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CO_2 emissions and logistics performance: a composite index proposal

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ABSTRACT

The importance of good logistics performance for low/no fossil-carbon economies is widely recognized, especially because the transport sector is responsible for a substantial portion of the world's greenhouse gas emissions. This research evaluates efficiency in the relationship between transport logistics performance, as measured by the Logistics Performance Index (LPI), and CO_2 emissions from the transport sector. The slacks-based measure (SBM) of the data envelopment analysis (DEA) was used to construct a low carbon logistics performance index (LCLPI) ranking a group of 104 countries that were selected using the available data. The empirical model adopted one input (CO_2 emissions for the transport sector) and seven outputs (gross domestic product [GDP] and the six components of the LPI). GDP has been included as a non-discretionary output because CO_2 emissions are directly dependent on a country's economic production, while the LPI is a qualifier. To evaluate how the composite index evolved over time, we used an approach that combines the techniques of window analysis and the Malmquist index. Considering the DEA results, the countries that performed best in terms of the LCLPI were Japan, Germany, Togo, Benin, and the United States and the more evolved countries were Luxemburg, Ireland, Lebanon, and Honduras. For the purposes of LCLPI validation and analysis, the performances of the BRICS (Brazil, Russia, India, China and South Africa) countries were analyzed, especially China, which is the world's second largest CO_2 emitter. The proposed composite index and the ranking of countries in terms of logistics performance and CO_2 emissions can help identify the best performing countries in low carbon logistics.

1. Introduction

The roles of transport and logistics enable international trade and commerce on a global scale. Logistics encompasses a series of activities, such as freight transportation, warehousing, border clearance, and payment systems. The importance of good logistics performance for economic growth and poverty reduction is widely recognized. Improved logistics performance is key to economic growth and competitiveness.

Notwithstanding this recognition, a source of concern is how economic performance and logistics performance are related to the CO_2 emissions of countries. Between 1970 and 2004, carbon dioxide emissions increased by 70%, with the transport sector accounting for 13.1% of the emissions; greenhouse gas (GHG) emissions from the transport sector also account for the fastest growing source of GHG emissions (Nilsson et al., 2013). The main compounds emitted in this sector are carbon dioxide (CO_2), nitrogen oxides (NOx), and carbon monoxide (CO) (Lloyd's, 1995).

Therefore, there is a growing trend in research and practice advocating the development of green logistics operations (e.g., Ostrom, 2008; Pålsson et al., 2013). Supply chain sustainability was a growing concern in the last Logistic Performance Index (LPI) report, in that approximately 37% of the respondents from Organization for Economic Co-operation and Development (OECD) countries and 10% of low GDP countries recognized a demand for environmentally friendly logistics solutions (Arvis et al., 2014). Among the noteworthy effective solutions to be adopted by countries with CO_2 saving potential are (a) traffic-reducing settlement development and transport planning, (b) promoting environmentally sound transport modes, (c) taxes and economic measures, (d)

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legislation to improve vehicle efficiency, and (e) improved consumer and driving behavior (Rodt et al., 2010).

In this context, an efficient conversion of logistics performance to environmental performance becomes extremely important; however, it is not clear which are the countries that have been successful in this process. Thus, this paper presents the following research question: how can an index be designed that allows for the ranking of countries based on efficiency in transforming CO_2 emissions into logistics performance?

To answer this question, we used the datasets from the International Logistics Performance Index (Arvis et al., 2014) and the CO_2 emissions in the transportation sector (World Bank, 2015) to conduct quantitative research. The dataset was modeled with Slack Based Measure (SBM) of the data envelopment analysis (DEA) technique, which allows for aggregations of multiple inputs and multiple outputs in a composite index (CI), without the need to convert them into a common unit of measure. The purpose is to build an alternative index to the LPI with DEA application, which allows the following improvements over the original index:

1. Incorporation of the environmental dimension by including the variable CO_2 emissions in transportation.
2. The use of variable weights for each dimension, so that each country can adopt weights that are most advantageous.
3. Construction of a relative index, where countries will be assessed in comparison to other countries in the group under study.

This index, which evaluates the performance of a country at a given point in time, allows for the ranking of countries. This ranking, in turn, can serve as a starting point for further research, offering guidance in order to identify the best practices that can serve as a basis for national or international public policy and the identification of possible priority targets for these practices and measures. In addition, a dynamic index was also built using the Malmquist index in order to evaluate the evolution of the performance of each country.

For the purposes of LCLPI validation, the BRICS's performance was analyzed, especially China's, which is a country in a period of sharp economic growth and the world's second largest CO_2 emitter. Another reason for focusing on this country is because of the abundance of studies on CO_2 emissions in its transport sector.

It is worth mentioning that this paper moves forward in terms of the existing literature by proposing a flexible index that allows for assigning weights to rank countries in relation to their performances in low carbon logistics emissions. A study that approached that goal was Lau (2011), which proposed the construction of a green logistics performance index (GLPI), in which various parameters based on green logistics concepts were used. This index, however, was based on questionnaires and weights were allocated based on principal component analysis (PCA), and its application was far less comprehensive than this work, as it was restricted to China and Japan.

Chen et al. (2015), on the other hand, applied the entropy weight method to propose a low carbon logistic index (LCLI), which analyzes only factors relating to carbon emissions without incorporating factors related to logistics performance. This index was used to evaluate only the city of Beijing.

Another work that deserves to be mentioned is the study by Markovits-Somogyi and Bokor (2014), which applied DEA to assess the logistics performance of European countries without considering the environmental dimension. Interestingly, in their work the focus was to determine the countries' effectiveness in logistics performance infrastructure conversions, which were evaluated in terms of quantity transported as well as transport quality. It should be noted that the authors did not use any approach to analyze the evolution of efficiency over time.

In addition to these articles, it is appropriate to mention that the SBM model of DEA was used in other studies on the subject of low-carbon economy; however, these works were not related to the construction of a logistic performance composite index.

Examples of SBM model application on the subject of low-carbon economy include: Zhang et al. (2017), which evaluated how the Chinese provinces are efficient in having a good economic performance with low carbon emissions; Camioto et al. (2016), which used the SBM to evaluate the efficiency of BRICS and G7 countries in generating GDP with low power consumption; Li and Hu (2012), who used a similar approach to assess the energy efficiency of China's regions; Gómez-Calvet et al. (2014), who used the SBM for the efficiency assessment in sustainable electricity generation in countries of the European Union; and Camioto et al. (2014), who used the SBM model to evaluate the Brazilian industrial sectors in relation to sustainability (including carbon emissions). In most of these articles, the SBM model was applied to evaluate the efficiency to generate economic performance with low CO_2 emissions and low power consumption in specific countries, provinces or regions.

Given the discussion above, we emphasize that the main contribution of this work is the proposition of a new composite index (the LCLPI), that is able to measure, in an integrated way, the logistics performance and carbon emissions level in the transport sector of selected countries. In addition, this index was used for the evaluation of 104 countries in three different periods of time. It is emphasized that this index can be used as a potential substitute of LPI, since it has the following advantages: (a) take into account a low carbon perspective and (b) it is built with data envelopment analysis, which gives it a number of advantages, such as flexibility weights (Despotis, 2005a,b; Mariano et al., 2015).

The outline of this paper is as follows. The theoretical review is presented in Section 2. The research method is described in Section 3. The results are explained and discussed in Section 4. And Section 5 presents some conclusions regarding this study. To facilitate reading and understanding the text, Table 1 lists the main acronyms and abbreviations used in this article.

