sustainability

Systematic Review

The Development of Efficiency Analysis in Transportation Systems: A Bibliometric and Systematic Review

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Abstract: This paper presents a literature review of efficiency analysis in transportation systems (TS). It builds a bibliometric review of published data-envelopment analysis and, for the first time, stochastic frontier analysis publications in TS. The retrieved publications were separated into five groups: highway/road transportation, air transportation, maritime/port transportation, railway transportation, and urban/bus transportation. The 135 data-envelopment-analysis rail-related publications were surveyed to assess the model used, the second-stage analysis (if any), the input–output variables, the model orientation, return-to-scale assumptions, and their methodological classification. The results show that frontier methods in transportation systems have gained relevance since 2017. Also, gaps in the literature and future directions have been identified in empirical rail research, such as eco-efficiency and safety-related issues, as well as the need for a better investigation of variable choice and scale return assumptions. Finally, this paper proposes a step-by-step methodology for data envelopment analysis in rail systems.

Keywords: data envelopment analysis; stochastic frontier analysis; efficiency; literature review; rail; transport

JEL Classification: L92; D24; R40

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1. Introduction

The operational performance analysis of firms has witnessed a revolution since the late 1970s [1]. Naturally, it has led to comparisons between firms and the public sector, paving the way for benchmarking analysis.

The word, *benchmarking* can be understood as a tool for the continuous improvement of quality, and identifying and comparing companies in the sector that are excellent in some aspect, which can be copied, incorporated, or adapted. This concept first appeared in 1989 [2], popularized by Xerox. Since then, it has been applied to almost all economic sectors, as the idea of benchmarking (frontier) is consistent with the economic theory of optimizing behavior as deviations from best practices, and enables the proposition of feasible corrective goals [3].

The methods for quantifying relative efficiency were mostly inspired by the work of Farrell [4], who presented the possibility of estimating an efficient productive frontier with the best practices and, by calculating the distance of each productive unit from that frontier, of estimating the relative efficiency. The two most popular methods to measure efficiency are a parametric and a non-parametric one. The parametric one, Stochastic frontier analysis (SFA), was first introduced in seminal articles by Aigner et al. [5] and Meeusen and van Den Broeck [6]. Their idea was implemented by specifying a statistical model characterized by a compound error term in which the classical stochastic disturbance, to capture the measurement error and any other classical noise, is complemented with a one-sided, non-negative disturbance that represents inefficiency. SFA models are generally estimated using maximum-likelihood-based methods, and their main advantage is to make inferences about both the frontier parameters and the inefficiency. An expanded review of these models can be found in Kumbhakar et al. [7].

Among the non-parametric methods, the data envelopment analysis (DEA) and the free disposable hull (FDH) models stand out, the former being the most popular. Data envelopment analysis was initially proposed by Charnes et al. [8], and incorporates a Pareto–Koopmans efficiency or full efficiency assumption and provides a relative efficiency measure of decision-making units (DMU). It allows the use of multiple inputs and outputs without imposing, a priori, any functional relationship between inputs and outputs to build an empirical frontier. It uses mathematical programming to obtain an ex post facto indicator of the relative efficiency of DMUs, identifying the benchmarks against which inefficient DMUs can be compared.

There has been some controversy over which technique (SFA or DEA) should be used to estimate and analyze efficiency. Lovell et al. [9] and Coelli et al. [10] suggest that there are advantages and disadvantages associated with the use of DEA and SFA, but neither approach strictly dominates the other. Lampe and Hilgers [11] analyzed both DEA and SFA publications in general, from 1978 to 2012, identifying seminal papers that have played a major role in the study of productivity, efficiency, and its determining factors. One important contribution of this work relates to the adoption rate of new knowledge. According to the authors, current research tends to build on recent and older literature, but not so much on middle-aged publications. Thus, for DEA and SFA, the authors were able to identify the use of modern techniques.

One of these popular innovations is models for robust analysis of productivity, efficiency, and determining factors using bootstrap DEA techniques and semiparametric second-stage DEA methods. From the seminal works of Simar [12] and Simar and Wilson [13], these approaches have emerged to deal with boundary issues arising from the deterministic and non-parametric nature of DEA estimators, creating a symbiosis that integrates the random term contained in methods of the type SFA to the frontier estimated by non-parametric methods of the DEA type. The last decade has seen an exponential growth in the use of the bootstrap approach in efficiency and productivity studies [14], with the number of citations of the bootstrap methods by Simar and Wilson [15–17] exceeding 7200.

In transportation systems—a part of what is known as utility services, along with telecommunications, electricity, water, and sanitation—benchmarking gained importance as an indispensable regulatory tool. During the 1990s, a wave of infrastructure privatization and denationalization began in many developing countries, associated with an attempt to reduce the public deficit, and attract foreign investment through the segmentation of vertically integrated companies, a new regulatory framework, and the creation of new independent regulatory agencies.

Until then, these utility services and natural monopolies were mainly controlled and operated by the state through direct administration bodies, autarchies, or public companies. However, in this new regulatory framework, efficiency and benchmarking are at the core of regulators' responsibilities when implementing incentive-based regulations [18]. One of the most important incentive-based regulation tool is the price-cap, with every OECD country adopting this regulation scheme in at least one industry [19].

In short, it consists of regulating maximum prices for each product offered or for a basket of them through a periodically reviewed CPI-X rate. This rate is equal to the change in the general price index (CPI) minus a productivity factor offset, commonly denoted by X. To determine X, agencies periodically carry out or order studies on the growth of total factor productivity (TFP) and the relative efficiency levels of companies in the sector. This procedure is, by definition, a benchmarking approach, mainly adopting frontier-based methods such as DEA and SFA, and its estimation is a complex matter [18].

Alongside its regulatory importance, transportation systems are of vital importance to economic development and regional integration but are also responsible for a set of undesired outputs. In 2021, according to data from the IEA (https://www.iea.org/topics/

transport accessed on the 10 June 2023), transportation was responsible for 37% of CO_2 emission from end-use sectors. According to the World Health Organization (https://www.who.int/en/news-room/fact-sheets/detail/road-traffic-injuries accessed on 10 June 2023), by 2030, road traffic accidents are expected to be the seventh largest cause of death, hence the importance of efficiency and performance assessment in TS.

Thus, the goal of this work is to offer a comprehensive bibliometric analysis of DEA and SFA applied to the transportation sector, from 1977 to 2022, and a systematic review of DEA papers applied to the rail sector, in an attempt to answer the research question: "How to assess the efficiency of transport systems and what are their determining factors?". To our knowledge, this is the first work that includes both SFA and DEA in transport.

From the posed question, we will be able to contribute to the academic discussion on literature gaps and future directions for data envelopment analysis and rail-related research, as well as propose a bibliometric update of DEA documents in transportation systems and, for the first time, a bibliometric assessment of stochastic frontier publications applied to TS, serving as a base for efficiency and performance analysis in TS.

This work is organized as follows: In Section 2, the referenced literature reviews are presented. In Section 3, the methods and materials are presented, including a detailed description of the databases and data treatment. Section 4 presents the results of the bibliometric analysis and the main statistics regarding DEA and SFA publications. Section 5 proposes a new segmentation for the surveyed literature and a detailed systematic review of DEA in railway sector is presented. Section 6 contains the final remarks and conclusions of the article.

2. Referenced Reviews

For the research regarding DEA in transportation sector, the main previous literature reviews considered in this study are those by Mahmoudi et al. [20] and Cavaignac and Petiot [21].

Mahmoudi et al. [20] used Google Scholar, Web of Science, and Scopus databases to identify more than 600 articles from 1989 to 2018 and classified the 40 most cited papers published from 2007 to 2018 to explore the DEA applications in transport. For those 40 papers, the authors investigated the most common DEA models used for transportation systems, stating that "CCR (Charles, Cooper & Rhodes), BCC (Banker, Charles & Cooper) and SBM (Slacks-Based Measure) are the most popular models used in the literature".

Cavaignac and Petiot [21] also surveyed DEA literature applied to transport sector using mainly Scopus, Google Scholar, and Econlit databases. They found 461 articles from 1989 to 2016, providing a summary of the 35 most cited articles presenting scope, models and results, as well as an analysis for articles dealing with ports and airports. From the analysis of the most cited papers, the authors identified that:

> *"The number of DMUs, inputs and outputs were far from obeying the rules which state that the number of DMUs should be greater or equal to twice the product of the number of inputs and the number of outputs or that the number of DMUs should be at least three times the number of inputs and outputs together".*

As for model decision, Cavaignac and Petiot [21] stated that more than half implemented DEA, CCR, or BCC. Also, all other analyses were completed using additional methods such as Malmquist indices, second-stage regression analyses, Simar and Wilson bootstrapping regression analysis etc. Most of the surveyed articles used a VRS formalization.

Mahmoudi et al. [20] proposed a literature segmentation with six sections: (1) DEA and highway transportation, (2) DEA and air transportation, (3) DEA and ports and maritime transportation, (4) DEA and railway transportation, (5) DEA, eco-design, sustainable development, and green issues in transportation, and (6) DEA and other transportation research.

The authors identified that a third of the retrieved articles relate to air transportation and 80% of the papers published between 2008 and 2018 are related to air transport. The authors also present the most cited articles, as well as the most active journals and most productive countries. Mahmoudi et al. [20] used social network analysis (SNA) for citation and co-citation analysis, collaboration among researchers, knowledge patterns, gaps, and emerging knowledge trends within each of the six categories.

In a similar manner, Cavaignac and Petiot [21] presented a monovariate and a multivariate analysis for a number of publications, journals, authors, geographical areas, articles, impact, and a segmentation for DEA research in transport systems, with six categories: air, maritime transport, transit, rail, road, and articles that deal with the transport system as a whole.

We highlight the findings for rail transportation in the work of Mahmoudi et al. [20]. From the 29 surveyed papers, the authors identified the following themes as the most important: (i) performance assessment of railway passenger and freight transportation companies; (ii) performance assessment of railway transport considering environmental issues; (iii) selection and location of urban railway stations; (iv) assessment of the effect of private sector participation, governance structure, policy changes and new investments on performance and efficiency; and (v) performance of rail transportation through time.

For future research in railway systems, Mahmoudi et al. [20] highlight the need for studying various perspectives such as environmental, economic, and social sustainability as well as user experience and quality of service.

Considering that railway transportation, especially in developing countries, has a governmental structure, the assessment of the effects of privatization on performance and efficiency is an important research subject, as well as the assessment of before/after policy/regulatory changes. In addition, Mahmoudi et al. [20] indicate that sustainability and safety issues are an emerging theme that can be analyzed through DEA.

Regarding literature reviews on SFA in transport, as stated in the Introduction, we were unable to identify any.

3. Materials and Methods

Bibliometrics is a research technique that studies publications to quantify, analyze, and critically evaluate relevant scientific production on specific topics. It measures the contribution of scientific knowledge derived from publications, identifying their authors, institutional affiliation, research networks, citations, and keywords. It is used to represent current research trends, identify new themes, methods, and gaps in the literature as a means of supporting the justification and planning of future investigations [22]. To stay current in their fields, researchers often recur to these studies.

The fundamental component of bibliometric research is a database of published documents and its analysis is both objective and subjective in essence [23]. In sum, the goal is to summarize large quantities of bibliometric data and present the state of the intellectual structure and emerging trends of a research topic or field and is used when the database is too big for a manual analysis [23].

The importance of bibliometric analysis has grown exponentially over the last few years [24–26], especially with the advances and popularization of bibliometric software such as VOSviewer and programming language packages such as Bibliometrix. Despite its ever-growing importance, it is still relatively new in management and business research [23].

The primary benefit of adopting this approach lies in its ability to overcome the limitations of qualitative reviews. Instead of relying on the judgement of a single expert, it harnesses the collective judgment of many experts in a given field.

Another method of review research is the systematic review. Its main objective is to provide a comprehensive synthesis of relevant studies in a single document [27]. It enables researches to analyze scientific contributions and summarize findings [28], and differs from traditional qualitative narrative reviews in that it adopts a reproducible process, creating a trail of author decisions, methods and findings.

We believe that the integration of a bibliometric and systematic review can be a powerful tool in analyzing literature. In this context, to answer the research question stated in the Introduction, we propose a bibliometric analysis, taking as reference the PRISMA Statement (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) for both

DEA and SFA publications related to transportation systems, followed by a systematic review for DEA rail-related papers, founded on the steps proposed by Tranfield et al. [29], when possible and applicable.

The PRISMA Statement is an evidence-based minimum set of items aimed at helping researchers report a wide array of systematic reviews and meta-analyses. It consists of a 27-item checklist and three phase diagram [30]. The three phases are: (i) identification; (ii) screening; and (iii) included. The description of each phase and the 27-item checklist can be found in The PRISMA 2020 statement: an updated guideline for reporting systematic reviews (bmj.com accessed on 17 August 2022).

Tranfield et al. [29] proposed 3 stages and 9 phases for systematic reviews in management sciences. We highlight Stage II—Conducting a Review and its phases of selection of studies; study quality assessment, data extraction; and data synthesis, applied in this research.

When comparing the proposed methodology to the reviews mentioned in Section 2, the approaches are similar in essence, but we opt for a more formal systematic review, overcoming the limitation of analyzing only a limited number of publications in a specific segment of TS and proposing a more in-depth discussion of important issues.

