1}^n z_i\ x_{ib}^*\ ;\ y_k\ \leq\ \sum_{i=1}^n z_i y_i\ ;\ \sum_{i=1}^n z_i = 1\ ; z_i\ \geq 0\ \}$

-Step 4: We repeat the steps 2–4: 2000 times (B =2000 times) to obtain a set of bootstrap estimates $\theta_{k,b}^*$ (b=1,…,B ; k=1,…,n.

Discussion of Data and Input-Output Variables

The objective of any transportation system is to deliver displacement services of passengers and freight through a production process that involves the interaction of two main factors: physical assets and human capital. The former consists of two elements: Infrastructures and Operations. Infrastructures are made up of tracks that shape the network rail, and stations in which passengers' transfers and freight maneuvers are performed. A railway infrastructure is known to be costly to implement and maintain, that is why it remains unchanged in the long run (De Jorge Moreno & Garcia-Cebrian, 1999, p. 337). Operations involve locomotives that provide the motive power of the train, passenger cars designed to carry passengers and freight cars or wagons to carry a host of goods. The human capital refers to all human resources involved into the management of train operations.

The data set of this study consists of twenty railways operating in developing countries over the period from 2013 to 2018. All the investigated railways are: state-owned, integrated (operations and infrastructure) and provide simultaneously passenger and freight transport services .To ensure more homogeneity amongst the sample, we prefer focus our interest only on developing countries where railways operate, to some extent, in similar economic, institutional and market conditions except for Spain. In fact, Despite the Spanish Railways FGC operates in a developed classified country , we include it into the sample to check the robustness of the Data Envelopment Analysis in providing reliable results. Indeed, one of the motivations of this study is to examine whether a DEA-based analysis suggest a railway that operate in a developed country being fully technically efficient compared to other railways that are in early stages of development. The observed railways of study are listed in Table N° 1.

Data on input and output variables were extracted from RAILISA (Rail Information System and Analysis), published by UIC (International Union of Railways) or in French "Union Internationale des Chemins de Fer"). The database provide numerous indicators for more than 100 railways such as: staff, rolling stock, train movements, financial results.. ,etc. since 1995 for some indicators (UIC, 2013-2018).

Table N°1
List of Railways observed in the study

Abbreviation	Denomination of the railway	Country
BC	Belarus Railways	Belarus
CD	CeskéDráhy	CzechRepublic
FGC	Ferrocarrils de la Generalitat de Catalunya	Spain
KORAIL	Korean National Railroad	Korea
LG	SPAB " Lietuvos Gelezinkeliai "	Lithuania
ONCFM	Office National des Chemins de Fer	Morocco
TCDD	Türkiye Cumhuriyeti Devlet Demiryollari Isletmesi	Turkey
SETRAG	Transgabonais	Gabon
SNTF	Société Nationale des Transports Ferroviaires	Algeria
BDR	Bangla Rail	Bangladesh
PR	Pakistan Railways	Pakistan
VN-DSVN	Tổng Công TyĐường SắtViệt Nam	Vietnam
RAI (IRIR)	Islamic Republic of Iran Railways	Iran
UZ-UTI	*O'zbekiston Temir Yo'llari*	Uzbekistan
ZFBH	Željeznice Federacije Bosnei Hercegovine	Bosnia Herzegovina
KTZ	Kazakhstan Temir Zholy	Kazakhstan
GR	Georgian Railway LLC	Georgia
AZ	Azerbaijan Railways (Azərbaycan Dəmir Yolları)	Azerbaijan
HZ	Hrvatske Željeznice	Croatia
SNCFT	Société Nationale des Chemins de Fer Tunisiens	Tunisia

Source: prepared by the authors.

(Hilmola, 2008, p. 261) argues that a joint-evaluation of two parts of railway operations is well justified as the use of railway inputs in many countries take care of both freight and passenger operations. Accordingly, for our Bootstrapped-DEA analysis, the inputs used consist of the major physical assets needed for any railway transportation service either for passenger or for freight operations:

1. Staff expressed as full time equivalent of the mean annual staff strength (Input 1).
2. Locomotives: include both electric powering and diesel powering (Input 2).
3. Passenger cars: Bodies in Multiple unit and trailers – coaches (Input 3).
4. Freight cars: Total number of wagons. (Input 4).