2. Theoretical review

2.1. The logistics performance index

Since 2007, the Logistics Performance Index (LPI) released by the World Bank has been central to the debate about the role of logistics for economic growth and the policies that support it. Composite indexes, such as the LPI, help policymakers by providing data on which to base their decisions.

The results of the last LPI report, named “Connecting to Compete”, indicate that Germany is the best-performing country in the LPI and Somalia is the worst-performing country (Arvis et al., 2014). In the 2014 LPI, 15 of 28 EU member states were ranked among the top 30 countries, but there were some developing countries in this part of the ranking as well: United Arab Emirates (24th), Malaysia (26th), China (27th), and South Africa (28th) (World Bank, 2014).

A slight convergence in low- and medium-income countries is perceived as a result from improvements in infrastructure and, to a lesser extent, in logistics services and border management. Infrastructure has provided basic connectivity and access to gateways for most developing countries; however, the service delivery is usually perceived as poor. Countries that performed better in the LPI had manufacturers and traders that already outsourced logistics

Table 1
List of acronyms.

Acronyms	Meaning
BRICS	Brazil, Russia, India, China and South Africa
CE	Catch-up effect of Malmquist Index
CI	Composite Index
DEA	Data Envelopment Analysis
G7	United States, United Kingdom, France, Italy, Germany, Canada and Japan
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GLPI	Green Logistic Performance Index
GSP	Green Shipping Practices
LCLI	Low Carbon Logistic Index
LCLPI	Low Carbon Logistic Performance Index
LPI	Logistic Performance Index
MI	Malmquist Index
OECD	Organization for Economic Co-operation and Development
PCA	Principal Component Analysis
SBM	Slack based Measure
SD	Strong disposable
TC	Technological Change of Malmquist Index
WD	Weak Disposable

to third-party providers and had focused on their core businesses while managing more complex supply chains.

The LPI is based on a standardized questionnaire and uses statistical techniques to aggregate the data into a single index that can be used to compare countries, regions, and income groups (Arvis et al., 2014). The LPI data collection is based on a structured online survey of logistics professionals, from multinational freight forwarders to the main express carriers, who are responsible for moving goods around the world; their choices of shipping routes and gateways influences decisions regarding production locations, choice of suppliers, and selections of target markets. Based on 125 countries, nearly 1000 logistics professionals took part in the 2013 survey for the 2014 LPI.

The first part of the LPI survey is composed of a questionnaire in which each survey respondent, who is randomly selected, evaluates eight overseas markets on the six components of logistics performance. The eight countries are chosen based on the most important export and import markets of the country where the respondent is located (Arvis et al., 2014). The six LPI components are:

1. The efficiency of customs and border clearance (“Customs”).
2. The quality of trade and transport infrastructure (“Infrastructure”).
3. The ease of arranging competitively priced shipments (“Ease of arranging shipments”).
4. The competence and quality of logistics services: trucking, forwarding, and customs brokerage (“Quality of logistics services”).
5. The ability to track and trace consignments (“Tracking and tracing”).
6. The frequency with which shipments reach consignees within scheduled or expected delivery times (“Timeliness”).

The international LPI is constructed from these six indicators using PCA, which is a standard statistical technique that is used to reduce the dimensionality of a dataset. The normalized scores for each of the six original indicators are multiplied by their component loadings and then summed.

Although LPI offers a comprehensive and country-based logistics data, it has two main limitations: (a) the experience of international freight forwarders may not represent the broader logistics environment in poor countries, because international operators might differ from traditional operators in their interactions with local government agencies; and (b) the LPI might reflect access problems outside landlocked countries, such as transit difficulties. The low rating of landlocked countries might not adequately reflect their trade improvement efforts, which depend on complex international transit systems.

2.2. Logistics and CO_2 emissions

Playing the role of transportation intermediary to facilitate trade flows in the global supply chain (Wong et al., 2009a; Yang et al., 2009a), many shipping firms have begun to respond to environmental concerns by embracing green shipping practices (GSPs) by greening their operations. GSPs are environmental management practices undertaken by shipping firms with an emphasis on waste reduction and resource conservation in the handling and distribution of cargoes.

Examples of such practices include counting the carbon footprint of shipping routes and using alternative transportation equipment aimed at reducing environmental damage during shipping. Following this trend, large service providers, notably the main express carriers (DHL, FedEx, UPS, and TNT), have developed products and programs aimed at responding to environmental concerns. These changes will likely help expand this greening logistics movement from rich-country-based operators to developing countries. Logistics performance is thus seen as an increasingly complementary objective to sustainability (Arvis et al., 2014). Therefore, there is a need to assess the impact of CO_2 emissions on logistics performance.

Freight transport is a significant and growing part of the emission of greenhouse gases. The majority of carbon emissions generated are from the freight transport industry. Estimates for Brazil in 2010 (ANTT, 2014), for example, indicate that road transport accounted for 82% of carbon dioxide (CO_2) emissions. Another study (Hao et al., 2014) indicated that China's CO_2 greenhouse emissions by urban passenger transport reached 335 million tons in 2010. There are growing international concerns about the environmental damages associated with the accelerated industrial activities in BRICS countries (Brazil, Russia, India, China and South Africa) (Lai and Wong, 2012). Among the developing economies, BRICS countries will have higher emission rates due to expected economic growth in upcoming years and the impact of transport conditions. These increased rates are a strain for developing countries trying to compete in the global arena and will lead to even greater international pressure and to the need to quickly transform the shipping and logistics transport sectors into low greenhouse gas emitters. Additionally, in these countries, stakeholders will demand that more firms respond by adopting green practices in logistics for their environmental sustainability (Lai and Wong, 2012).

A green logistics and transportation approach requires a modal shift from roads to rail; however, influencing the rail demand beyond bulk markets will be a challenge for policymakers, except for a few high income countries (Arvis et al., 2014).

To reduce CO_2 emissions from a logistics perspective, a holistic approach needs to be practiced. Different measurements need to be included, such as economic activity and value density, as well as the transportation intensity, traffic intensity, energy intensity, and emissions intensity (Nilsson et al., 2013). The four latter are discussed below:

- *Reduce transport intensity*: local sourcing, decentralized distribution, CO_2 emission taxation.
- *Reduce traffic intensity*: increase the utilization of co-modality, larger capacity vehicles, mandatory mixed vehicles in cities, obligatory spot market for vacant transport. Freight consolidation between supply chains, namely pooling supply chains, is also a new concept that helps reduce GHG emissions, especially CO_2 emissions (Pan et al., 2013). The possibility of reducing CO_2 emissions obviously depends on consolidating a mass of flows that will be shipped together to increase the vehicle load factor of each shipment (Ergun et al., 2007).
- *Reduce energy intensity*: eco-driving reduces CO_2 emissions by approximately 5%, streamlined vehicles, increased tire pressure, lower friction in moving parts, reduced loads and speeds.
- *Reduce CO_2 emissions intensity*: policies that encourage the production and adoption of vehicles with improved CO_2 fuel efficiency (such as switching to electric, hybrid, and biofuel-powered vehicles). However, these assumptions do not take into account that these policies may result in overall greater CO_2 emissions if the electricity and/or biofuel production is intense in CO_2 emissions and/or the number of these vehicles increases.

Despite the importance of reducing CO_2 emissions in the logistics sector in the literature, two research lines have appeared. One line addresses modeling and simulation for predicting long-term freight and environmental trends (e.g., Sarraj et al., 2014), while the other line addresses the simulation and modeling of logistics variables to increase the efficiency in costs and CO_2 emissions (e.g., Canhong et al., 2014). Less attention has been given to examining the quantitative relationships between CO_2 emissions and the efficiency of the logistics sector.