In particular, Cavaignac and Petiot [21] provided a descriptive summary and commented analysis of a reduced sample of 22 papers published in 2014 on the airport and port sectors. Mahmoudi et al. [20] broadened the scope of analysis by assessing a limited number of papers in each pre-defined category. We provide a systematic review of all DEA rail-related papers.

For this work, we considered mainly research written in English. The database used as the main source of information was Web of Science (WoS), consulted on the 5th of August of 2022. WoS is a multidisciplinary global citation database originally developed by the Thomson Institute for Scientific Information (ISI), currently maintained by Clarivate Analytics and its platform allows for the search of almost 1.9 billion cited references from over 171 million records.

We have not included the Scopus database since, as presented by the R package "bibliometrix" documentation [31], "Scopus data needs a huge cleaning phase to match reference items (often the same reference is written in several different ways!)", making it virtually impossible to conduct a citation and co-citation analysis on Scopus database.

At first, using the keywords (efficiency OR productivity) AND (transport OR transportation), WoS returned more than 12,000 results, with an substantial part dealing with energy or engine efficiency, much like the results from Yakath Ali et al. [32] when reviewing literature on air transportation efficiency. As energy or engine efficiency are not necessarily the scope of this work, we restricted the keywords to concentrate only on documents dealing with DEA and SFA in transport systems, with no date restriction.

The keywords used in WoS search engine were:

- ("data envelopment analysis") AND (transportation OR transport);
- ("data envelopment analysis") AND (road OR highway);
- ("data envelopment analysis") AND (rail OR railway OR railroad);
- ("data envelopment analysis") AND ("air transport" OR "air transportation" OR airport OR airline);
- ("data envelopment analysis") AND (maritime OR "port");
- ("stochastic frontier") AND (transport OR transportation);
- ("stochastic frontier") AND (road OR highway);
- ("stochastic frontier") AND (rail OR railway OR railroad);
- ("stochastic frontier") AND ("air transport" OR "air transportation" OR airport OR airline);
- ("stochastic frontier") AND (maritime OR "port").

The retrieved documents from the selected database contain the information registered in Table 1.

Table 1. WoS Retrieved Variables.

Variable	Description
AU	Authors
TI	Document title
SO	Publication name (or source)
JI	Iso source abbreviation
DT	Document type
DE	Authors' keywords
ID	Keywords associated by scopus or isi database
AB	Abstract
C1	Author address
RP	Reprint address
CR	Cited references
TC	Times cited
PY	Year
SC	Subject category
UT	Unique article identifier
DB	Bibliographic database

Figure 1 presents a modified version of the PRISMA flow diagram for updated systematic reviews which included searches of databases and registers only.

In identification phase shown in Figure 1, the 1910 identified registers from WoS's database were analyzed by an automation tool to remove all books and conference papers.

In the screening phase, we checked both the articles' titles and abstracts to identify registers that had no efficiency analysis or those that were not related to transportation systems. Then, the 1217 remaining articles assessed for eligibility were analyzed through publication-related metrics, citation-related metrics, and science mapping techniques. This Bibliometric analysis is an important intermediate step to locate efficiency research in transportation.

After the bibliometric analysis on DEA and SFA transport publications, we categorized the articles in 5 groups, representing each transportation system: highway/road transportation, air transportation, maritime/port transportation, railway transportation, and urban/bus transportation.

Then, we conducted a systematic review on DEA publications related to rail transportation and assessed the intellectual structure of the field through a co-citation, coupling, and keyword analysis. Citation analysis is a major bibliometric approach, as "a scientific paper does not stand alone" [33]. It shows the structure of a research field and is usually consists of two different analyses: coupling and co-citation [31], and can be applied to both authors and journals.

Bibliographic coupling is a similarity measure for clustering research papers [34]. It occurs when two papers reference a common third document in their bibliography and its strength increases as the number of references in common increases. Co-citation occurs when two documents are cited by a third document [35]. Co-citation is larger when two documents are cited by many other documents. Figure 2 illustrates a bibliographic coupling and a bibliographic co-citation, respectively.

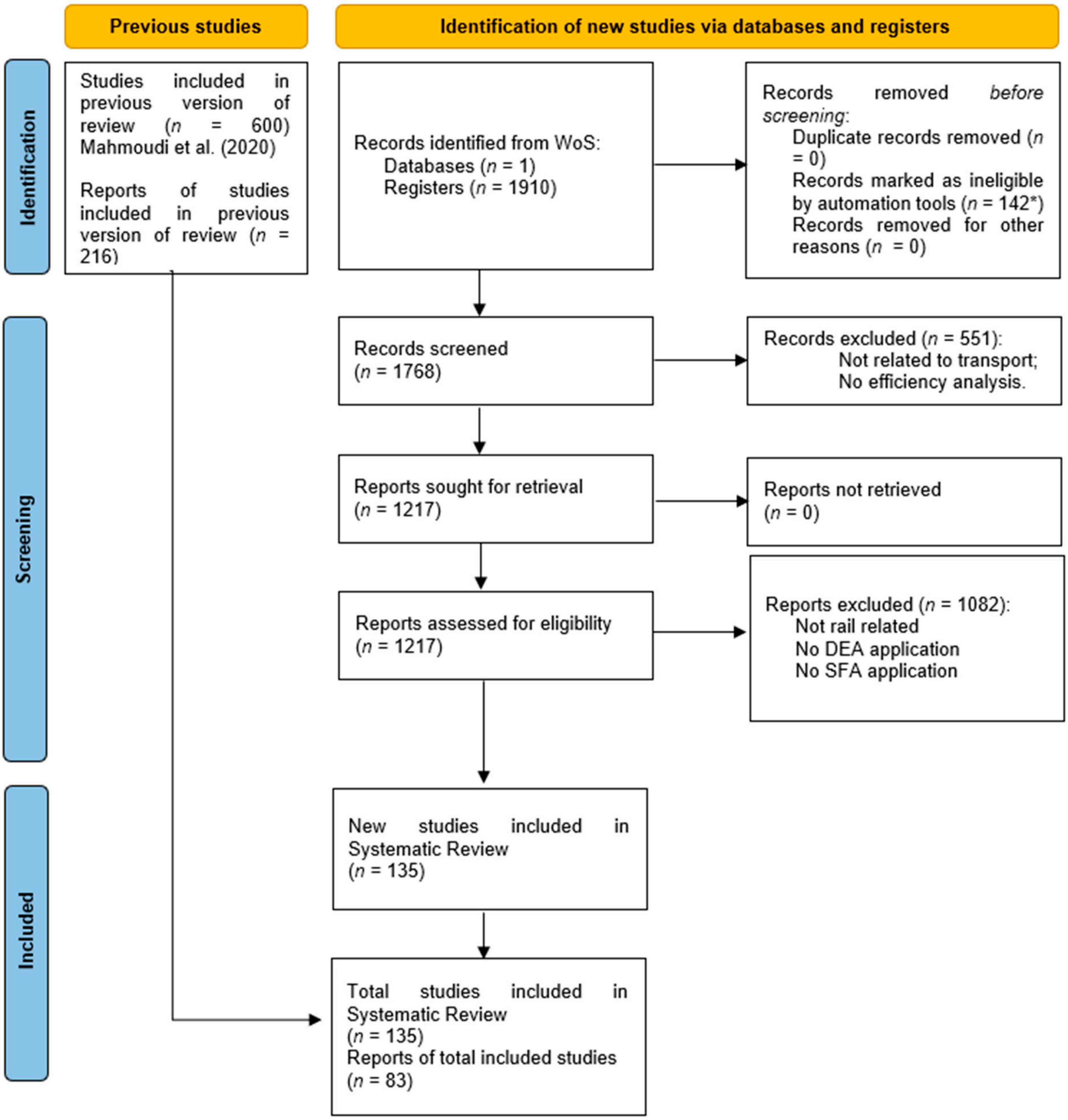

Figure 1. PRISMA's Flow Chart. * Books and conference papers were removed.

Articles A and B are coupled when they cite papers 1, 2, and 3. Papers A and B are associated with each other because they are both cited by papers 1, 2, and 3.

This knowledge mapping is especially important, as it does not constitute the authors' opinion, but a quantitative view of the intellectual structure of the field. In this work, we use both methods as it is our goal to explore older papers in different time periods, better represented by co-citation analysis, and explore current research subjects, better represented by bibliographic coupling [31].

Lastly, the categorized rail publications were reviewed to assess their objectives, used method for efficiency analysis, input–output variables, and results. With the proposed methodology, we intend to identify trends in research subjects, as well as gaps and future directions.

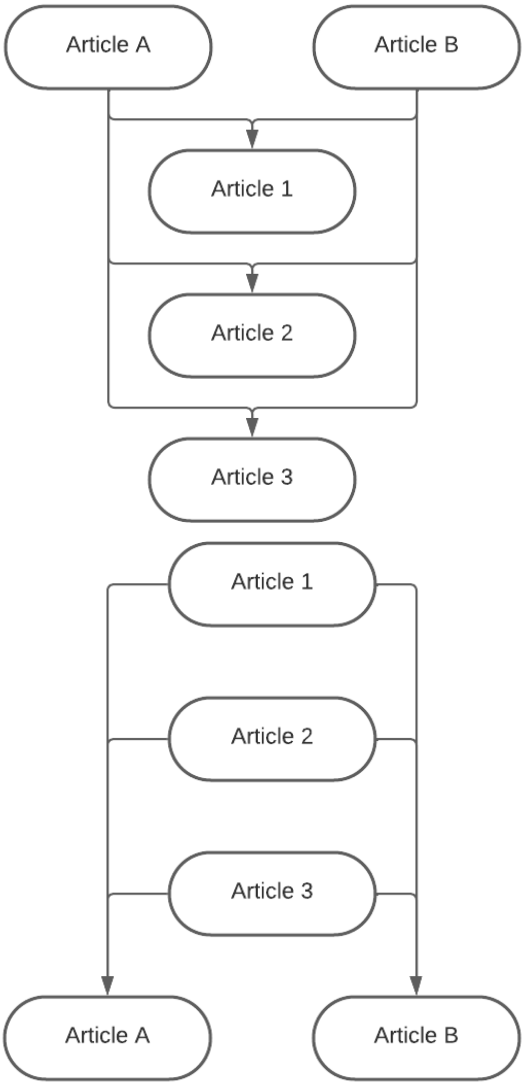

Figure 2. Bibliographic coupling and bibliographic co-citation.

Data Treatment

With WoS database of DEA and SFA publications in transport systems, we proceeded a data treatment using the R Programming language. The first step is to adjust misspelled author names or differently written names in different documents. This is a known problem in digital bibliography databases and its non-treatment can compromise the bibliometric analysis [36], especially citation and productivity metrics, and invalidate conclusions.

For author name disambiguation, we used the algorithm proposed by Fournier et al. [37], operationalized in refsplitr package for the R programming language. The proposed approach, as cited by the package developers, is to identify clusters by iteratively building webs of authors using mainly ORCID and RID numbers, as well as other available information such as address, email, or middle name. If one of these variables match when comparing different spelling names, the package assumes it is the same author. If it doesn't, the package calculates a confidence score from provided information and Jaro–Winkler textual matching. For this work, we used a confidence score of 5, cited by the package authors as "nearly always correct".

Regarding citations, data cleaning was not necessary as WoS pre-processes databases' reference lists, rewriting them as first author, year, journal, issue, and DOI, making it possible to perform citation and co-citation analysis.

Lastly, we analyzed author keywords and keywords plus to create clusters when the same word/idea were written in different ways. As a brief example, we considered the keywords, "data envelopment analysis", "dea", "data envelopment analysis (dea)" as the same keyword.

4. Results

As presented in Section 3, we identified 1910 documents resulting from the keywords used in WoS search engine. In PRISMA's identification phase, 142 books and conference papers were removed and in the screening phase; another 551 papers were excluded as they do not present an efficiency analysis or are not transport related. This resulted in a total of 1217 articles, 1041 DEA papers and 318 SFA papers. It is important to mention that the sum of DEA and SFA papers did not result in the total 1217 papers, as some of the retrieved documents apply both DEA and SFA.

Thus, as stated in Item 3, we present a preliminary assessment of the main statistics regarding those 1217 papers, such as the number of publications, growth rate, most productive authors, most productive countries, and most cited articles. Before entering each specific mode of transport, we considered this a relevant intermediate step to locate efficiency research in transportation and its main actors.

4.1. Statistics on DEA Publications

4.1.1. Number of Publications

As stated, 1041 published articles were identified for DEA in transportation. The publications range from 1989 to 2022, with an annual growth rate of 15% and an average citation per year of 2.83. Figure 3 presents the publication time series of DEA documents in the transport sector.