These inputs are used in a production technology to provide the following outputs evaluated as quantity times distance (train-KM):

1. Passenger-km achieved: number of kilometers travelled × number of seats available on the service freight (Output 1).
2. Freight Tons- km achieved: number of kilometers travelled × freight train cargo capacity in tones (Output 2)

In our study we have favored the use of train-KM output variable instead of the absolute values (number of passengers and freight tons) due to the high regulations on the railway industry that limit the ability of railways to optimize other outputs (Merkert, Smith, & Nash, 2009, p. 44). It is worth noting that some studies that a large number of studies that focus on railways efficiency and productivity use the network length (Tracks) as a major input, however we faced difficulties to collect consistent data on this variable. In some countries, the UIC does not provide comprehensive data of railway lines during the whole period of the analysis. Moreover, when we check the missing values in their respective official websites, we found inconsistencies in particular points of the period.

Table N° 2

Descriptive Statistics of Inputs and Outputs (Mean Values over the Period 2013-2018. Nbr.Obs : 120)

	Staff	Locomo-tives	Passen-cars	wagons	Passenger Trafic	Freigth traffic
Indicators	**Nbr**	**Nbr**	**Nbr**	**Nbr**	**Millions-KM**	**Millions-KM**
DMU	**Input1**	**Input2**	**Input3**	**Input4**	**Output1**	**Output2**
Korea	26936	479	2427	11096	23040	9004
Turkey	24832	645	1406	19227	4329	10554
Pakistan	72078	478	1743	16159	24903	8080

Croatia	3131	125	450	826	2652	1236
Gabon	1157	24	35	538	137	2722
Vietnam	28701	289	1022	4875	3883	3748
Iran	9158	892	2113	23686	15019	27379
Algeria	12718	275	364	10722	1355	965
Tunisia	4868	141	129	3477	1225	714
Morroco	7743	201	570	5480	5160	4454
Spain	1317	12	309	148	868	42
Lithuania	459	231	225	8466	402	14629
Uzbekistan	283	63732	788	21819	3973	22936
czech	22673	1502	3923	24928	7405	10848
Bosnia	3466	97	84	2143	22	809
Belarus	71442	792	2905	33906	7142	45303
Azarbejan	21160	290	441	15428	525	5976
Bangladesh	26575	278	1491	12813	8760	723
Georgia	8729	187	69	12215	557	3962
Kazakhstan	12725	1846	2486	69122	18507	208646

Source: prepared by the authors.

Discussion of Results

We estimate separate Bootstrap-DEA models under Variable Return on Scale VRS for each year over the period 2013-2018 assuming that technology might change during that period. Thus, the efficiency estimates are based on annual frontiers. *The* estimated scores range between 0 to 1 with high values indicating a fully efficient railway. Due to space constraints, we present in Table N°3 the technical details of results derived from the bootstrap-DEA only for the last year of the analysis (2018). The column 3 in Table N°3 shows the technical efficiency score based on the traditional DEA model (without bootstrapping) whereas column 4 in Table N°3 displays the bias-corrected technical efficiency score when the bootstrap is applied. Column 6 and 7 in Table N°3 represent the upper bound and lower bound confidence interval of estimated efficiency, respectively.