Fan and Wang (2013) conducted an empirical study—one of few exceptions—that included 25 provincial logistics sectors in China, correlating CO_2 emissions with the technical efficiency of the logistics sector. According to the authors, reducing 1% of the CO_2 emission leads to a technical efficiency enhancement of 0.231% of the logistics sector in China, which raises the question of how much of the CO_2 emissions are related to changes in efficiency (changes in the relative performance of one country) and how much is related to changes in the general state of technology (changes in the relative performance of all countries). One critical related issue is the capacity to convert CO_2 emissions into logistics performance.

3. Method

A composite index (CI) can be defined as a synthetic index that condenses a series of indicators into a single value (Booysen, 2002). In this study, data envelopment analysis (DEA) was used to build a CI of low carbon logistic performance; the window analysis and the Malmquist index, on the other hand, were used to evaluate this index over time. The DEA technique has been successfully used to assess the relative performance of a set of decision-making units (DMUs), which use a group of inputs to produce some outputs. The DEA has its origins in the work of Charnes et al. (1978), who proposed an empirical model to measure relative efficiency.

The major advantage of DEA is the weighting of indicators within the CI, as DEA allows extracting a set of weights from the data itself, which eliminates the arbitrariness in choosing them (Mariano et al., 2015). According to Ramanathan (2006), the DEA-based CIs often have the following characteristics: (a) the weights implemented for each indicator vary from unit to unit; (b) the weights used are the most advantageous for each unit; (c) the aggregation between indicators is done as a linear combination; and (d) the index obtained is related to the units analyzed, ranging from 0 to 1.

In the LCLPI, eight variables are used: seven desirable outputs and one undesirable output. Six of the desirable outputs correspond to the components of the LPI (customs, infrastructure, ease of arranging shipments, quality of logistics services, tracking and tracing, and timeliness) and the other is the GDP of each country; the only undesirable output is the CO_2 emissions in the transportation sector. The GDP was included to try to counterbalance the fact that CO_2 emissions directly depend on the size of a country's economy, while the LPI is only a qualifier that does not depend on economic production; the GDP was adopted as a non-discretionary variable because it was considered an external variable to the proposed model.

It is noteworthy that analyzing the map of transport emissions, which is expressed in Fig. 1, it is possible to easily see that the countries with the largest economies, such as the US, China, Brazil and the United Kingdom, also have the largest GDPs in absolute terms (not per capita).

In a statistical analysis it was found that the adjusted R^2 of the linear regression between the logarithms of these two variables in 2011 was around 0.9 while the p-value was around 7.52×10^{-55}, as shown in Fig. 2.

It is noteworthy that the variable "CO_2 emission in the transport sector" considers emissions from the combustion of fuel for all transport activities, with the exceptions of international marine bunkers and international aviation. In addition, the data that were used were not collected in a way that allows the autoproducer consumption to be split by specific end-use (e.g., to generate electricity); therefore, transport emissions data from auto producers were not considered in this analysis (World Bank, 2015).

According to Sahoo et al. (2011) and Yang and Pollitt (2010), there are many ways to treat undesirable outputs in DEA, which can be grouped into two classes: strong disposability (SD) and weak disposability (WD). WD models consider that CO_2 emissions cannot be reduced freely, and the emissions can be considered a cost of producing the desired outputs; in this type of approach, which tends to be more consistent with the assumptions of production theory, the outputs do not need to be transformed, as the mathematical models are adjusted (Sahoo et al., 2011). The SD models consider that emissions can be reduced, regardless of what happens with the desirable inputs and outputs, the original models are used and unwanted output must undergo some kind of transformation, and the most recommended is the additive inverse transformation (Sahoo et al., 2011). There is still no consensus on the best approach to dealing with unwanted outputs (Yang and Pollitt, 2010), whereas the comparative research already carried out, in relation to the different models, tended to get very close results (Sahoo et al., 2011; Korhonen and Luptacik, 2004).

Considering the objective of this study, which is to build an index, and considering all opportunities to reduce emissions presented in the previous section, it was decided to adopt the SD, and the variable CO_2 emissions in the transport sector were treated as if they were an input.

The DEA results depend on the adopted model. Each model, depending on the type of returns to scale and orientation, will lead the index to a different value, which must be interpreted in accordance with the assumptions of the model that is used. The slacks-based measure (SBM) model with variable returns to scale (VRS) was the chosen DEA model. The justification for using the SBM is that this model, introduced by Tone (2001), considers a simultaneous orientation to the inputs and outputs, which is more suitable for the type of analysis performed.

According to Mariano et al. (2015) there is a gap in the literature related to studies in which the SBM model is used to construct CIs; there is also a gap in knowledge about building indexes using a temporal approach, either with window analysis or by a Malmquist

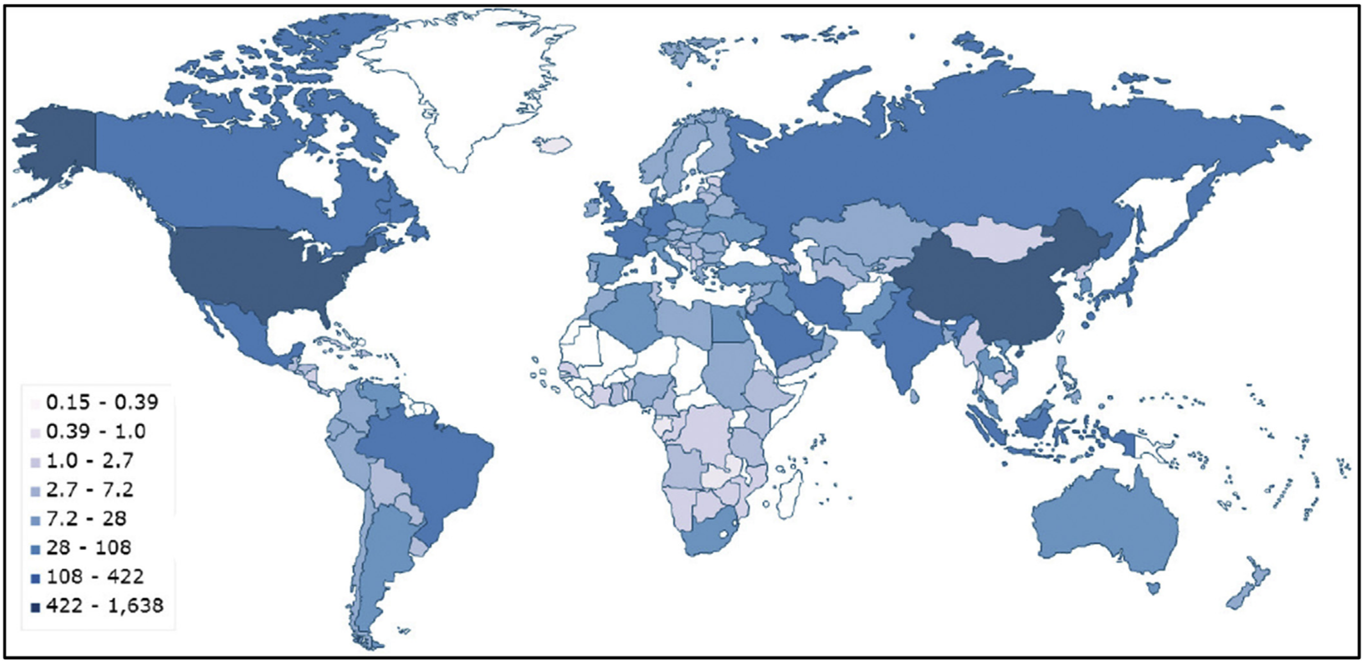

Fig. 1. CO_2 of the transport sector.
Source: INDEX MUNDI (2016).

index. This work advances these two questions. The fact that a model with variable returns to scale was used, which is unusual in CIs (Mariano et al., 2015), is due to a relationship between GDP and CO_2 emissions in the transport sector that is not linear, and it is better expressed by a log–log model as showed in Fig. 2.