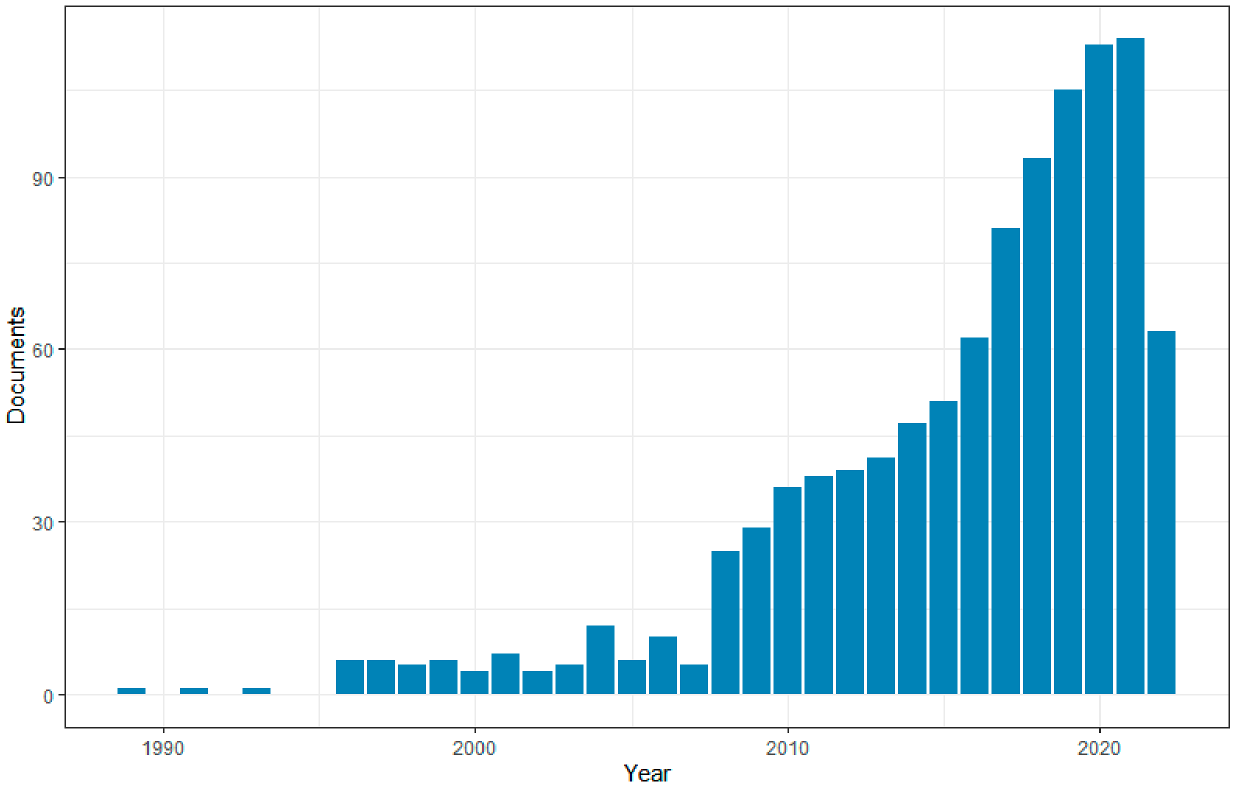

Figure 3. DEA publications time-series.

From those 1041 published articles, there were 1020 articles and 21 reviews. The most productive year was 2021, with 114 published documents.

Regarding journals, we identified 283 sources with a less concentrated database when compared to Cavaignac and Petiot [21] findings. These authors verified that one publication out of three was published in a group of only five journals. This time around, we found that one paper out of three was published in a group of 26 journals.

It is also interesting to note that the five journals cited by Cavaignac and Petiot [21] as having the most published articles for DEA in transportation—*Journal of Air Transport Management* (JATM), *Transportation Research Part E* (TRE), *Transportation Research Part A* (TRA), *International Journal of Transport Economics* (IJTE), *and Transport Policy* (TP)—still constitute an significant part of DEA publications in this updated literature review.

However, we can identify a newcomer: *Sustainability*. This journal was not even cited by Cavaignac and Petiot [21] and appears with only eight publications in Mahmoudi et al.'s review [20], but has become the journal with the second-most DEA publications in transport, with 45 articles. Indeed, when looking at the retrieved database, it seems that operational research in transport was included as a topic of interest in *Sustainability*, with its first publication in 2015.

Furthermore, it seems that transportation journals in general have become more relevant over the years, and DEA publications also seem to have reached more relevant journals. In the Cavaignac and Petiot [21] review of journals with at least five DEA publications in transport, only two had an h-index (The h-index is an author and scholarly journal-level metric that measures the productivity and citation impact of publications, initially used for an individual scientist or scholar.) higher than 100. This time around, we found 8 out of the 15 journals had an h-index higher than 100.

Table 2 shows the top 15 journals in number of publications.

Table 2. Journals with the most DEA-TS publications.

Sources	Articles	Impact Factor 2021	H-Index 2021
Journal Of Air Transport Management	76	5.97	82
Sustainability	45	4.17	109
Transport Policy	42	6.36	103
Transportation Research Part A-Policy And Practice	42	5.59	142
Maritime Economics & Logistics	31	3.12	55
Transportation Research Part E-Logistics And Transportation Review	29	10.75	122
Transportation Research Part D-Transport And Environment	26	7.04	113
European Journal Of Operational Research	21	6.39	274
Journal Of Cleaner Production	19	10.96	232
Maritime Policy & Management	16	3.41	61
Accident Analysis And Prevention	15	6.49	164
International Journal Of Transport Economics	15	0.18	24
Journal Of Transport Economics And Policy	14	0.65	57
International Journal Of Shipping And Transport Logistics	13	1.31	25
Journal Of Advanced Transportation	13	2.47	51

From the listed 15 journals, 12 are transport-specific and they represent 20% of all published DEA documents in TS. The mean impact factor (The impact factor (IF) or journal impact factor (JIF) of an academic journal is a scientometric index calculated by Clarivate that reflects the yearly mean number of citations of articles published in the last two years in a given journal, as indexed by Clarivate's Web of Science.) (IF) 2021 of the 15 journals is 5, with only two presenting an IF lower than 1. This shows clear growth when compared to Cavaignac and Petiot [21] results, as they verified that the "average Impact Factor of the 23 most publishing journals in the field is rather low (1.5446 in 2015) which results in a small extra-sectorial diffusion", and can be interpreted as increased academic importance regarding DEA publications in transport, reaching higher-impact-factor journals and increasing extra-sectorial diffusion.

4.1.2. Authors

For authors, we identified 2033 for 1041 documents, with an average of 3 co-authors per document and an international co-authorship of 29%. We identified a high concentration of publications when analyzing authors, where 30 authors comprise more than a third of all 1041 published documents, a result that can be compared to Cavaignac and Petiot [21], where they identified a quarter of the authors is involved in 61.4% of the articles. Figure 4 presents the top 30 most productive authors.

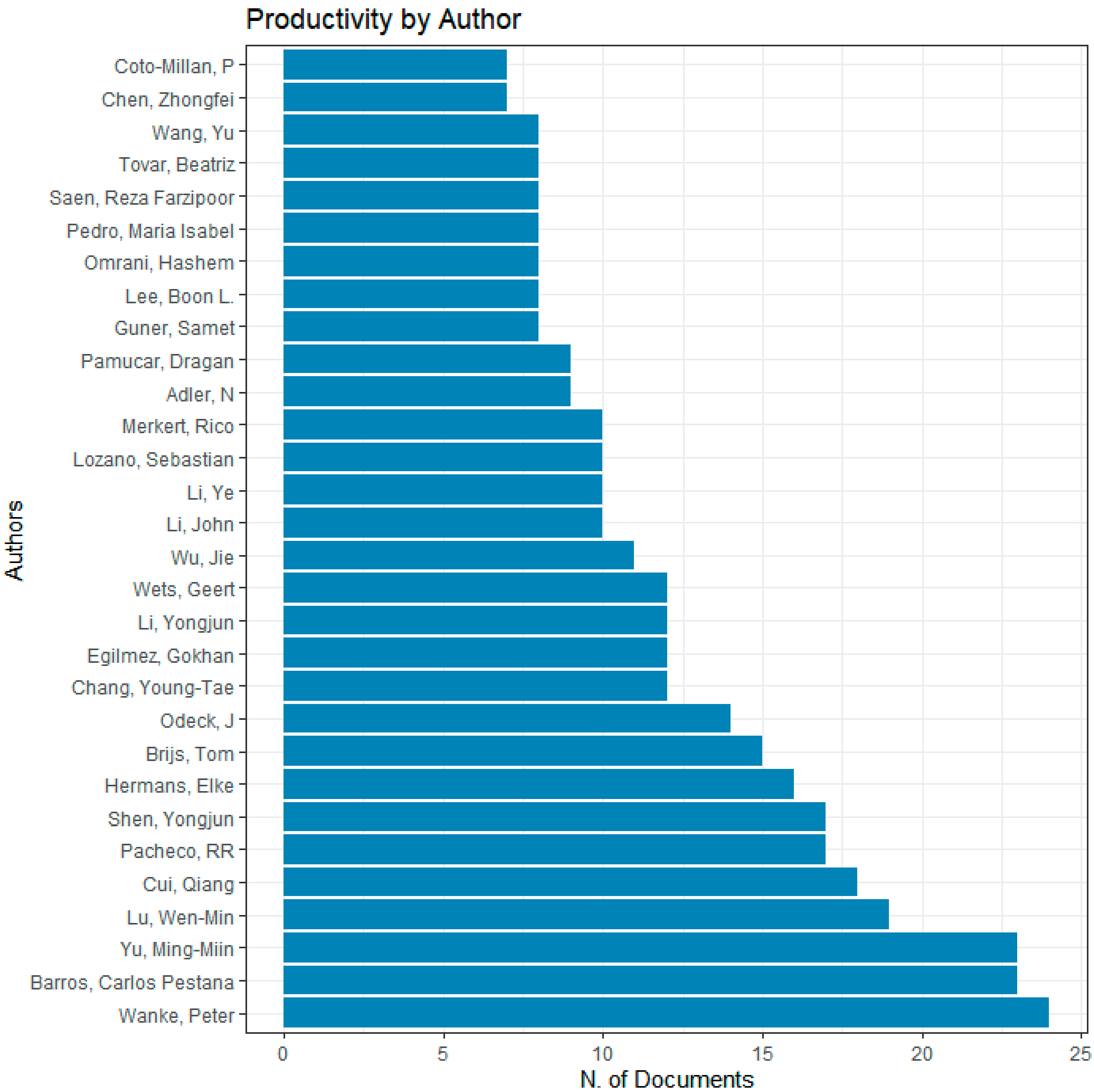

Figure 4. Productivity by author.

4.1.3. Countries

As identified in author analysis, it can also be said that publications are highly concentrated geographically, with China representing 27% of all the 1041 articles as shown in Figure 5. These results are also comparable to Cavaignac and Petiot [21] and Mahmoudi et al. [20].

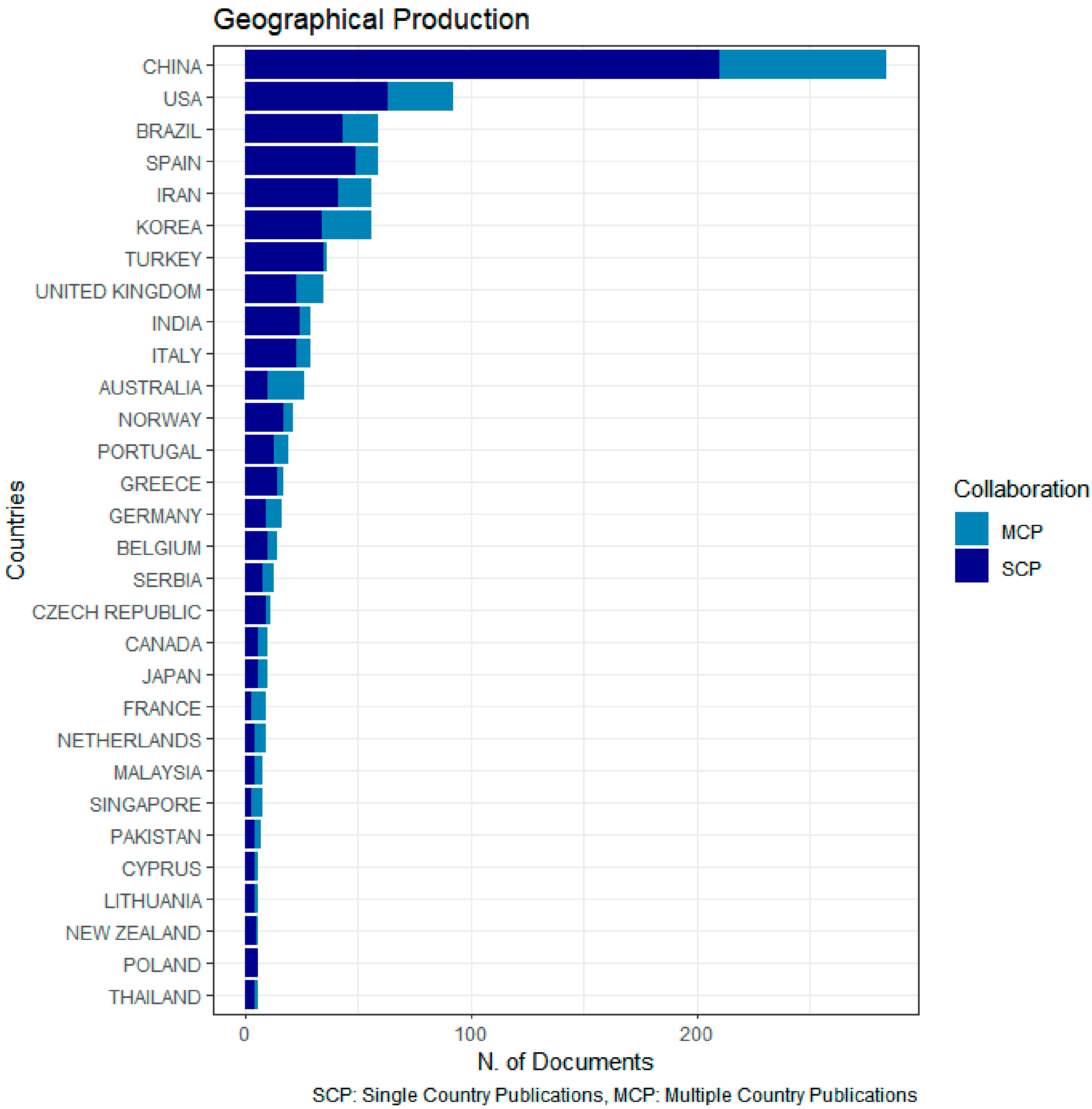

Figure 5. Productivity by country.