Table N° 3
Results of the Bootstrap-DEA Technical Efficiency Estimates

Railways	Country	Traditioal-DEA Score	Bootstrap-DEA Score	Bias	CI. Lower	CI. Upper
KORAIL	Korea	1.000	0.799	0.201	0.579	0.999
TCDD	Turkey	0.336	0.320	0.017	0.278	0.336
PR	Pakistan	1.000	0.793	0.207	0.575	0.999
HZ	Croatia	1.000	0.843	0.157	0.631	0.999
SETRAG	Gabon	1.000	0.797	0.203	0.587	0.999
VN-DSVN	Vietnam	0.445	0.407	0.037	0.325	0.445
RAI	Iran	1.000	0.798	0.202	0.575	0.999
SNTF	Algeria	0.416	0.388	0.027	0.321	0.415
SNCFT	Tunisia	0.822	0.769	0.054	0.627	0.822
ONCF	Morroco	0.766	0.704	0.062	0.548	0.766
FGC	Spain	1.000	0.787	0.213	0.575	0.999
LG	Lithuania	1.000	0.794	0.206	0.575	0.999
UZ-UTI	Uzbekistan	1.000	0.787	0.213	0.575	0.999
CD	Czech	0.359	0.327	0.033	0.245	0.359
ZFBH	Bosnia	0.343	0.310	0.033	0.212	0.343
BC	Belarus	0.580	0.524	0.057	0.359	0.580
AZ	Azerbaïdjan	0.261	0.233	0.028	0.175	0.260
BDR	Bangladesh	0.599	0.550	0.048	0.401	0.598
GR	Georgia	1.000	0.851	0.149	0.645	0.999
KTZ	Kazakhstan	1.000	0.791	0.209	0.575	0.999
Mean	-	0.605	0.531	0.058	0.400	0.604
STD	-	0.284	0.213	0.080	0.155	0.284

Source: Authors' calculations using "deaR", a software package in R developed by (Vicente , Rafael , & Bolos, 2020)

It can be seen from Table N°3 that the process of estimating efficiency by the bootstrap-DEA has enabled us to correct the bias efficiency estimates by 0.058 in the average (see column 5 in Table N°3). For example, the naïve DEA has assigned a score efficiency of a unity (one) for KORAIL (Korea) which means that the projected point of KORAIL lies on the efficient frontier and hence is free from any slacks inefficiencies. Whilst, the bootstrap technique has estimated a bias corrected score of 0.799 meaning that the railways KORAIL (Korea) could potentially reduce the utilization of its inputs (Staff, Tracks, passenger-freight cars) by 20.1 % to produce the same quantity of outputs (passenger and freight transportation delivered) compared to the best-practice railways of the sample given the same market and industry conditions. Accordingly, we assume that bootstrapping the DEA estimates provides more consistent and realistic results. In contrast with the naïve DEA in which the height of the DEA frontier is biased downwards leading to efficiency scores biased upwards (Coelli, Rao, O'Donnell, & Battese, 2005, p. 202) . Particularly, when the analysis deals with a finite sample that does not include all the DMUs in a population, which is our case.

Hypothesis 1 is accepted: The bootstrap technique has corrected the traditional DEA efficiency results and assigned a more consistent score. Especially, for railways that obtain a full score of unity (1.00). It is hard to admit the non-existence of slack inefficiencies when dealing with efficiency analysis. There are always areas of over used inputs or under produced outputs to readjust.

Table N°4 shows the evolution of railways technical efficiency over the period from 2013 to 2018. The results suggest that the average technical efficiency score for the railway transportation systems over the whole sample period is 0.561 indicating a 43,9 % average potential reduction in inputs utilization. The railway technical efficiency varies largely amongst the railways with a standard deviation around 21.8 % - 25 % over the observed period. Railways like KORAIL (Korea), PR (Pakistan), HZ (Croatia), ONCF (Morocco), SNCFT (Tunisia), SETRAG (Gabon) and FGC (Spain) represent the best benchmark for the other railways, with a technical efficiency score above 80 % in average. In contrast, SNTF (Algeria), TCDD (Turkey), VN-DSVN (Vietnam), CD (Czech) are the less railways performer getting a technical score efficiency less than 40% in average. The company AZ (Azerbaijan) has demonstrated the worst average efficiency score of 0.222.

Hypothesis 2 is accepted: A standard deviation of 21,3 % in average indicates a high variability in the observed railways technical efficiency. Also, if we refer to the stuff figures (see Descriptive statistics in Table 2) as one of the major indicators of the firm size. We notice that many of small sized railways such as SETRAG (Gabon), LG (Lithuania) , UZ-UT (Uzbekistan), FGC (Spain) obtained a higher efficiency score compared to some large-sized railways like TCDD (Turkey), VN-DSVN (Vietnam), CD (Czech), AZ (Azerbaijan). In line with (De Jorge-Moreno & Isabel Garcia-Cebrian, 1999), these findings indicate how the choice of an inappropriate operating size ends up with scale inefficiencies and badly affect the railways performance.