Equation (1) shows the formulations of the SBM-VRS model with a non-discretionary output (Saen, 2005), wherein x_{jk} represents the amount of input j of DMU k, y_{ik} represents the amount of output i of DMU k, x_{j0} represents the amount of input j of the DMU under analysis, y_{i0} represents the amount of output i of the DMU under analysis, λ_k represents the contribution of DMU k for the goal of the DMU under analysis, S_j and S_i represent the slacks of the inputs and outputs, t represents a linearization variable, m represents the number of outputs analyzed, n represents the number of inputs analyzed, and z represents the number of DMUs analyzed.

$$\text{Min } \tau = t - \frac{1}{n}\sum_{j=1}^{n} S_j^- \Big/ x_{j0}.$$

Subject to:

$$\begin{aligned}
& t + \frac{1}{m}\sum_{i=1}^{m} S_i^+ \Big/ y_{i0} = 1, \\
& \sum_{k=1}^{z} x_{jk}\cdot\lambda_k - t\cdot x_{j0} + S_j^- = 0, \ \text{ to } j = 1,2,\ldots,n, \\
& \sum_{k=1}^{z} y_{ik}\cdot\lambda_k - t\cdot y_{i0} - S_i^+ = 0, \ \text{ to } i = 1,2,\ldots,m, \\
& S_i^+ \text{ or } S_j^- = 0, \ \text{ if } y_i \text{ or } x_j \text{ is non-discretionary}, \\
& \sum_{k=1}^{z} \lambda_k = t, \\
& \lambda_k,\ S_j \ e \ S_i \geq 0 \ e \ t > 0.
\end{aligned} \tag{1}$$

The LPI and GDP data were used for the years 2007, 2010, and 2012. However, as there were data only until 2011 in the case of CO_2 emission in the transportation sector, it was necessary use the data of 2011 as a proxy of this variable in the year of 2012. By extracting the flaws in the panel, 104 countries remained in the sample. Matlab software was used to run the model.

The procedures relating to the window analysis and the Malmquist index will be detailed in the following sections.

3.1. Window analysis

One way to include the time factor within the DEA technique is by performing window analysis, details of which can be found in Cooper et al. (2000). The window analysis consists of a structured method to blend in a single application the DMU data for a variety of different years, using multiple applications of the DEA considering different combinations of years (window). Thus, the window analysis is also an important means to circumvent the problem of a low number of DMUs, which, according to Cooper et al. (2000), must be at least three times the sum of the amount of inputs to the amount of outputs.

The window analysis covers the separation of the years that are being analyzed into different groups (windows); thus, from the available data in this analysis, the first step is to determine the size

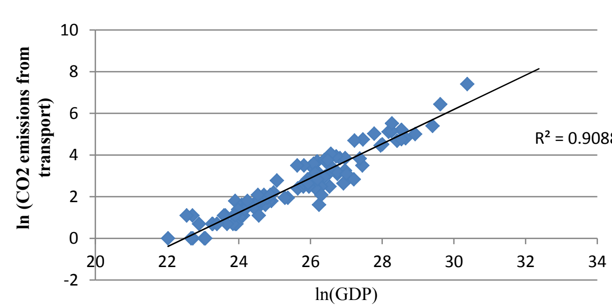

Fig. 2. CO_2 emissions for transport sector and GDP.

Table 2
Results of window analysis.

Ranking	Country	Window 1		Window 2		Mean	Standard deviation
		2007	2010	2010	2012		
1	Switzerland	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
2	Japan	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
3	United States	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
4	Benin	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
5	Togo	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
6	Hong Kong	100.00%	96.45%	100.00%	100.00%	99.11%	1.77%
7	Macedonia	90.12%	100.00%	100.00%	100.00%	97.53%	4.94%
8	Haiti	84.98%	100.00%	100.00%	100.00%	96.25%	7.51%
9	Moldova	90.01%	100.00%	86.89%	100.00%	94.23%	6.79%
10	Norway	76.50%	100.00%	100.00%	100.00%	94.13%	11.75%
11	Armenia	79.49%	100.00%	100.00%	87.36%	91.71%	10.09%
12	Singapore	100.00%	100.00%	63.39%	100.00%	90.85%	18.30%
13	Cyprus	90.14%	100.00%	85.74%	86.58%	90.62%	6.54%
14	Germany	100.00%	100.00%	58.76%	100.00%	89.69%	20.62%
15	Kyrgyz Republic	50.12%	100.00%	100.00%	100.00%	87.53%	24.94%
16	Netherlands	100.00%	100.00%	48.39%	100.00%	87.10%	25.80%
17	United Kingdom	90.36%	78.79%	82.21%	79.55%	82.73%	5.30%
18	Estonia	90.77%	100.00%	54.84%	81.70%	81.83%	19.48%
19	Bahrain	100.00%	100.00%	59.35%	65.89%	81.31%	21.75%
20	Sweden	72.14%	100.00%	52.23%	100.00%	81.09%	23.30%
21	Denmark	71.12%	83.20%	63.30%	85.03%	75.66%	10.29%
22	France	74.63%	82.10%	53.23%	82.92%	73.22%	13.84%
23	Luxembourg	67.68%	100.00%	20.48%	100.00%	72.04%	37.60%
24	Ireland	41.62%	97.24%	34.74%	100.00%	68.40%	35.03%
25	Belgium	54.73%	71.78%	64.99%	71.78%	65.82%	8.06%
26	Latvia	60.78%	100.00%	38.40%	61.27%	65.11%	25.59%
27	Italy	60.86%	64.93%	64.67%	68.37%	64.71%	3.07%
28	Côte d'Ivoire	100.00%	54.74%	44.64%	58.36%	64.43%	24.41%
29	Mongolia	40.64%	75.57%	56.36%	82.88%	63.86%	19.10%
30	Jamaica	43.36%	54.03%	100.00%	52.27%	62.41%	25.49%
31	Senegal	44.50%	100.00%	42.65%	60.40%	61.89%	26.63%
32	Nepal	80.08%	42.65%	74.62%	42.83%	60.05%	20.10%
33	Panama	55.20%	76.92%	43.19%	53.87%	57.30%	14.14%
34	Lebanon	34.80%	100.00%	32.61%	48.84%	54.06%	31.46%
35	Austria	60.30%	39.99%	58.67%	55.73%	53.67%	9.32%
36	Dominican Republic	24.25%	48.63%	100.00%	37.32%	52.55%	33.16%
37	Honduras	31.61%	100.00%	31.33%	41.90%	51.21%	32.90%
38	Tanzania	28.48%	40.61%	95.09%	36.32%	50.12%	30.40%
39	Australia	35.12%	47.00%	63.77%	50.81%	49.18%	11.80%
40	Namibia	79.28%	35.38%	45.17%	36.58%	49.10%	20.59%
41	Uruguay	36.02%	45.87%	63.34%	49.20%	48.61%	11.30%
42	Finland	51.71%	49.07%	33.65%	56.57%	47.75%	9.90%
43	Jordan	31.99%	30.52%	100.00%	26.80%	47.33%	35.18%
44	Ethiopia	73.36%	34.89%	38.26%	37.53%	46.01%	18.29%
45	Lithuania	29.84%	72.27%	33.48%	47.43%	45.75%	19.24%
46	Greece	28.23%	20.92%	100.00%	29.10%	44.56%	37.14%
47	Spain	42.35%	45.84%	33.38%	48.36%	42.48%	6.55%
48	El Salvador	36.58%	54.71%	40.24%	36.63%	42.04%	8.62%
49	Cameroon	55.68%	36.27%	38.34%	35.60%	41.47%	9.54%
50	Cambodia	45.96%	43.61%	31.49%	42.63%	40.92%	6.44%
51	Turkey	35.63%	42.23%	38.15%	44.94%	40.24%	4.15%
52	China	26.16%	41.17%	50.06%	43.46%	40.21%	10.10%
53	Bosnia and Herzegovina	32.23%	40.76%	43.52%	38.01%	38.63%	4.82%
54	Slovak Republic	27.56%	45.62%	35.26%	40.85%	37.32%	7.76%
55	Brazil	25.53%	38.57%	38.79%	40.73%	35.91%	6.99%
56	Slovenia	49.63%	32.47%	20.06%	36.60%	34.69%	12.19%
57	Canada	32.82%	37.62%	27.10%	37.86%	33.85%	5.06%
58	Paraguay	34.06%	36.17%	36.49%	27.80%	33.63%	4.03%
59	New Zealand	35.61%	34.87%	25.42%	37.92%	33.45%	5.51%
60	Tunisia	30.22%	37.21%	33.24%	30.73%	32.85%	3.19%
61	Oman	48.02%	33.68%	21.19%	26.38%	32.32%	11.66%
62	Costa Rica	28.29%	41.79%	25.23%	33.09%	32.10%	7.22%
63	India	30.39%	30.08%	34.39%	32.18%	31.76%	1.99%
64	Poland	22.72%	38.14%	24.21%	39.72%	31.19%	8.97%
65	Azerbaijan	27.24%	29.69%	29.38%	33.42%	29.93%	2.57%
66	Kenya	37.40%	24.08%	29.98%	26.24%	29.43%	5.85%
67	Angola	36.28%	21.20%	33.89%	25.77%	29.28%	7.02%
68	Croatia	26.16%	27.18%	30.59%	30.66%	28.64%	2.32%
69	Kuwait	25.23%	20.95%	43.65%	24.47%	28.57%	10.22%
70	Sudan	23.46%	16.93%	54.65%	19.14%	28.54%	17.61%
71	Qatar	29.16%	26.35%	31.88%	26.29%	28.42%	2.67%
72	Nigeria	10.22%	22.95%	50.91%	29.09%	28.29%	17.00%