4.1.4. Citation Order

Lastly, we present the 10 most cited DEA-transport publications in Table 3, arranged by total citations (TC).

Table 3. Most cited DEA publications.

Document	Title	TC	TCperYear
[38]	A Survey of Dea Applications	424	42.40
[39]	The Technical Efficiency of Container Ports: Comparing Data Envelopment Analysis and Stochastic Frontier Analysis	348	20.47
[40]	Measuring Eco-Efficiency of Production with Data Envelopment Analysis	335	18.61
[41]	A Comparison Of Parametric and Non-Parametric Distance Functions: With Application to European Railways	307	12.79
[42]	Fuzzy Multicriteria Decision-Making: A Literature Review	273	34.12
[43]	Developing Measures of Airport Productivity and Performance: An Application Of Data Envelopment Analysis	262	10.08
[44]	Efficiency Measurement of Selected Australian and Other International Ports Using Data Envelopment Analysis	251	11.41
[45]	Efficiency and Effectiveness in Railway Performance Using a Multi-Activity Network Dea Model	200	13.33
[46]	An Analysis of the Operational Efficiency of Major Airports in the United States	198	8.61
[47]	Evaluation of Deregulated Airline Networks Using Data Envelopment Analysis Combined With Principal Component Analysis with An Application to Western Europe	180	8.18

The first application of DEA in the transport sector can be traced back to Adolphson et al. [48] in an attempt to measure obsolescence in railways. It uses the classic DEA–CCR model and derives best practices based on one input, rate of return, and one output, transportation performance. The authors compare the DEA approach to the Wisconsin approach, indicating that DEA allows for multiple inputs and outputs, as well as an evaluation of performance levels considering the resources required to reach the efficiency frontier. Since then, the number of DEA models applied to transport sector publications has grown rapidly, gaining importance and relevance, reaching higher impact factor journals.

From the articles listed in Table 3, two are literature surveys/reviews, including the first systematic review of DEA [38]. The other eight articles are all applications of different DEA models. Cullinane et al. [39] is the most cited between application articles, as it compares DEA and SFA efficiency results for container ports and concludes that the results are "relatively robust to the DEA models applied or the distributional assumptions under SFA", with a high degree of correlation between efficiency scores from both models.

4.2. Statistics on SFA Publications

4.2.1. Number of Publications

For SFA publications in TS, 318 published documents were identified ranging from 1995 to 2022, an annual growth rate of 10.81% and an average citation per year of 2.2. Figure 6 presents the publication time series of SFA documents in transport sector. All the retrieved documents are articles, and the most productive year was 2021, with 35 published documents.

We identified 156 journals with a high concentration of publications, higher than DEA. Considering our database, half the published documents are concentrated in only 22 journals, as listed in Table 4. It is interesting to notice that from the top 15 journals listed in Table 4, 9 are also listed in Table 2 for DEA publications, showing that these transportation journals are model agnostic.

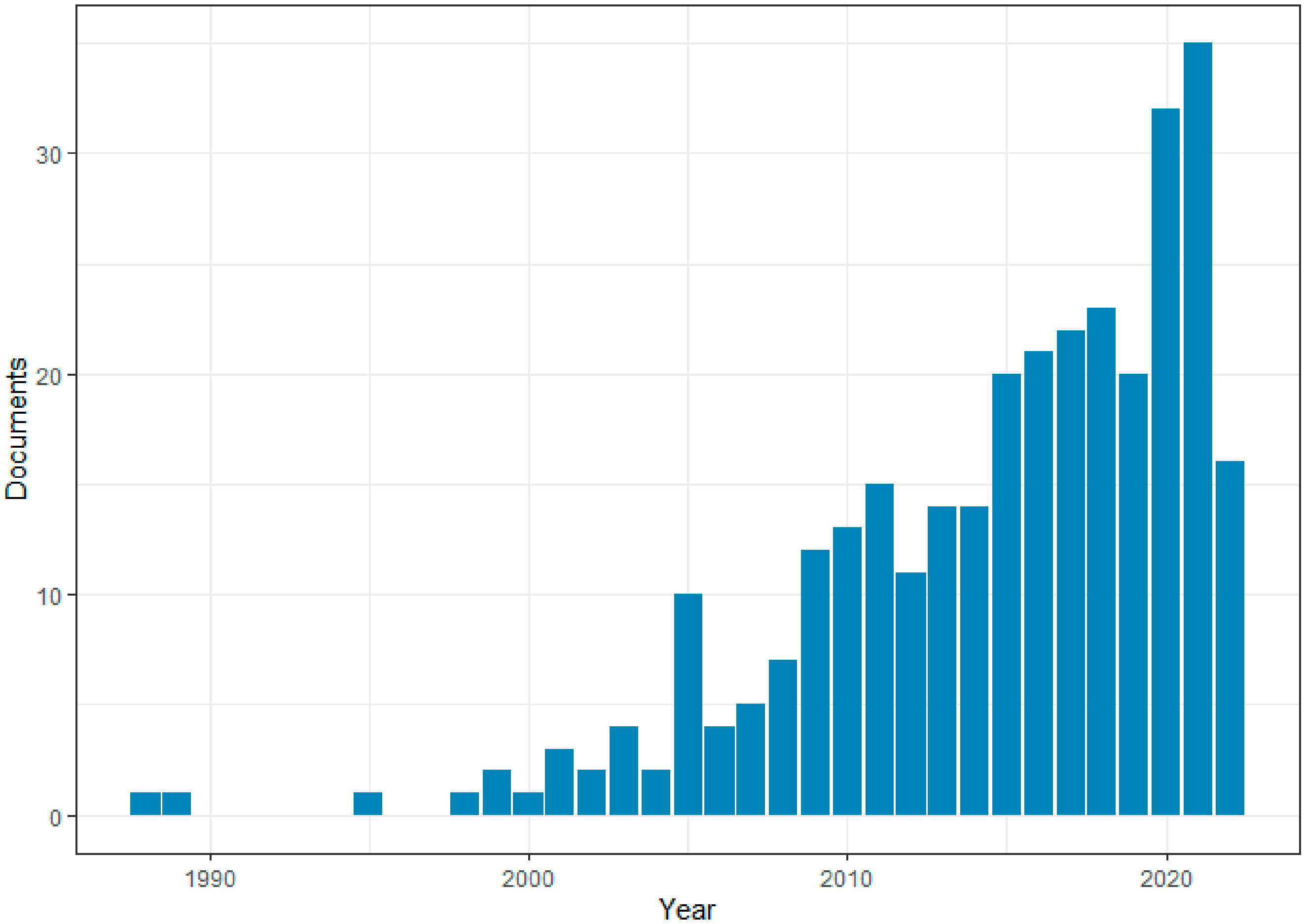

Figure 6. SFA publications time-series.

Table 4. Journals with the most SFA-TS publications.

Sources	Articles	Impact Factor 2021	H-Index 2021
Transportation Research Part A-Policy And Practice	22	5.59	142
Transport Policy	13	6.36	103
Transportation Research Part E-Logistics And Transportation Review	12	10.75	122
Journal Of Productivity Analysis	11	2.57	84
Maritime Economics & Logistics	11	3.12	55
Maritime Policy & Management	11	3.41	61
European Journal Of Operational Research	7	6.39	274
Journal Of Air Transport Management	7	5.97	82
Utilities Policy	7	3.35	54
International Journal Of Shipping And Transport Logistics	6	1.31	25
International Journal Of Transport Economics	6	0.18	24
Research In Transportation Economics	6	2.75	52
Applied Economics	5	2.01	91
Journal Of Cleaner Production	5	10.96	232
Energy Policy	4	7.37	234

As SFA and DEA share most of their journals in terms of number of publications, they also share similar relevance and impact factor numbers. The mean impact factor 2021 of the 15 journals shown in Table 4 is 4.8, with only one presenting an IF lower than 1. Thus, in terms of academic importance and extra-sectorial diffusion, DEA and SFA seem to be on the same level for transportation systems.

4.2.2. Authors

For authors, we identified 642 for 318 documents, with an average of 2.7 co-authors per document and an international co-authorship of 27.36%. Like journals, we also identified a high concentration of publications when analyzing authors, appreciably greater than the concentration verified for DEA documents. 30 authors concentrate 45% of all 318 published documents. Figure 7 presents the top 30 most productive authors.

However, DEA and SFA do not share the same authors, with only Peter Wanke and Carlos Pestana Barros appearing in both most productive author lists. This may relate to the findings of Lampe and Hilgers [11], where the authors indicate that DEA seems to be mostly applied in operational research and SFA seems to be mostly applied in an econometrics context. Thus, they are two different research areas, even though both SFA and DEA deal with efficiency frontier analysis.

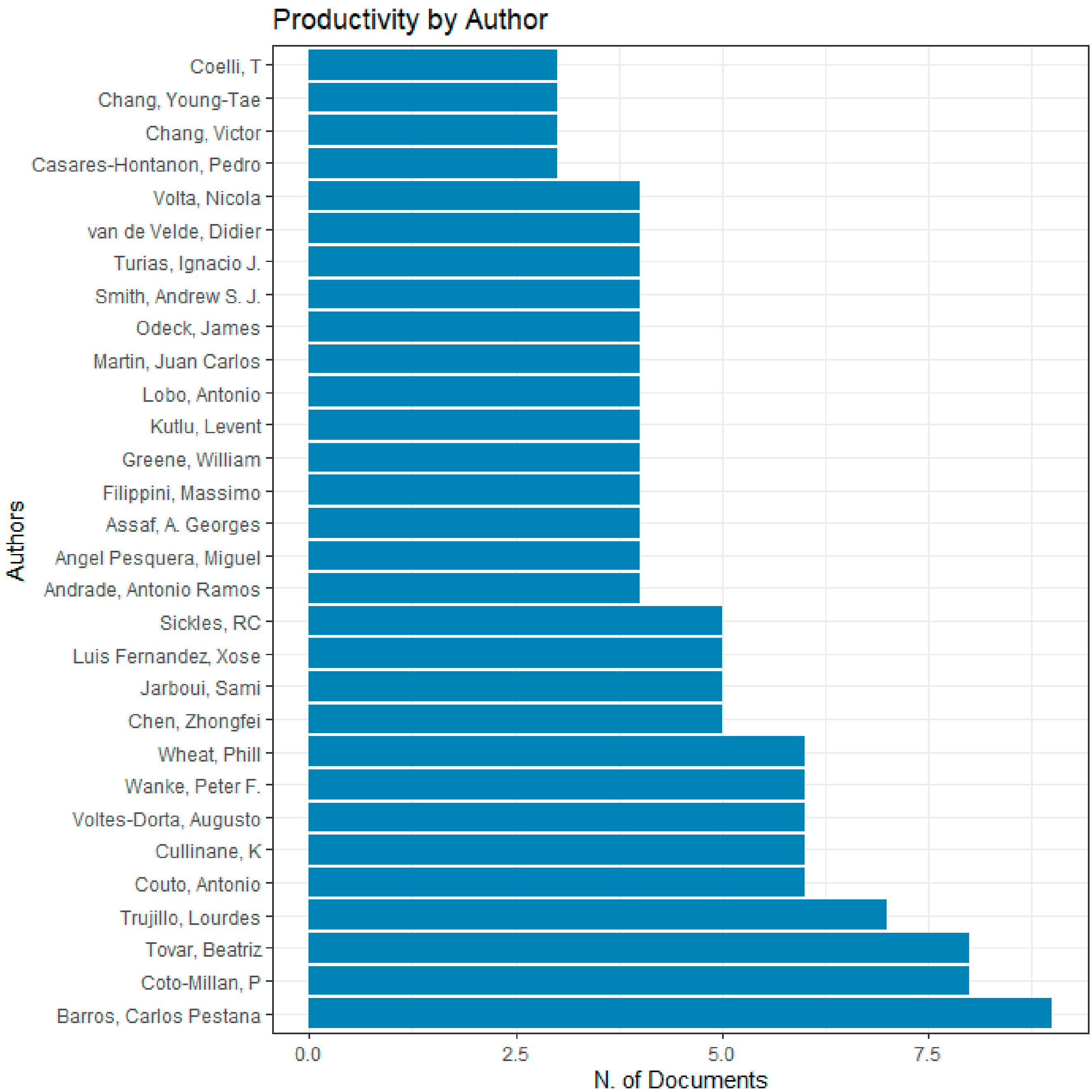

Figure 7. Productivity by Author.