The Figure N°1 in the Appendix shows a network representation of the observed railways' technical efficiency scores where we can identify the peer benchmark group for each DMU.

Table N° 4
Yearly Technical Efficiency (Bootstrap DEA model under VRS)

Railways	Country	Corre-TE. 2013	Corre-TE. 2014	Corre-TE. 2015	Corre-TE. 2016	Corre-TE. 2017	Corre-TE. 2018	Mean-Year TE	STD-Year
KORAIL	Korea	0.833	0.806	0.798	0.813	0.804	0.799	**0.809**	0.012
TCDD	Turkey	0.302	0.355	0.338	0.341	0.354	0.320	**0.335**	0.019
PR	Pakistan	0.910	0.899	0.868	0.880	0.808	0.793	**0.860**	0.044
HZ	Croatia	0.868	0.855	0.856	0.863	0.856	0.843	**0.857**	0.008
SETRAG	Gabon	0.834	0.813	0.796	0.823	0.807	0.797	**0.812**	0.014
VN-DSVN	Vietnam	0.478	0.443	0.448	0.366	0.413	0.407	**0.426**	0.036
RAI	Iran	0.841	0.823	0.802	0.815	0.812	0.798	**0.815**	0.014
SNTF	Algeria	0.319	0.299	0.308	0.413	0.416	0.388	**0.357**	0.050
SNCFT	Tunisia	0.946	0.956	0.929	0.921	0.815	0.769	**0.889**	0.071
ONCF	Morocco	0.957	0.947	0.926	0.924	0.937	0.704	**0.899**	0.088
FGC	Spain	0.833	0.814	0.796	0.817	0.805	0.787	**0.809**	0.015
LG	Lithuania	0.835	0.817	0.798	0.803	0.799	0.794	**0.808**	0.014
UZ-UTI	Uzbekistan	0.843	0.811	0.796	0.809	0.812	0.787	**0.810**	0.017
CD	Czech	0.302	0.279	0.303	0.325	0.337	0.327	**0.312**	0.019
ZFBH	Bosnia	0.922	0.690	0.514	0.310	0.284	0.310	**0.505**	0.236
BC	Belarus	0.730	0.540	0.519	0.512	0.528	0.524	**0.559**	0.077
AZ	Azerbaïdjan	0.191	0.193	0.161	0.318	0.237	0.233	**0.222**	0.050
BDR	Bangladesh	0.655	0.561	0.603	0.711	0.591	0.550	**0.612**	0.056
GR	Georgia	0.905	0.931	0.517	0.868	0.855	0.851	**0.821**	0.139
KTZ	Kazakhstan	0.828	0.815	0.795	0.807	0.810	0.791	**0.808**	0.012
Mean-Sample	-	0.573	0.551	0.517	0.569	0.548	0.531	0.561	-
STD-Sample	-	0.250	0.246	0.237	0.236	0.231	0.218	-	-

Source: Authors' calculations using "deaR", a software package in R developed by (Vicente , Rafael , & Bolos, 2020)

The yearly results seem to indicate that most of the railways witnessed a decline in technical efficiency figures across the period from 0.573 in 2013 to 0.531 in 2018, with differences in the magnitude of the decrease trend (see the standard deviation in column 10 Table N°4). However, in the middle periods, each railways performance evolves differently and most of them show the same efficiency scores over the years studied with shifts representing occasional back and forth developments.

Some interesting facts can be outlined from the evolution of technical efficiency in specific periods (see Figure N° 2 in the Appendix). In fact, the railways (ZFBH) have experienced a significant worsening of its performance from 0.95 in 2013 to 0.28 in 2017. The Moroccan ONCF has maintained a steady technical efficiency score above 0.92 from 2013 to 2017 but its performance drastically decreased to 0.704 in 2018. The same evolution is observed in BC (Belarus), the company has kept the same level of performance (0.52 in average) for five consequent years after a substantial decrease in efficiency from 0.730 in 2013 to 0.540 in 2014. Finally, only four railways have made the exception with regard to the negative trend of technical efficiency. Interestingly, the railways that have been identified as the worst performers in the group are those that have made an improvement in their technical efficiency over the period. In fact, SNTF (Algeria) showed a highest performance progress (+ 0.07) through the years studied, followed by AZ (Azerbaijan), TCDD (Turkey) and CD (Czech).