(continued on next page)

Table 2 (*continued*)

Ranking	Country	Window 1		Window 2		Mean	Standard deviation
		2007	2010	2010	2012		
73	United Arab Emirates	22.62%	18.44%	36.82%	25.95%	25.96%	7.87%
74	Ghana	23.89%	23.13%	31.91%	24.07%	25.75%	4.13%
75	Portugal	21.61%	21.74%	26.86%	29.17%	24.85%	3.78%
76	Guatemala	23.95%	26.34%	24.75%	23.71%	24.69%	1.19%
77	Sri Lanka	16.19%	17.67%	44.82%	19.33%	24.50%	13.60%
78	Romania	20.77%	19.43%	32.14%	25.63%	24.49%	5.75%
79	Czech Republic	16.56%	26.32%	19.24%	33.24%	23.84%	7.50%
80	Colombia	11.77%	18.93%	37.33%	26.67%	23.67%	10.95%
81	Hungary	20.00%	21.50%	25.08%	27.14%	23.43%	3.27%
82	Kazakhstan	13.37%	19.80%	31.61%	25.97%	22.69%	7.86%
83	Yemen	19.56%	23.66%	27.15%	20.30%	22.67%	3.48%
84	Bulgaria	22.38%	19.31%	26.81%	21.47%	22.49%	3.15%
85	Bolivia	22.29%	21.17%	19.80%	20.34%	20.90%	1.08%
86	Mexico	19.26%	18.17%	22.48%	19.14%	19.76%	1.87%
87	Peru	18.78%	16.70%	20.87%	21.98%	19.58%	2.33%
88	Chile	15.05%	16.84%	22.87%	22.52%	19.32%	3.97%
89	Uzbekistan	10.36%	24.66%	18.59%	19.43%	18.26%	5.91%
90	Russia	13.07%	15.04%	26.74%	15.98%	17.71%	6.14%
91	Argentina	11.06%	15.14%	24.08%	19.19%	17.36%	5.57%
92	South Africa	12.82%	15.47%	18.89%	19.77%	16.74%	3.21%
93	Indonesia	13.10%	14.49%	22.60%	15.54%	16.43%	4.23%
94	Philippines	10.68%	14.18%	19.66%	18.59%	15.78%	4.14%
95	Venezuela	7.52%	13.67%	17.07%	16.87%	13.78%	4.45%
96	Saudi Arabia	10.24%	11.37%	14.39%	12.93%	12.23%	1.81%
97	Malaysia	8.46%	10.03%	13.72%	14.17%	11.59%	2.79%
98	Ecuador	10.85%	12.62%	9.58%	13.23%	11.57%	1.67%
99	Thailand	8.39%	10.54%	11.27%	14.16%	11.09%	2.38%
100	Pakistan	6.85%	7.30%	16.80%	9.69%	10.16%	4.60%
101	Vietnam	8.36%	8.05%	11.18%	10.07%	9.41%	1.47%
102	Egypt	5.46%	7.93%	12.91%	10.59%	9.22%	3.23%
103	Algeria	6.46%	7.38%	11.28%	9.74%	8.72%	2.20%
104	Ukraine	6.85%	6.81%	11.65%	8.93%	8.56%	2.28%

of each window and the number of windows to be built. This information can be obtained through equations (2) and (3), where p represents the number of periods and s the window size, which should be rounded when necessary.

$$\text{Window size } (s) = (p+1)/2, \tag{2}$$

$$\text{Number of windows} = p - s + 1. \tag{3}$$

To illustrate the use of these formulas and the subsequent construction of windows in this analysis, which evaluates available data from 2007, 2010, and 2012 ($p = 3$), the window size should be two, and the number of windows also should be two, comprising data from (a) Window 1 (2007 and 2010); and (b) Window 2 (2010 and 2012).

3.2. Malmquist index

Among the many existing functions for an index number, highlighting its use in the construction of inflation indicators, one of the most interesting is its ability to measure the changes in the productivity of DMU applications over time and in the productivity differences between two different DMUs.

The Malmquist index (MI), which was developed by Caves et al. (1982) and inspired by Malmquist (1953), is an index number determined from the distances of the DMUs from the efficiency frontier. The Malmquist index, which measures productivity changes over time, can be calculated from the DEA efficiency scores. The MI can be decomposed into two parts, one of which indicates that the evolution of productivity is due to productive efficiency (catching-up effect [CE]) and that the other is due to changes in the efficiency frontier (technological change [TC]).