4.2.3. Countries

Regarding the geographical distribution of published SFA articles, China is the most productive country, but the distance between and the second place is much shorter than the one identified for DEA publications. Additionally, Brazil's importance in SFA publications in transport is much less pronounced than for DEA publications, where Brazil is the third-most productive country. Figure 8 presents the geographical production.

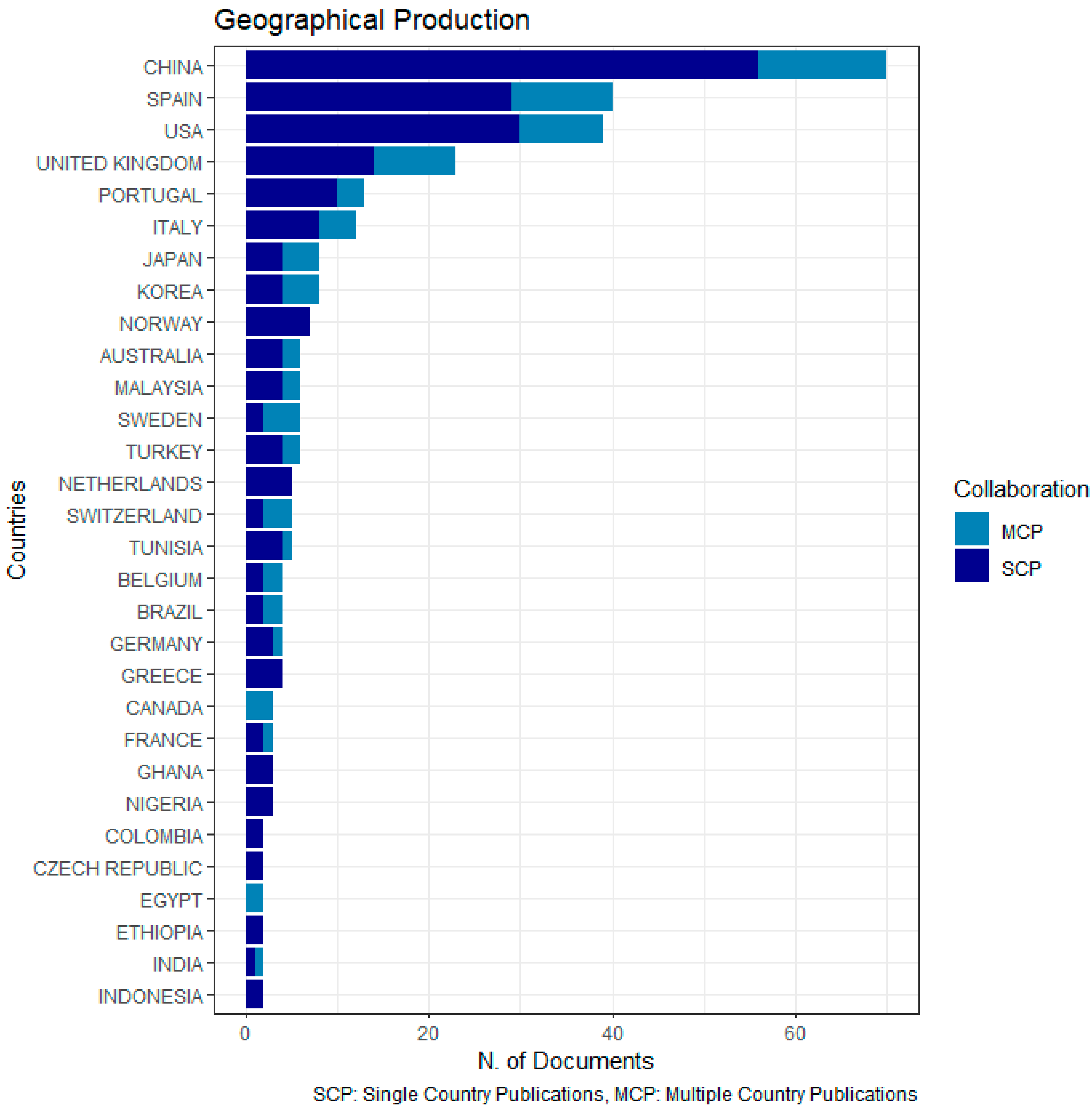

Figure 8. Productivity by Country.

4.2.4. Citation Order

Finally, we present the 10 most cited SFA-transport publications in Table 5, arranged by total citations (TC). It is interesting to note that two articles are in both DEA and SFA's most cited tables: Cullinane et al. [39] and Coelli and Perelman [49].

Table 5. Most Cited SFA Publications.

Document	Title	TC	TCperYear
[39]	The Technical Efficiency Of Container Ports: Comparing Data Envelopment Analysis And Stochastic Frontier Analysis	348	20.47
[50]	Port Privatization, Efficiency And Competitiveness: Some Empirical Evidence From Container Ports (Terminals)	342	19.00
[51]	A Stochastic Frontier Model Of The Efficiency Of Major Container Terminals In Asia: Assessing The Influence Of Administrative And Ownership Structures	188	8.95
[52]	Inefficiencies And Scale Economies Of European Airport Operations	168	8.40
[53]	Ownership Forms Matter For Airport Efficiency: A Stochastic Frontier Investigation Of Worldwide Airports	164	10.93
[49]	Accounting For Environmental Influences In Stochastic Frontier Models: With Application To International Airlines	161	6.71
[12]	Trajectories Of Efficiency Measurement: A Bibliometric Analysis Of Dea And Sfa	145	18.12
[54]	A Bayesian Approach To Imposing Curvature On Distance Functions	131	7.28
[55]	A Stochastic Frontier Model Of The Productive Efficiency Of Korean Container Terminals	124	6.20
[56]	Persistent And Transient Productive Inefficiency: A Maximum Simulated Likelihood Approach	105	15.00

The first SFA application to the transport sector when considering Scopus, WoS, Google Scholar, and Scielo databases can be traced back to 1987, by Greene [57] in an attempt to measure the technical improvements in automotive fuel efficiency by estimating stochastic frontier cost functions for automotive fuel economy in 1978 and 1985. Since then, SFA applications in the transport sector have increased, but have been largely outpaced by DEA publications.

From the listed papers, there is only one literature review that surveys both DEA and SFA production [11]. All of the other nine papers are stochastic frontier applications, with two of them proposing a methodological evolution and are both were applied to the railway sector [54,56]. It is also important to mention that four of the most cited articles deal with container port efficiency [39,50,51,55], in what seems to be an important subject in stochastic frontier analysis.

5. Applications in Transportation Systems

As described in Section 3, we separated the articles into five groups, representing each transportation system: highway/road transportation, air transportation, maritime/port transportation, railway transportation, and urban/bus transportation. This classification differs from the one proposed by Mahmoudi et al. [20] in two aspects. First, we did not create an exclusive category for "Green and environmental issues" as this seems to be a subcategory in transportation research rather than a main one. Our intention was to directly observe what mode of transport is more concerned with "Green and environmental issues" and whether it is a growing subject or a literature gap. Secondly, we added the category of urban/bus transportation, also known as urban mobility, as specialized literature regarding transportation tends to also separate road/highway from bus/urban transportation.

Figure 9 presents the proposed separation for DEA articles. The sum of articles will be greater than total of articles in our database, as some documents deal with more than one transportation mode.

Only DEA-rail related articles will be reported here.

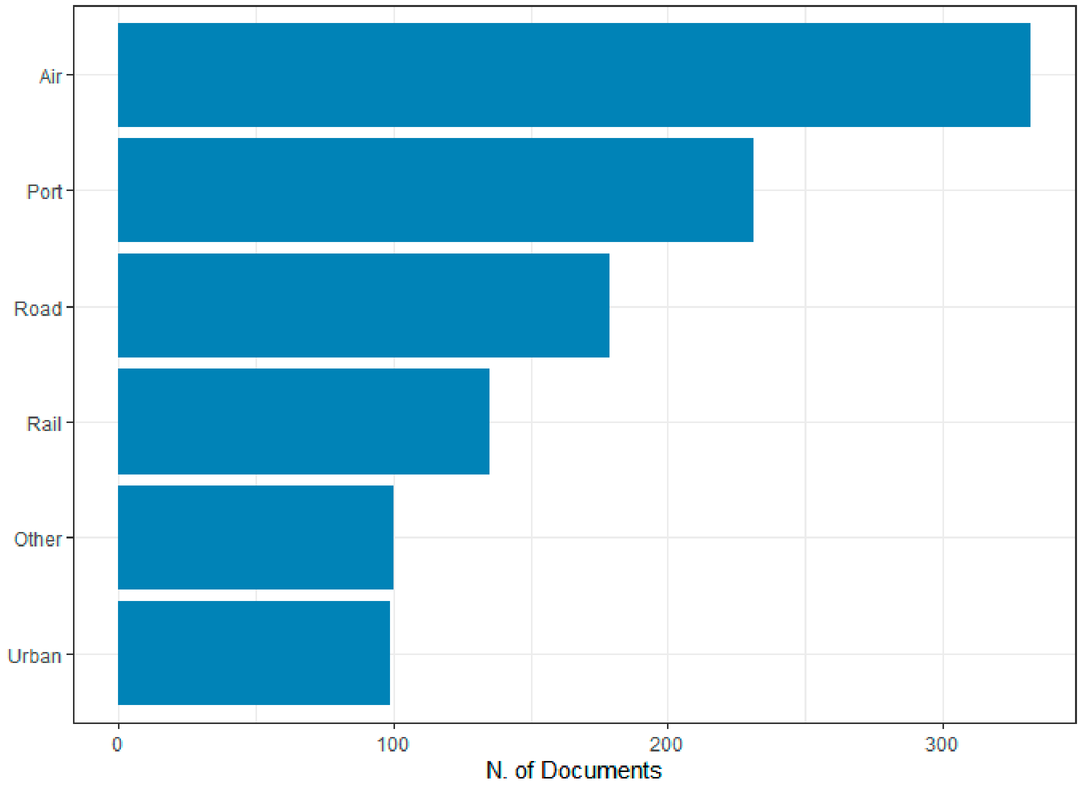

Figure 9. Proposed separation for TS publications.

5.1. DEA in Railway Transport

From those 135 articles, more than half were published in the last 10 years. From surveying all 135 DEA publications dealing with rail transportation, we identified that 31 are transport-related, but not rail-specific; three are not DEA-related; six are literature reviews; and we were not able to access 15 papers.

As a result, we read 83 papers and determined the DEA model used; the second-stage analysis, if any; the input–output variables; the model orientation; return-to-scale assumptions; and its methodological classification. As for the DEA models used, Figure 10 presents the main results.

The most common DEA model used in railway sector is the classic CCR, with constant returns to scale (CRS), and its variable returns to scale (VRS) counterpart as the second-most common, the BCC. These findings are in line with Mahmoudi et al. [20] results.

The third-most used model is the network DEA (NDEA), introduced by Färe and Grosskopf [58]. From the selected papers in this research, NDEA seems to be one of the most relevant DEA applications when considering the total citations number. From the five most cited rail-related papers, three of them apply the NDEA model, including a sector-seminal paper by Yu and Lin [45]. Its recent growth can be seen as a natural development of efficiency research in railways, especially in more complex production processes in which the final outputs depend on more than one stage of production or in a context where a DMU engages in simultaneous activities and its performance in each activity must be determined simultaneously, as its outputs cannot be stored [59]. Also, the NDEA addresses an innate problem of DEA regarding DMU treatment as "black-boxes", and it is able to consider intermediate production phases.

This modelling is especially relevant in research regarding the environmental impact of rail activities [60–62].

