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# Do energy efficiency and export quality affect the ecological footprint in emerging countries? A two-step approach using the SBM-DEA model and panel quantile regression

Emad Kazemzadeh<sup>1</sup>, José Alberto Fuinhas<sup>\*2</sup>, Matheus Koengkan<sup>3</sup>, Fariba Osmani<sup>1</sup>, and Nuno Silva<sup>2</sup>

<sup>1</sup> Department of Economics, Faculty of Economics and Administrative Sciences, Ferdowsi University of Mashhad, Mashhad, Iran

<sup>2</sup> CeBER, and Faculty of Economics, University of Coimbra, Coimbra, Portugal

<sup>3</sup> DEGEIT, University of Aveiro, Aveiro, Portugal

**Abstract:** The research was performed in sixteen emerging countries from 1990 to 2014, using a two-step approach. First, a slacks-based (SBM) - data envelopment analysis (DEA) model annually estimates countries' resources and energy efficiency. In the second step, a panel quantile regression was used to assess the impacts of resources and energy efficiency, export quality, and the other variables on the ecological footprint. The SBM-DEA model revealed that Turkey and Hungary were the countries that got the better rank, and China and India got the worst rank on resources and energy efficiency mean. Quantile regression revealed that resources, energy efficiency, and trade openness reduce the ecological footprint. On the other hand, GDP, consumption of fossil fuels, and population contribute to deteriorating the environmental footprint. Export quality and urban population worsen the ecological footprint but only in some quantiles. Export quality in 10th and 25th quantiles and the case of the urban population all quantiles except the 10th one aggravates the ecological footprint. Thus, from a policy perspective, we have variables that require different kinds of intervention to mitigate/reduce the ecological footprint, i.e., requires many policy measures and the active collaboration of citizens.

**Keywords:** energy efficiency; export quality; ecological footprint; SBM-DEA model; panel quantile regression.

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\* Corresponding author: [fuinhas@uc.pt](mailto:fuinhas@uc.pt); Faculty of Economics, University of Coimbra, Av. Dias da Silva 165, 3004-512 Coimbra, Portugal.

<sup>1</sup> Department of Economics, Faculty of Economics and Administrative Sciences, Ferdowsi University of Mashhad, Mashhad, Iran. [Emad.kazemzadeh67@mail.um.ac.ir](mailto:Emad.kazemzadeh67@mail.um.ac.ir).

<sup>2</sup> CeBER, and Faculty of Economics, University of Coimbra, Av. Dias da Silva 165, 3004-512 Coimbra, Portugal. Research supported by: CeBER, R&D unit funded by national funds through FCT – Fundação para a Ciência e a Tecnologia, I.P., project UIDB/05037/2020. [fuinhas@uc.pt](mailto:fuinhas@uc.pt) (J.A. Fuinhas) and [nunos@fe.uc.pt](mailto:nunos@fe.uc.pt) (N. Silva).

<sup>3</sup> Faculty of Economics, University of Coimbra, Av. Dias da Silva 165, 3004-512 Coimbra, Portugal.

<sup>4</sup> DEGEIT, University of Aveiro, 3810-193, Aveiro, Portugal. [matheuskoengkan@ua.pt](mailto:matheuskoengkan@ua.pt).

<sup>1</sup> Department of Economics, Faculty of Economics and Administrative Sciences, Ferdowsi University of Mashhad, Mashhad, Iran. [faribaosmani10@gmail.com](mailto:faribaosmani10@gmail.com).

## 1. Introduction

In recent years, environmental threats and risks have accelerated as economic growth and development accelerated due to increased energy demand. Therefore, the optimal use of scarce resources and energy is a priority for different countries' environmental goals, so one of the three main goals of the European Climate Commission is to improve energy efficiency. Improving energy efficiency will help countries achieve green economic growth (Adnan Bashir et al., 2020).