In this study, we used the approach of Asmild et al. (2004), who proposed the decomposition of the results of the DEA window analysis to build the Malmquist index, as shown in Equation (4):

$$\begin{aligned} \mathrm{MI}(a,b) &= \frac{\theta_{w_k,b}}{\theta_{w_k,a}}, \\ \mathrm{CE}(a,b) &= \frac{\theta_{w_{k+1},b}}{\theta_{w_k,a}}, \\ \mathrm{TC}(a,b) &= \frac{\mathrm{MI}(a,b)}{\mathrm{CE}(a,b)}, \end{aligned} \tag{4}$$

wherein:
$\theta_{w_k,a}$: Efficiency of a DMU in year a in window k;
$\theta_{w_k,b}$: Efficiency of a DMU in year b in window k;
$\theta_{w_k+1,b}$: Efficiency of a DMU in year b in window $k+1$;
$\mathrm{MI}(a,b)$: Malmquist index between years a and b;
$\mathrm{CE}(a,b)$: Catching-up effect between years a and b;
$\mathrm{TC}(a,b)$: Technological change between years a and b.

4. Results and discussion

4.1. Window analysis

Table 2 shows the results of LCLPI of the 104 countries that were analyzed in this study based on the results of the window analysis.

Considering the average LCLPI from 2007, 2010, and 2012, the following countries had the highest performances (maximum result of 100% for all years): Japan, Switzerland, Togo, Benin, and the United States. The four lowest average efficiency indices belong to

Table 3
Ranking of the countries in the LPI and LCLPI.

Country	LPI			LCLPI			Mean of difference of positions
	2007	2010	2012	2007	2010	2012	
Malaysia	25	27	23	97	98	96	−72.00
Thailand	29	32	32	98	100	97	−67.33
South Africa	23	26	33	89	93	86	−62.00
Saudi Arabia	38	36	43	95	96	99	−57.67
Vietnam	51	50	44	99	102	101	−52.33
United Arab Emirates	20	23	25	74	71	75	−50.67
Chile	30	44	37	85	89	81	−48.00
Portugal	26	31	24	77	81	64	−47.00
Czech Republic	35	24	30	83	84	59	−45.67
Argentina	42	45	54	91	90	89	−43.00
Canada	10	12	12	52	61	50	−43.00
Philippines	60	42	53	93	94	92	−41.33
Hungary	31	48	31	79	82	68	−39.67
Indonesia	40	69	47	87	92	95	−39.33
Mexico	53	46	46	81	88	90	−38.00
New Zealand	19	21	21	48	66	49	−34.00
Ukraine	66	86	56	101	104	104	−33.67
Poland	37	28	29	73	65	47	−30.33
Egypt	82	78	57	104	101	100	−29.33
Romania	48	57	39	78	77	77	−29.33
Venezuela	62	74	66	100	95	93	−28.67
Bulgaria	52	59	45	75	83	83	−28.33
Ecuador	64	67	74	92	99	98	−28.00
Kuwait	41	33	51	68	62	78	−27.67
Pakistan	63	93	64	101	97	103	−27.00
Qatar	43	51	27	59	68	72	−26.00
Peru	55	61	63	82	91	82	−25.33
Australia	17	18	16	49	39	35	−24.00
China	28	25	26	65	45	41	−24.00
Spain	24	22	18	40	51	38	−21.67
Finland	15	11	22	33	47	31	−21.00
Austria	5	19	20	29	43	32	−20.00
Belgium	12	8	3	32	26	25	−20.00
India	36	43	49	56	63	61	−17.33
Greece	27	49	40	62	35	65	−15.33
Slovenia	34	53	35	35	76	54	−14.33
Turkey	32	37	28	47	50	40	−13.33
Ireland	11	13	11	41	30	1	−12.33
Slovak Republic	47	34	38	63	48	45	−12.33
Sweden	4	4	7	24	20	1	−10.00
United Kingdom	9	9	4	13	15	24	−10.00
Russia	83	79	77	88	86	94	−9.67
Italy	21	20	19	27	34	26	−9.00
Luxembourg	22	6	8	26	36	1	−9.00
Oman	45	55	55	36	74	71	−8.67
Algeria	104	98	82	103	103	102	−8.00
France	18	16	14	22	28	21	−7.67
Croatia	58	68	50	65	69	63	−7.00
Denmark	13	17	17	25	23	20	−7.00
Guatemala	68	75	68	70	79	80	−6.00
Netherlands	2	3	2	1	22	1	−5.67
Germany	3	1	1	1	17	1	−4.67
Brazil	57	38	59	67	52	46	−3.67
Colombia	72	64	84	90	70	70	−3.33
Uzbekistan	97	63	96	94	85	87	−3.33
Singapore	1	2	5	1	14	1	−2.67
Kazakhstan	101	58	76	86	78	74	−1.00
Lithuania	54	41	42	58	41	39	−0.33
Norway	16	10	6	21	1	1	3.00
Nigeria	80	84	65	96	55	66	4.00
Costa Rica	67	52	75	61	60	60	4.33
Japan	6	7	10	1	1	1	6.67
Sri Lanka	79	99	78	84	64	88	6.67
Switzerland	7	5	13	1	1	1	7.33
Hong Kong	8	14	15	1	11	1	8.00
Jordan	50	72	60	54	33	69	8.67
Latvia	39	35	34	28	25	28	9.00
Tunisia	56	60	91	57	59	62	9.67
Kenya	69	85	67	43	75	73	10.00
Paraguay	65	71	69	51	57	67	10.00
Yemen	91	81	103	80	80	85	10.00
Bolivia	90	94	94	76	87	84	10.33

(continued on next page)

Table 3 (*continued*)

Country	LPI			LCLPI			Mean of difference of positions
	2007	2010	2012	2007	2010	2012	
United States	14	15	9	1	1	1	11.67
Panama	49	47	41	31	37	33	12.00
Sudan	59	102	104	72	58	90	15.00
El Salvador	61	73	58	44	44	53	17.00
Ghana	96	95	85	71	73	79	17.67
Dominican Republic	81	56	61	69	21	52	18.67
Bahrain	33	29	48	1	16	27	22.00
Estonia	44	39	36	12	18	23	22.00
Lebanon	84	30	73	50	29	37	23.67
Angola	75	101	92	45	72	76	25.00
Azerbaijan	92	77	95	64	67	58	25.00
Bosnia and Herzegovina	76	76	71	53	46	48	25.33
Cyprus	46	40	52	14	13	19	30.67
Honduras	73	65	87	55	32	44	31.33
Uruguay	70	70	79	46	40	36	32.33
Cambodia	71	97	72	37	53	43	35.67
Cameroon	74	90	100	30	54	57	41.00
Senegal	85	54	86	38	24	29	44.67
Tanzania	102	83	98	60	27	56	46.67
Ethiopia	88	96	88	23	56	51	47.33
Jamaica	93	91	62	39	19	34	51.33
Namibia	98	104	81	20	49	55	53.00
Côte d'Ivoire	86	89	70	1	42	30	57.33
Nepal	99	103	89	18	38	42	64.33
Mongolia	103	100	97	42	31	22	68.33
Macedonia	78	66	93	15	1	1	73.33
Benin	77	62	90	1	1	1	75.33
Moldova	89	88	83	16	12	1	77.00
Armenia	100	92	80	19	1	18	78.00
Kyrgyz Republic	87	82	102	34	1	1	78.33
Haiti	95	87	101	17	1	1	88.00
Togo	94	80	99	1	1	1	90.00

the countries Vietnam (9.41%), Egypt (9.22%), Algeria (8.72%), and Ukraine (8.56%).