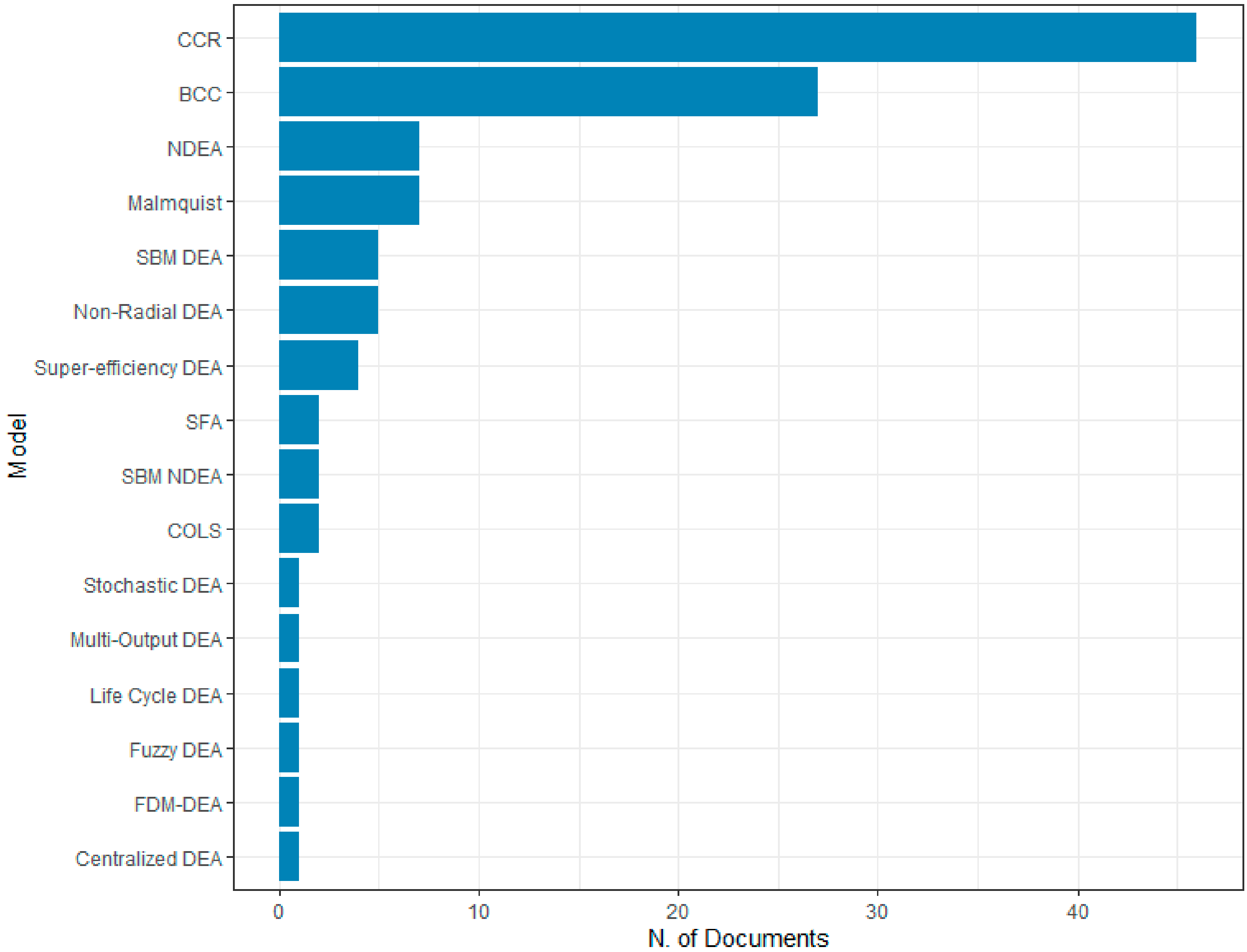

Figure 10. Most recurrent DEA models in rail research.

In addition, from the 83 surveyed papers, only 2 used both DEA and SFA to analyze efficiency: Lerida-Navarro et al. [63] and Lan and Lin [64]. In this sense, rail transportation seems to take a mutually exclusive stance on methodology selection, even though some authors do use both approaches in transportation systems, including the second-most cited transportation-specific paper: Cullinane et al. [39].

With respect to returns to scale definition, even though there is a greater number of papers that assume CRS, there does not seem to be a clear-cut definition regarding the most adequate one, as some of the surveyed papers take an arbitrary approach to scale return assumptions. Growitsch and Wetzel [65] defend the use of the CRS approach because an efficiency comparison between firms must consider a long-term perspective. In this sense, the authors indicate that, in a European context, regulation and political influence warding off scale optimization will not stand in the long-run and sub-optimally-scaled railways should be identified as inefficient. On the contrary, Cowie [66] affirms that there is relevant evidence that variable returns-to-scale exist at what he calls “the lower end of the rail industry”.

Determining the underlying technological process as increasing, constant, or decreasing returns-to-scale is an essential part of investigating productive efficiency. The analysis of efficiency without an adequate testing on return-to-scale can warp efficiency scores and invalidate conclusions if the underlying technology displays a different return-to-scale than what is arbitrarily assumed [17], hence the importance of testing returns to scale in rail transportation.

Regarding the so-called second-stage analysis, the most common in rail-related papers is Tobit regression. However, the number of papers that do use the techniques presented in Figure 11 is considerably low, with most papers using only one DEA stage.

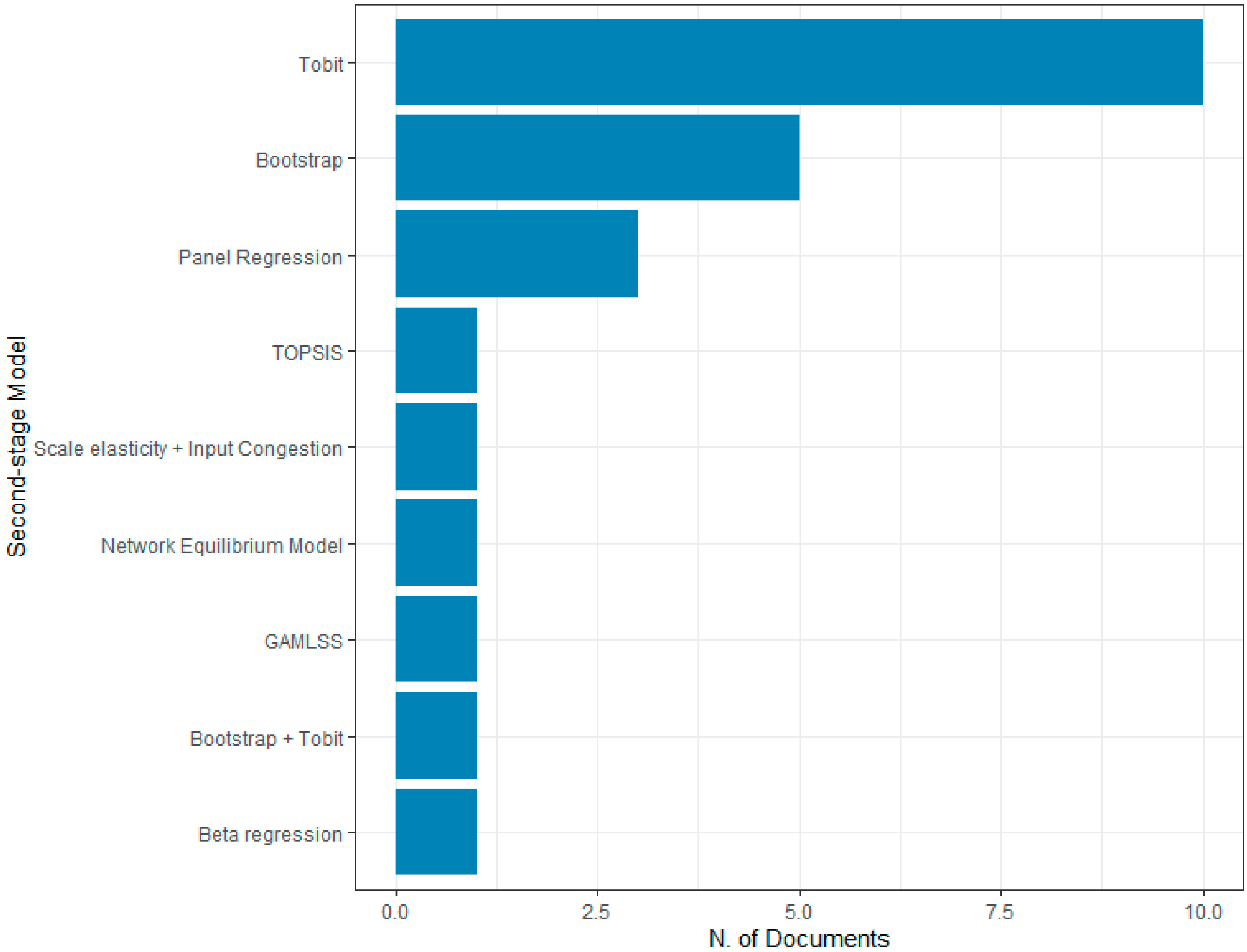

Figure 11. Most recurrent second-stage models in rail research.

Fried et al. [67] suggest that non-parametric frontier models are deterministic, with no statistical interpretation, and founded on an unknown data generating process. In other words, all deviations from the frontier are interpreted as inefficiency, which is not often the case. In 1998, Simar and Wilson [13] proposed a bootstrap approach to manage the deterministic nature of DEA, invalidating one of DEA's main critics. Also, regression analysis of efficiency scores based on additional contextual variables are an important part of this second-stage.

Yet, as stated by Simar and Wilson [17], papers published in relevant journals often ignore this statistical interpretation, and this seems to be the case for part of the collected database on rail efficiency research.

Regarding dynamic DEA, only nine papers used Malmquist indexes and one paper used Window analysis. Most of the surveyed papers use a cross-sectional approach, or a time series approach without measuring productivity change over time.

In line with the findings of Mahmoudi et al. [20], as shown in Figure 12, the most common input variables are labor, rolling stock, and line extension, with more than half of the 83 surveyed papers using at least one of these inputs. Regarding outputs, we verify that ton–km and passenger–km are also used in almost half the surveyed papers.

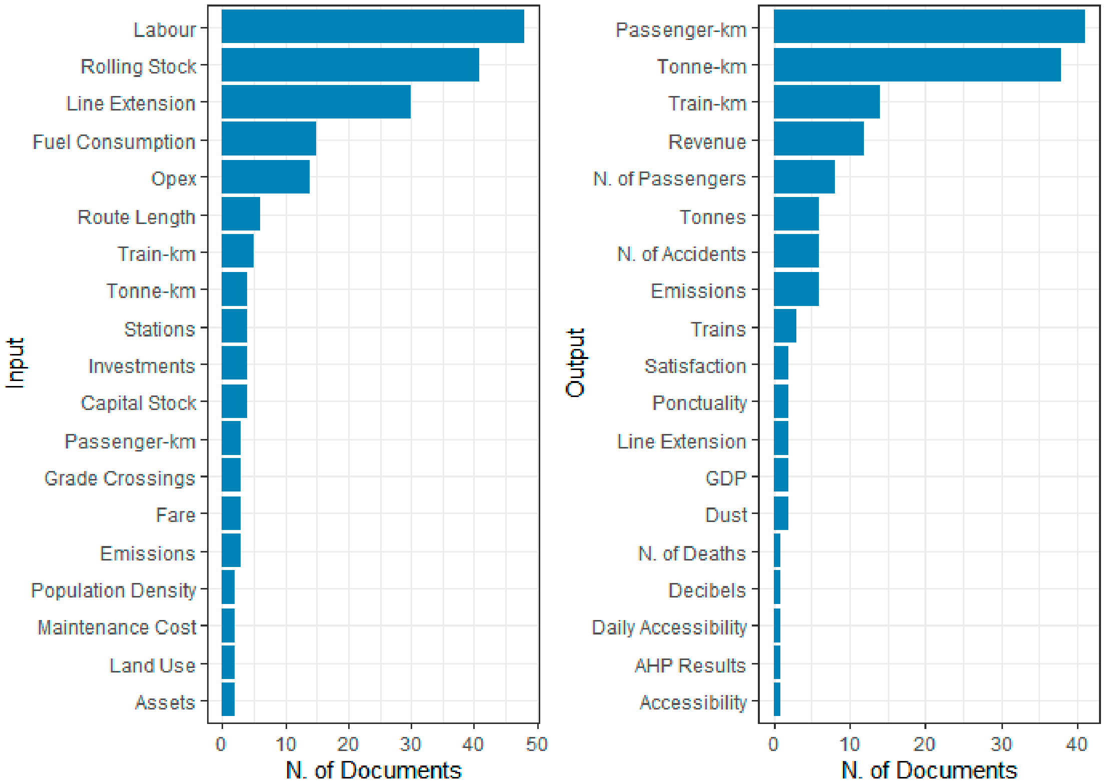

Figure 12. 20 Most Recurrent Input and Output Variables in Rail Research.

Apart from the mentioned variables, environmental/sustainability inputs and outputs are also relevant, as fuel consumption is the fourth-most used input. However, safety issues and accident analysis seem to be an underexplored topic in DEA research, with few very recent papers [68–71]. This seems to be a literature gap and an important area of development in rail research.

From this analysis, a variable selection discussion arises. Cullinane et al. [72] presented an extensive discussion on that matter, applied to the port sector, and stated that variable selection must reflect the processes and objectives of sector production, as the observed performance of a port is closely related to its objective. Cullinane et al. [72] also observed that input–output choice may change depending on the perspective, and variables that were considered as inputs in one model can be outputs in another.

When assessing transportation system performance, we must consider a multitude of factors and goals simultaneously. However, these goals may change from country to country, as rail transport can be of private, public, or mixed-provision. The variable choice is directly related to these factors and goals, as a strict market-oriented cost or technical model to assess performance and efficiency may misrepresent the goals of the system as a whole, especially when rail transportation service is of public or mixed-provision, operating in a broader social structure, where performance is also guided toward mobility, environmental improvements, land use, and financial commitments [73].

De Borger et al. [59] discusses this matter in a literature survey on production and cost frontiers models for public transit operators. The authors found that, similarly to rail transportation, the input selection consists mainly of capital, labor, and energy. What this group of variables does not consider is the differences between operators in the quality and composition of these inputs. Different locomotives with different purposes and different pattern of fuel consumption may be considered as the same when assessing rail efficiency. This is not a problem per se, but one must ask if this implicit assumption opposes the goal of the whole system. The same might be said about labor and its possible deterioration or rail extension shrinkage.

For outputs, De Borger et al. [59] brings a similar discussion that can be applied to the rail sector. There is a distinction between supply-sided indicators, often associated with service provision (number of formed trains, seat–km etc.) and demand-sided indicators, often associated with the product itself (ton–km, passenger–km etc.). From the reading of the DEA-related articles, authors rarely make this distinction clear or justify the use of one over the other.