Hypothesis 3 is accepted: The dynamic changes in technical efficiency of railways are not obvious as the efficiency scores of the most observed railways evolve with a low magnitude over the period (with a standard deviation under 5% for most of them). In fact, the railways transportation is a complex industry and requires huge investments in operations and infrastructures. Hence, any policy readjustment made by the managers to improve the railways performance would not be observable in the short run.

Conclusion

This paper has employed the Bootstrap DEA analysis to estimate the technical efficiency of 20 railway companies from developing countries in the time frame of 2013-2018, based on an Input-Output orientation model under Variable Return on Scale. In general, the empirical findings demonstrate that bootstrapping methodology is useful for the analysis as it provides more consistent and realistic efficiency estimates in contrast with the conventional DEA. In this respect, The Bootstrap DEA results suggest that the average technical efficiency score for the railway transportation systems over the whole sample period is 0.561 indicating a 43,9 % average potential reduction in inputs utilization.

The findings also reveal the existence of significant gaps in technical efficiency across the observed railways. In general, the reasons that stand behind the existence of efficiency gaps between the railway companies depend on many factors (Arne , Heiner , & Martin , 2013, p. 5) : Regulations and infrastructures constraints that affect the freight and passenger train length. Indeed, government and regulatory institutions can significantly affect the efficiency of railway companies by opening the rail market to competition and providing a consistent and reliable funding for rail infrastructures and operations that improve the quality of public mobility. Similarly, Technology plays a crucial role to enhance railway efficiency through the use of effective maintenance of assets, automation of process, state-of-art technologies of communication.,*etc*. For better understanding of how county or region-specific factors impact the performances of railways, we suggest conduct a two-stage DEA in future research to empirically identify the determinants of railway efficiency in developing economies.

With regard to the evolution of the investigated railways, the results show a decline in railways performances from 0.573 in 2013 to 0.531 in 2018 with shifts representing occasional back and forth developments in the middle periods. Applying the Malmquist Productivity Index MPI is more appropriate if the analyst is concerned with identifying the nature of dynamic changes in efficiency whether improvements are due to better internal management of inputs and outputs (pure technical efficiency), or just attributed to shifts in the frontiers (technological change).

The key limitation of our analysis is probably the lack of studies that tackle the efficiency of railways in the context of developing countries, yet, we cannot check the consistency of our research outcomes with other studies. From this perspective, we think that further evidence would greatly benefit our understating in this topic from the perspective of economies in development. We suggest apply another frontier technique such as the Stochastic Frontier Analysis.

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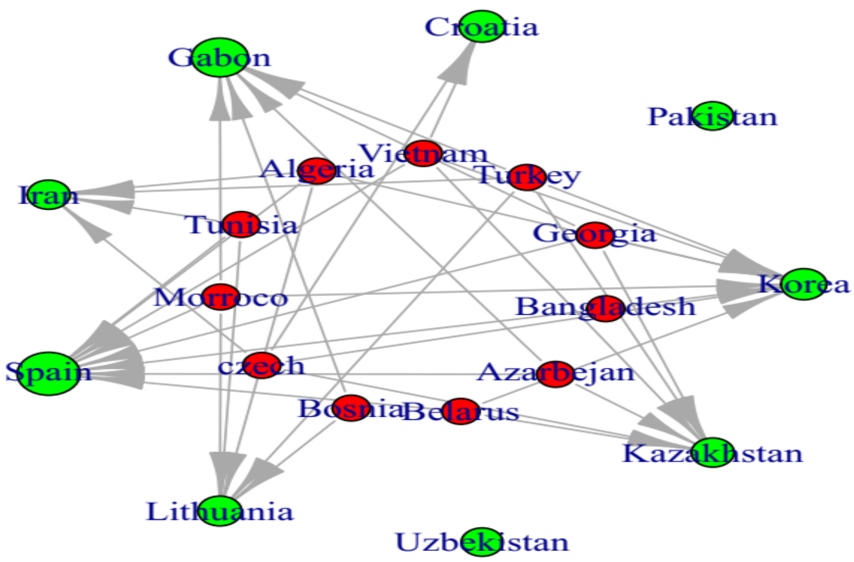
Appendix