When comparing the ranking obtained and the ranking of the original LPI, several changes can be seen, so that it can be concluded that the new index is obtained in an entirely new informational base. This is clear from analyzing the correlation ratios between the rankings LCPI and the ILP, which were 0.23 to 2007, 0.24 to 2010, and 0.28 to 2012.

It is noteworthy, however, that this new setting is not motivated only by being added to a new variable, so the fact that the weights assigned have been more flexible, adapting to the strengths of each country, also helped to make the index have a more relevant informational base. Table 3 shows the positions of each country in the LPI rankings and LCLPI.

By analyzing Table 3, the first conclusion to be reached is that unlike the logistics gap between high and low income countries in LPI, this factor alone cannot explain the LCLPI. Some of the over-performing, low income countries are Togo, Benin, Armenia, Kyrgyz Republic, and Haiti, which are the countries that had their positions changed the most when comparing the LPI and the LCPI. Some of the over-performing countries in LPI, such as Germany and Singapore, appear in LCLPI in the respective 14th and 12th positions. These results lead to interesting suppositions, as some low income countries lack enough resources, which drives (apparently in some cases) higher transport capacity utilization.

On the other hand, the countries that have worsened their position in the new index were Malaysia, Thailand, South Africa, Saudi Arabia, Vietnam, and United Arab Emirates. As noted, there is a strong predominance of East Asian and Middle Eastern countries that emit a huge amount of CO_2 compared to the quality of its logistics infrastructure, mainly due to the high use of fossil fuels in the transport sectors in these countries; it is emphasized that these countries are heavily based (more of 90% in Thailand) on road transportation modalities (ESCAPE, 2011).

In the case of the leading performing countries, Switzerland, US, and Japan, manufacturers tend to favor rail for transport, at least over the longer distances that are more typical of the US context, and rail is often regarded as a lower environmental impact mode of transport compared to roads (Nieuwenhuis et al., 2012).

Some of the middle performing countries in LCLPI (such as Australia, Brazil, and Canada) are larger commodity producers and had higher economic growth in this period, which generated more emissions compared to a decade ago, due to growth in transport activity and the number of road vehicles. This situation challenges the capacity to reduce environmental impact, however, as Abaresh and Molla (2013) found, the transport and logistics sectors of these countries are undergoing transformation towards greener logistics practices and routines.

Some of the low performing countries are also larger fossil fuel-based economies, such as Saudi Arabia, Russia, and Venezuela, or they are from South East Asia (Indonesia, Philippines, Malaysia, Thailand and Vietnam), Latin America (Argentina and Ecuador), and Africa countries (South Africa, Algeria, and Egypt).

Among the BRICS countries, China was the best performer (52nd place, with an average index of 40.21%). Brazil and India held the 55th and 63rd places, respectively (with 35.91% and 31.676% index values, respectively). Russia was the worst performer (91st place, with an index of 17.71%).

Despite its good position in relation to other BRICS countries, China's transport sector is a major energy consumer and CO_2 emitter world-wide. Moreover, it is the most rapidly growing sector in terms of energy demand (especially oil demand) and CO_2 emissions in this country (Xu and Lin, 2015a). Therefore, China has become a focus of global efforts to reduce CO_2 emissions amidst

Table 4
Results of Malmquist index.

		Malmquist índex (MI)			Components of MI (2007–2010)	
		2007–2010	2010–2012	Mean	CE	TC
1	Luxembourg	1.48	4.88	3.18	0.30	4.88
2	Ireland	2.34	2.88	2.61	0.83	2.80
3	Honduras	3.16	1.34	2.25	0.99	3.19
4	Lebanon	2.87	1.5	2.18	0.94	3.07
5	Lithuania	2.42	1.42	1.92	1.12	2.16
6	Senegal	2.25	1.42	1.83	0.96	2.34
7	Uzbekistan	2.38	1.05	1.71	1.8	1.33
8	Mongolia	1.86	1.47	1.66	1.39	1.34
9	Czech Republic	1.59	1.73	1.66	1.16	1.37
10	Poland	1.68	1.64	1.66	1.07	1.58
11	Sweden	1.39	1.91	1.65	0.72	1.91
12	Latvia	1.65	1.6	1.62	0.63	2.60
13	Netherlands	1	2.07	1.53	0.48	2.07
14	Kyrgyz Republic	2	1	1.5	2	1
15	Slovak Republic	1.66	1.16	1.41	1.28	1.29
16	Nigeria	2.25	0.57	1.41	4.98	0.45
17	Venezuela	1.82	0.99	1.40	2.27	0.8
18	Costa Rica	1.48	1.31	1.39	0.89	1.66
19	Germany	1	1.7	1.35	0.59	1.7
20	France	1.1	1.56	1.33	0.71	1.54
21	Panama	1.39	1.25	1.32	0.78	1.78
22	Finland	0.95	1.68	1.31	0.65	1.46
23	Estonia	1.1	1.49	1.29	0.6	1.82
24	Singapore	1	1.58	1.29	0.63	1.58
25	Brazil	1.51	1.05	1.28	1.52	0.99
26	Canada	1.15	1.4	1.27	0.83	1.39
27	Ecuador	1.16	1.38	1.27	0.88	1.32
28	Spain	1.08	1.45	1.26	0.79	1.37
29	Thailand	1.26	1.26	1.26	1.34	0.94
30	Denmark	1.17	1.34	1.25	0.89	1.31
31	Slovenia	0.65	1.82	1.23	0.4	1.62
32	New Zealand	0.98	1.49	1.23	0.71	1.37
33	China	1.57	0.87	1.22	1.91	0.82
34	Belgium	1.31	1.1	1.20	1.19	1.1
35	El Salvador	1.5	0.91	1.20	1.1	1.36
36	Dominican Republic	2.01	0.37	1.19	4.12	0.49
37	Turkey	1.19	1.18	1.18	1.07	1.11
38	Colombia	1.61	0.71	1.16	3.17	0.51
39	Norway	1.31	1	1.15	1.31	1
40	Cambodia	0.95	1.35	1.15	0.69	1.38
41	Kazakhstan	1.48	0.82	1.15	2.36	0.63
42	Philippines	1.33	0.95	1.14	1.84	0.72
43	Egypt. Arab Rep.	1.45	0.82	1.13	2.36	0.61
44	Moldova	1.11	1.15	1.13	0.97	1.15
45	South Africa	1.21	1.05	1.13	1.47	0.82
46	Azerbaijan	1.09	1.14	1.11	1.08	1.01
47	Malaysia	1.19	1.03	1.11	1.62	0.73
48	Haiti	1.18	1	1.09	1.18	1
49	Argentina	1.37	0.8	1.08	2.18	0.63
50	Hungary	1.08	1.08	1.08	1.25	0.86
51	Tunisia	1.23	0.92	1.07	1.1	1.12
52	Australia	1.34	0.8	1.07	1.82	0.74
53	Italy	1.07	1.06	1.06	1.06	1
54	Armenia	1.26	0.87	1.06	1.26	1
55	Bosnia and Herzegovina	1.26	0.87	1.06	1.35	0.94
56	Cyprus	1.11	1.01	1.06	0.95	1.17
57	Bahrain	1	1.11	1.05	0.59	1.68
58	Macedonia	1.11	1	1.05	1.11	1
59	Chile	1.12	0.98	1.05	1.52	0.74
60	Portugal	1.01	1.09	1.05	1.24	0.81
61	Guatemala	1.1	0.96	1.03	1.03	1.06
62	Uruguay	1.27	0.78	1.02	1.76	0.72
63	Croatia	1.04	1	1.02	1.17	0.89
64	Saudi Arabia	1.11	0.9	1.00	1.41	0.79
65	Benin	1	1	1	1	1
66	Japan	1	1	1	1	1
67	Switzerland	1	1	1	1	1
68	Togo	1	1	1	1	1
69	United States	1	1	1	1	1
70	Algeria	1.14	0.86	1	1.75	0.65