Thus, a careful and detailed discussion must take place when choosing model variables at the risk of a biased analysis that misrepresents the processes and objectives of the sector.

Lastly, we present the publication time series of DEA rail-related papers to further assess the trends of research topics and how they have changed through time. We also highlight the research focus during each proposed period.

As seen in Figure 13, there is an initial period of slow adoption of DEA in railway performance analysis, from late 1980s to 2010. From then on, DEA solidifies itself as an important tool and its adoption in railway performance analysis begins an exponential growth. To better understand the presented results, we propose a three-period segmentation, as shown in Figure 13. Period 1: from late 1980s to 2010; Period 2: from 2011 to 2015; and Period 3: from 2015 to 2023.

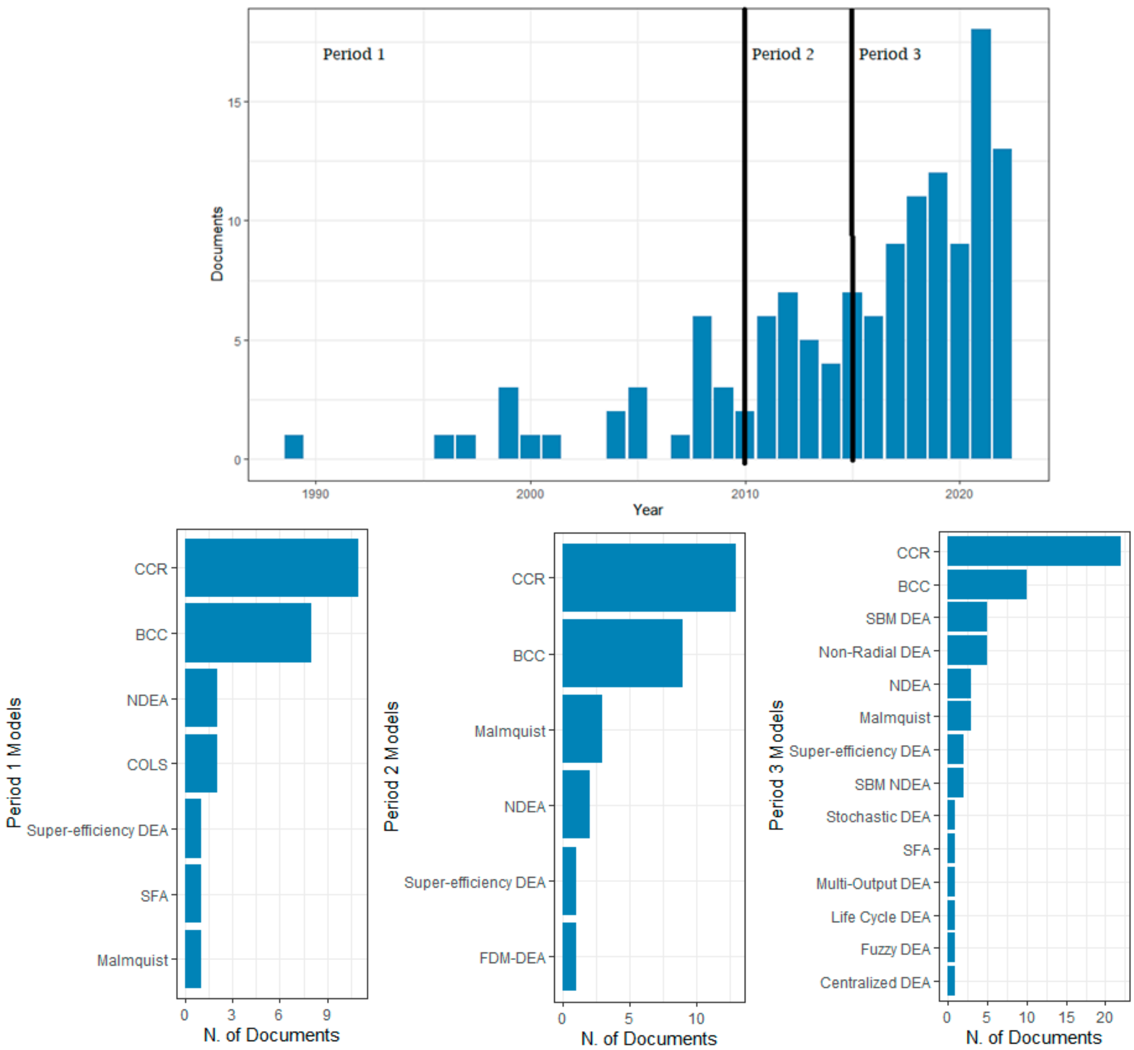

Figure 13. DEA rail-related publications time series and most recurrent models in each period.

There were 23 publications in Period 1. Four of them are not rail-specific and we had no access to two, resulting in seventeen remaining articles. The classic CCR and BCC models are used in almost all articles, with two important exceptions: Yu [74] and Yu and Lin [45], who applied network DEA models. As they were the first to adopt this model in railway efficiency analysis, these are highly cited articles with 96 and 200 citations, respectively. The other adopted models were used together with CCR and BCC.

As to variable choice, all but one used either train–km, ton–km, or passenger–km as outputs, and all but two used a combination of land, capital, and labor inputs, either as cost or physical values. The two notable exceptions to input selection are the work of Ramanathan [75,76], who used a measure of energy as input.

This initial period, from the late 1980s to 2010, is not characterized by great innovation, but rather by an early phase of efficiency assessment grounded on production theory classic variables and DEA classic models.

Period 2 has 31 publications from which 8 are not rail related, 3 were not accessible, and 1 is a literature review, with 18 remaining. In this phase, there is a greater adoption of second-stage methods such as regressions, bootstrap bias correction, and analytic hierarchy process (AHP) to efficiency assessment, while first-stage models are still classic CCR and BCC.

This second phase is an initial experimentation with different variables and techniques, benefiting from advances in DEA literature as well as better data on rail operation. In this sense, five papers adopted a measure of energy as input, while outputs remain mostly the same from Period 1.

Period 3 has 81 documents, from which 13 are not rail-specific, 4 have no DEA application, 5 are literature reviews, and 9 were not accessible, with 50 remaining. Giving continuity to the developments of Period 2, this phase further explores not previously discussed topics, such as carbon emissions as undesired outputs, input congestion, quality of service and, of great importance, rail safety, presenting a handful of innovative analyses. For first-stage efficiency measures, slack-based measure DEA gains importance as a more consistent alternative to BCC [77], as well as non-radial DEA models and fuzzy data treatment. In second-stage measures, there is a greater use of regression models to assess the impact of exogenous variables, most (8) of them with Tobit regressions but with beta regression and generalized additive models for location scale and shape (GAMLSS) are also used. As to variable choice, there is a greater diversity in both inputs and outputs. For inputs, we highlighed the use of energy measures, travel time, fare/tariff, government subsidy, grade crossings, operational capacity, number of stations, and dwell time. For outputs, service quality variables appear more prominently and are incorporated to production assessment models with punctuality, accidents, passenger satisfaction, wage growth, noise complaints, and decibel levels from train operation.

5.1.1. Co-Citation Network Analysis

For co-Citation analysis, we used the *bibliometrix* R package [30]. Figure 14 presents the author co-citation network.

The structure of the network illustrated in Figure 14, showing a high concentration of co-citations, as expected. It is worth mentioning that two papers are clearly emphasized in the network: Charnes et al. and Banker et al. [8,78]. It is also possible to verify a cluster on sector-seminal papers by Yu and Yu and Lin [45,74].

The four cited articles have indeed impacted the operational research field and corroborate the findings in Table 6, as [8,78] they introduce the BCC and CCR models, and [45] proposed a model that represents both production and consumption technologies in a unified framework, through network DEA. Coelli and Perelman [41] is also highlighted in the network and presents the first comparison between parametric and non-parametric distance function models in transport sector. Farrell [4] is also a relevant publication, as he presented the possibility of estimating an efficient productive frontier with best practices and, by calculating the distance of each productive unit from this frontier, estimating the relative efficiency, before the introduction of both DEA and SFA.

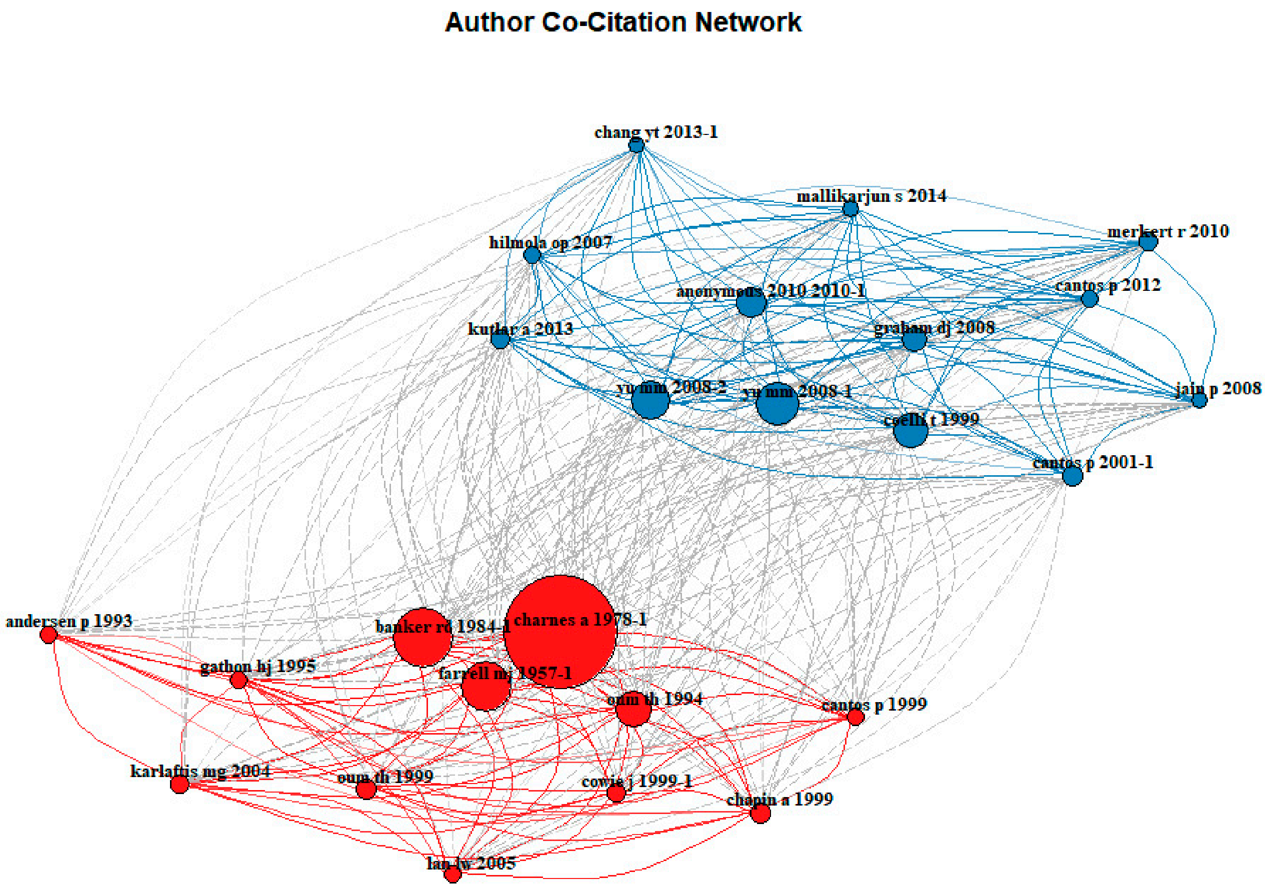

Figure 14. Author Co-Citation Network.

It is also worth mentioning that none of Simar and Wilson's work regarding bootstrap DEA techniques, semiparametric second-stage DEA methods, or return-to-scale tests appears in the co-citation network, corroborating the finding that the number of papers that do use second-stage models is considerably low.

Lastly, the resulting co-citation network has two clearly defined clusters. Assessing the papers in each cluster, it becomes clear that the blue cluster is related to rail transportation applied studies [45,74,79–84], whereas the red cluster is related to theorical methodological papers and review/survey papers. Appendix A presents the coupling and keyword analysis.

Table 6. Most cited DEA rail papers from the last 5 Years.

Document	Title	TC
[20]	The Origins, Development And Future Directions Of Data Envelopment Analysis Approach In Transportation Systems	46
[84]	Non-Radial Dea Model: A New Approach To Evaluation Of Safety At Railway Level Crossings	23
[85]	Performance Evaluation Of Rail Transportation Systems By Considering Resilience Engineering Factors: Tehran Railway Electrification System	21
[68]	Evaluation Of Energy-Environment Efficiency Of European Transport Sectors: Non-Radial Dea And Topsis Approach	14
[86]	Efficiency, Effectiveness, And Impacts Assessment In The Rail Transport Sector: A State-Of-The-Art Critical Analysis Of Current Research	14
[69]	A Novel Entropy-Fuzzy Piprecia-Dea Model For Safety Evaluation Of Railway Traffic	13
[87]	Selection Of Efficient Types Of Inland Intermodal Terminals	13
[88]	Transportation Efficiency Evaluation Considering The Environmental Impact For China's Freight Sector: A Parallel Data Envelopment Analysis	12
[89]	Multi-Output Efficiency And Operational Safety: An Analysis Of Railway Traffic Control Centre Performance	12

5.1.2. Recent Relevant Publications

Finally, as a source of direction to recent DEA rail research, we present the 10 most cited papers published in the last five years in Table 6, considering that the most recent literature review analyzed published papers until 2018 [20].