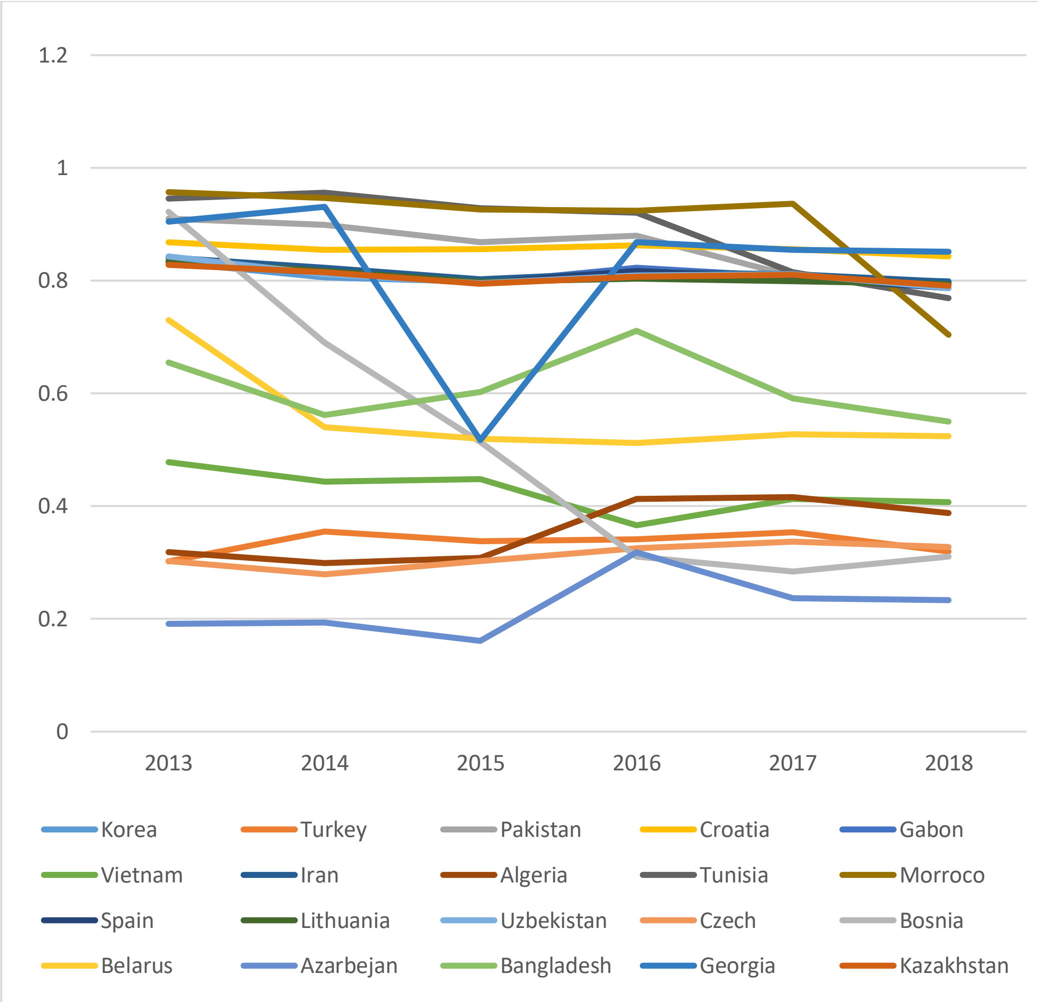
Figure N° 1
Network Graph of Railways' Technical Efficiency Scores



Source: Authors' calculations using "deaR", a software package in R developed by (Vicente , Rafael , & Bolos, 2020)

Note: The green circles represent the efficient DMUs and the red circles the inefficient ones. The size of the circle aims to convey the idea of how important is the efficient DMU for the set of inefficient DMUs. Lines of direction refer to the set of the peer benchmark group of each DMU.

Figure N° 2 : Evolution of Technical Efficiency



Source: prepared by the authors.