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Table 4 (*continued*)

		Malmquist índex (MI)			Components of MI (2007–2010)	
		2007–2010	2010–2012	Mean	CE	TC
71	Bolivia	0.95	1.03	0.99	0.89	1.07
72	Hong Kong	0.96	1	0.98	1	0.96
73	Yemen	1.21	0.75	0.98	1.39	0.87
74	Oman	0.7	1.25	0.97	0.44	1.59
75	Peru	0.89	1.05	0.97	1.11	0.8
76	India	0.99	0.94	0.96	1.13	0.87
77	Côte d'Ivoire	0.55	1.31	0.93	0.45	1.23
78	Vietnam	0.96	0.9	0.93	1.34	0.72
79	United Kingdom	0.87	0.97	0.92	0.91	0.96
80	Paraguay	1.06	0.76	0.91	1.07	0.99
81	Tanzania	1.43	0.38	0.90	3.34	0.43
82	Indonesia	1.11	0.69	0.90	1.73	0.64
83	Mexico	0.94	0.85	0.89	1.17	0.81
84	Jamaica	1.25	0.52	0.88	2.31	0.54
85	Ukraine	0.99	0.77	0.88	1.70	0.58
86	Russia	1.15	0.6	0.87	2.05	0.56
87	Romania	0.94	0.8	0.87	1.55	0.6
88	Qatar	0.9	0.82	0.86	1.09	0.83
89	Ghana	0.97	0.75	0.86	1.34	0.72
90	Bulgaria	0.86	0.8	0.83	1.20	0.72
91	Pakistan	1.07	0.58	0.82	2.45	0.43
92	Austria	0.66	0.95	0.80	0.97	0.68
93	Cameroon	0.65	0.93	0.79	0.69	0.95
94	United Arab Emirates	0.82	0.7	0.76	1.63	0.50
95	Kenya	0.64	0.88	0.76	0.80	0.80
96	Sri Lanka	1.09	0.43	0.76	2.77	0.39
97	Ethiopia	0.48	0.98	0.73	0.52	0.91
98	Kuwait	0.83	0.56	0.69	1.73	0.48
99	Angola	0.58	0.76	0.67	0.93	0.63
100	Namibia	0.45	0.81	0.63	0.57	0.78
101	Jordan	0.95	0.27	0.61	3.13	0.31
102	Nepal	0.53	0.57	0.55	0.93	0.57
103	Sudan	0.72	0.35	0.53	2.33	0.31
104	Greece	0.74	0.29	0.51	3.54	0.21
Mean		1.22	1.09	1.15	1.35	1.11

increasing international pressure. In order to cope with the increasingly severe environmental challenge in China, researchers have studied CO_2 emissions in China's transport sector. Zhang and Nian (2013) and Xu and Lin (2015a), for example, agree in their studies that passenger transport in China is more critical than freight transport in emissions reduction. According to Zhang and Nian (2013), the urgency may be attributed to the fact that passenger transport is more pollutant intensive than freight transport. Road and aviation transport play important roles in passenger transport, while freight transport heavily relies on rail and water. Besides, incremental increases in passenger transport incurred by increasing incomes and other reasons outpace those of freight transport in China. The increase in passenger transport has been seriously referred to as a result of urbanization and income growth. Nowadays, China is in the process of rapid urbanization with quick income growth.

This rapid urbanization process can be observed in other BRICS countries, which helps to explain the low positioning of the members of this group in the ranking presented. In the case of Brazil, there is the aggravating factor that the predominant mode is road freight transport, which contributes to the increase in GHG emissions. These suggestions could be implemented in the other emerging countries in order to contribute to carbon mitigation.

4.2. Malmquist index analysis

The Malmquist index enables researchers to verify a country's productivity evolution (the ability to convert CO_2 emissions into good logistics performance) and to segregate how much of this progress was due to the country's relative performance changes from how much resulted due to effect it had on technological patterns (changes that were seen in all countries). Table 4 shows the results of the Malmquist index (MI), the catching-up effect (CE), and the technological change (TC). It should be noted that the window analysis method does not allow the decomposition of the Malmquist index between 2010 and 2012.

The countries that on average showed the most progress between 2007 and 2012 were Luxembourg, Ireland, Lebanon, Honduras, and Lithuania. The countries that most regressed in this period were Namibia, Nepal, Jordan, Sudan, and Greece. It is noteworthy that, with the exception of Sudan, the countries that had evolved were more or less are in the top half, roughly between the first and second quartiles of the LCLPI ranking.

In addition, considering the average MI values, 64 countries evolved over the period under consideration, six remained constant and 34 regressed. Other than that, it was seen that 37 countries have evolved in the two intervals considered (2007–2010 and 2010–2012), 29 evolved in the first interval and regressed in the second, 13 regressed in the first interval and evolved in the second, and 21 regressed in two intervals. Considering the MI average values, there was been more development between 2007 and 2010 than between 2010 and 2012.

Among the countries that evolved from 2007 to 2010, it is noted that the changes were more influenced by shifts in the frontier than by changes in relative position. It means that although on average the countries have improved their absolute performance, the relative ranking has changed little over the period.

Among the BRICS, Brazil (25th place), China (33rd place), and South Africa (45th place) evolved in the two periods analyzed. Russia (86th place) evolved in the first period and regressed a great deal in the second period, and India (76th place) regressed in the two periods. Despite performing at a higher position than shown in the ranking, China can still improve. In their study, Xu and Lin (2015b) emphasize that China should implement targeted measures to reduce CO_2 emissions in the transport sector at the different stages of economic growth, however, China is likely to continue its opposition to taking on legally binding GHG targets (Harris et al., 2013).

5. Conclusion

In the present study, the variables of CO_2 emissions in the transport and logistics sector's performance were aggregated in the form of a static and a dynamic low carbon logistic performance index (LCLPI) using, respectively, the DEA and Malmquist index techniques. Such indices, despite their limitations, are helpful in identifying a global index that measures the performance of different countries to translate the logistic performance and economic improvements to CO_2 emission reductions.

Among the main findings of this study is the fact that developed countries tend to stand out more in terms of good logistics performance with low CO_2 emissions. The level of development, however, does not explain the fact that the performance of Togo and Haiti was higher than Norway and the United Kingdom. Another important finding is that there was more development in the ability to convert CO_2 emissions into good logistics performances between 2007 and 2010 than there was between 2010 and 2012, due more to shifts in the technological frontier than to changes in relative positions among the studied countries. Furthermore, the composite index that was presented in this work and the ranking of countries can help identify the best sustainable practices for the logistics sector. In this regard, special attention should be given to Japan, Switzerland, Togo, Benin, and the US. Additionally, the countries that progressed the most on average were Luxemburg, Ireland, Lebanon, and Honduras. This investigation will be used to guide future studies.

While this research is an important step toward identifying a global CO_2 emissions efficiency index, there are some limitations that should be mentioned. The first limitation is the lack of available data from other variables to improve the model, including variables related to the ecological footprint, loss of biodiversity, and social impacts as generated by the increased mobility that accompanies an improved logistics network. The second limitation is that the analyzed countries were chosen based on available data, which may have biased some of the analysis.

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