From the listed publications, as well as from the analysis regarding input–output variables and the proposed three-period segmentation, it seems clear that safety research and sustainability research are emerging topics in DEA rail applications, as it is the main theme for six out of the ten most cited papers published in the last five years. Also, considering the presented papers in Table 6, along with the presented analysis from Figure 13, there seems to be a departure from the classic CCR and BCC models, with the adoption of more modern techniques.

6. Conclusions

This paper presented a bibliometric analysis of efficiency in transportation systems, including an overview of stochastic frontier analysis, a first regarding transportation literature reviews. The retrieved publications were separated in five groups: highway/road transportation, air transportation, maritime/port transportation, railway transportation, and urban/bus transportation.

Also, a systematic review of DEA rail-related papers was presented, where 83 rail-related publications were reviewed to assess model choice; second-stage analysis, if any; input–output variables; model orientation; return-to-scale assumptions; and their methodological classification.

The main results regarding the bibliometric analysis of DEA and SFA publications presented in Sections 4.1 and 4.2 are listed below:

- DEA in transportation systems has undergone exponential growth since 2008. The most productive year was 2021, with 114 published documents;
- Concerning journals, when compared to the last literature review, publications of DEA in transportation systems are less concentrated and more relevant, with an average impact factor of 5;
- Regarding author productivity, publications of DEA in transportation systems are also highly concentrated where 30 authors concentrate more than a third of all 1041 published documents;
- For country productivity, publications of DEA in transportation systems are also highly concentrated, with China representing 27% of all the 1041 articles;
- SFA in transportation systems has also undergone exponential growth since 2000. The most productive year was 2021 with 35 published documents;
- Regarding journals, publications of SFA in transportation systems are more concentrated than DEA, half the published documents are concentrated in only 22 journals, and equally relevant, with an average impact factor of 4.8;
- For authors, publications of SFA in transportation systems are highly concentrated, appreciably greater than the concentration verified for DEA documents; 30 authors concentrate 45% of all 318 published documents;
- Regarding country productivity, publications of SFA in transportation systems are also highly concentrated, with China representing 22% of all the 318 articles.

For DEA in Railway transport, the main results from the systematic review of the 135 selected papers are listed below:

- The most common DEA model used in the railway sector is the classic CCR, with constant returns-to-scale (CRS), and its variable returns-to-scale (VRS) counterpart as the second-most common, the BCC;
- The third-most used model is the Network DEA, and is one of the most relevant DEA applications when considering the total citations number;
- Regarding returns-to-scale, even though there is a greater number of papers that assume CRS, there does not seem to be a clear-cut definition regarding the most

adequate one and most of the published documents do not test the data generating process for scale returns;

- For second-stage analysis, the most common in rail-related papers is Tobit regression, but the number of papers that do use these techniques is considerably low, a finding corroborated by the co-citation network;
- Regarding input variables, labor, rolling stock, and line extension are present in more than half of the reviewed papers;
- Concerning output variables, ton–km and passenger–km are also used in almost half the surveyed papers;
- Environmental/sustainability inputs and outputs are also relevant, as fuel consumption is the fourth-most used input;
- Safety issues and accident analysis seems to be an underexplored topic in DEA research, with very little recent research, but is surely an emerging topic, as shown in Table 6;

Few publications explore rail quality of service, an important topic in countries where rail transportation is a public service.

From the listed results, an important conclusion is that efficiency research in transportation systems do not follow a structured path. As stated in Section 5, even though there is a greater number of papers that assume CRS, some of the surveyed papers take an arbitrary approach to scale return assumptions, despite the fact that there is a known test for the identification of the type of scale returns [17]. Also, some of the surveyed papers do not consider a second-stage analysis method such as bootstrap, Tobit regression, etc., as shown by the co-citation analysis. Furthermore, most of the documents do not propose a sensitivity analysis of the chosen input–output variables or a deeper discussion on the assumptions behind the variable selection. Lastly, only one rail-specific surveyed paper compares the efficiency results from DEA to other efficiency frontier models.

With this in mind, we propose a guided path to efficiency analysis in railway transportation, that can be extrapolated to other knowledge fields, when using the classic CRR and BCC models:

- Preliminary analysis—careful and detailed discussion about a system's objectives and variable choice, as well as a preliminary data-cleaning analysis;
- 1st step—application of the classic CCR and BCC models;
- 2nd step—super-efficiency and super-inefficiency using an inverted frontier to better explore outliers and possible data errors, along with other outlier detection measures;
- 3rd step—stepwise/sensitivity analysis for a possible variable reduction or as an assessment of the importance of each variable;
- 4th step—return-to-scale testing, such as that proposed by Simar and Wilson (2002);
- 5th step—second-stage analysis, such as bootstrap and regressions on contextual variables;
- 6th step—dynamic efficiency analysis using Malmquist productivity indexes to identify changes in efficiency and technological innovations over time;
- 7th step—comparison with another relevant efficiency frontier model such as SFA.

It is important to mention that there are several limitations to this study. The most important is that all data were retrieved from the Web of Science database. Even though it is the largest and most important academic database available, the use of only one database excludes publications from journals not included in the WOS database. The second limitation, also mentioned by Lampe and Hilgers [11] and verified in this research, is the challenge of creating a complete dataset of SFA publications, as not all economic and econometric papers cite the SFA method, even though it is a frontier analysis. Lastly, as with most literature reviews, it is virtually impossible to cite each and every indirectly mentioned document.

We believe that the presented systematic review can support authors in advancing efficiency analysis in transportation systems, as well as reveal gaps in the literature, and emerging but underexplored themes.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su151310300/s1, Table S1: Documents Database.

Author Contributions: Conceptualization, T.V. and C.R.P.; methodology, T.V.; software, T.V.; validation, T.V. and C.R.P.; formal analysis, T.V.; investigation, T.V.; resources, T.V. and C.R.P.; data curation, T.V.; writing—original draft preparation, T.V. and C.R.P.; writing—review and editing, T.V. and C.R.P.; visualization, T.V.; supervision, C.R.P. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

For Coupling analysis we used the bibliometrix R package [31].

The author-coupling network in Figure A1 shows a much less concentrated graph than co-citation, with a degree of centralization of 0.23, compared to the 0.755 degree of centralization computed for the author co-citation analysis.

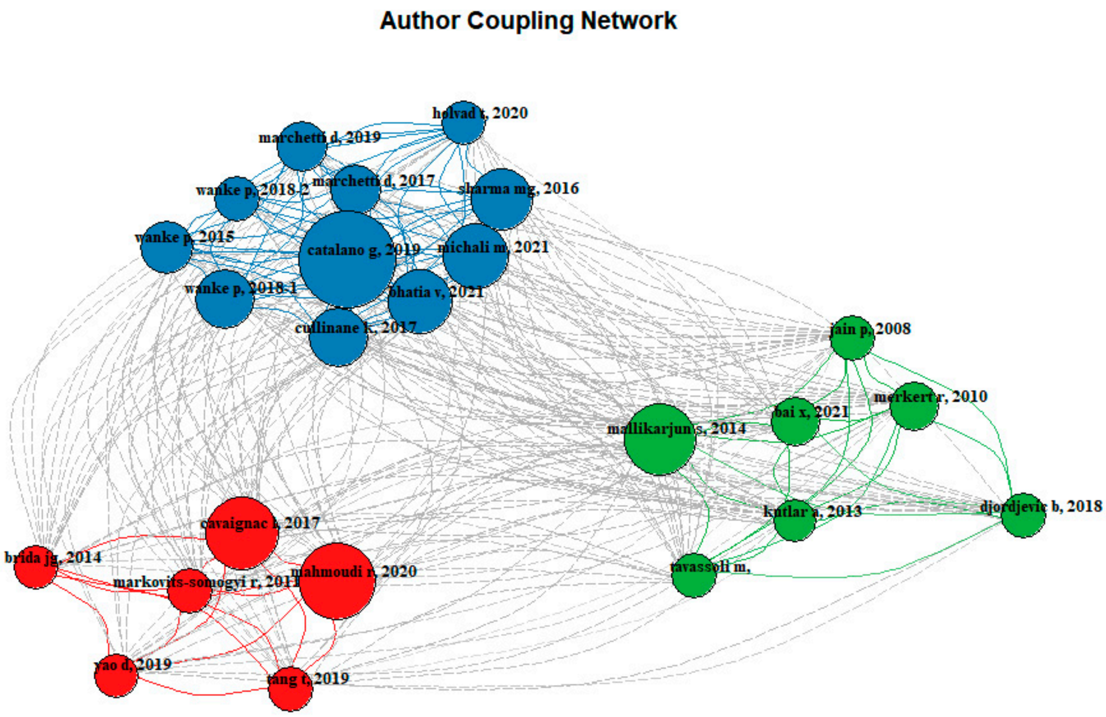

Figure A1. Author-coupling network. References: Brida jg, 2014 [90], Yao d, 2019 [91], Tang t, 2019 [88], Markovits-Somogyi r, 2011 [92], Cavaignac [21], Mahmoudi r, 2020 [20], Tavassoli m, 2015 [93], Mallikarjun s, 2014 [94], Kutlar a, 2013 [95], Bai x, 2021 [96], Djordjevic b, 2018 [84], Merkert r, 2010 [83], Jain p, 2008 [82], Wanke p, 2015 [97], Wanke p, 2018-1 [98], Wanke p, 2018-2 [99], Cullinane k, 2017 [100], Catalano g, 2019 [86], Bhatia v, 2021 [101], Michali m, 2021 [60], Marchetti d, 2017 [102], Marchetti d, 2019 [103], Sharma mg, 2016 [70], Holvad t, 2020 [104].

From the presented clusters, we can see both cited literature reviews, Cavaignac and Petiot (2017) [21] and Mahmoudi et al. (2020) [20], as well as a concentration of rail-applied publications in the blue cluster related to technical efficiency.

Lastly, for keyword analysis we used the bibliometrix R package [31].

As mentioned before from input–output variable analysis, most DEA rail research relates to technical efficiency. The keyword co-occurrences presented in Figure A2 corroborates these findings. They also corroborate the lack of safety-related research and the need for more sustainability-/emissions-related publications.

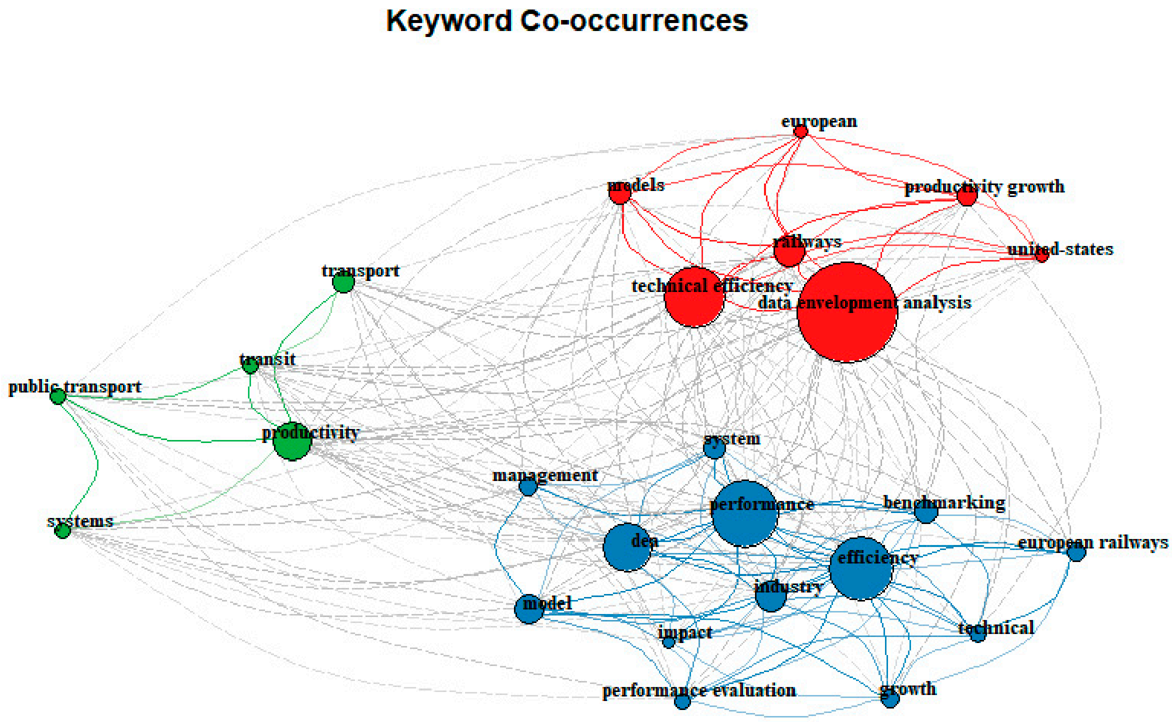

Figure A2. Keyword co-occurrence network.

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