Given the importance of economic growth and environmental protection, many studies have examined the relationship between economic growth, energy consumption and environmental degradation (e.g., Pao & Tsai, 2010; Liu et al., 2018; and Acheampong, 2018). In addition to economic growth and energy consumption, some studies have examined the relationship between other variables (such as financial development, population density, trade openness, urbanisation, and globalisation) on environmental degradation (e.g., Shahbaz et al., 2013; Kasman & Duman, 2015; Tang & Tan, 2015; Wang et al., 2016; Dogan & Turkekul, 2016; Zhu et al., 2016; Raza & Shah, 2018; Moghadam & Dehbashi, 2018; and Albulescu et al., 2019). Recently, some studies have examined the impact of export quality indicators and energy efficiency on environmental degradation (Fang et al., 2019; Ke et al., 2020; Murshed & Dao, 2020; Yao et al., 2021; Wang et al., 2021). The export quality is enhanced by advancing knowledge and increased investment in research and development, promoting environmentally friendly technologies (Dogan et al., 2020; Murshed & Dao, 2020).

Previous studies have often considered carbon dioxide emissions (CO<sub>2</sub>) as an indicator of environmental degradation (Shahbaz et al., 2016). However, the CO<sub>2</sub> index considers only one aspect of environmental degradation while economic activities affect various aspects of the environment, such as water, air and land (Neagu, 2020). For this reason, a new ecological footprint index for environmental degradation has recently been used in some studies (e.g., Ozturk et al., 2016; Alola et al., 2019; Chen et al., 2019; Destek & Sarkodie, 2019; and Dogan et al., 2020). The Comprehensive Ecological Footprint Index measures the biological capacity required to produce goods and services and the capacity necessary to absorb waste from human activities. This index is more comprehensive and complete than the CO<sub>2</sub> emission index. The Ecological Footprint Index evaluates the depreciation of the environment caused by various human activities (Nijkamp et al., 2004). Despite researchers' attention to the ecological footprint index as an environmental proxy, no study has analysed the impact of export quality on the EF index.

Since energy consumption is needed for economic growth, reducing energy consumption leads to reduced economic growth. Therefore, to increase economic growth and protect the environment, improving energy efficiency and preventing energy waste is an important goal of most countries, especially those with emerging economies, because improving energy efficiency helps preserve the environment (Zhu et al., 2016). In addition, efficient use of energy reduces energy costs. Increasing energy efficiency also increases the added value of economic activities, leading to lower energy demand (Pao & Tsai, 2010). Since there are no single standards and criteria for energy efficiency, the data envelopment analysis (DEA) approach provides policymakers with an ample opportunity to fully calculate energy efficiency (Simeonovski et al., 2021).

One of the factors affecting the environment is the optimal use of resources, so some studies have examined the effect of energy efficiency on environmental degradation (e.g., Ozbugday & Erbas, 2015; Kuittinen & Takano, 2017; Ke et al., 2021; and Yao et al., 2021). Energy efficiency means using less energy at a certain level of gross domestic product (GDP), so increasing energy efficiency reduces energy consumption and thus improves the environmental quality (e.g., Shahbaz et al., 2015; Tajudeen et al., 2018; Yao et al., 2021; and Shokoohi et al., 2022). This study calculates

energy efficiency by the slacks-based (SBM) - data envelopment analysis (DEA) method for emerging economies. In addition, calculating energy efficiency for a group of converging countries gives policymakers a direction in implementing sustainable development policies. Therefore, the effect of energy efficiency on ecological footprint can also be analysed by evaluating energy efficiency and orienting the policies of specific countries and ranking countries in terms of energy efficiency.

In recent decades, the share of international trade in countries worldwide, especially emerging economies, has been increasing. Countries accelerate economic growth and further environmental degradation by increasing trade and producing more goods (e.g., Zhang et al., 2017; and Apergis et al., 2018). Therefore, the expansion of trade regardless of the production process, type of technology and quality of export products cause more damage to the environment (e.g., Dogan & Turkekul, 2016; and Zhang et al., 2017). On the other hand, trade development contributes to the quality of exports by creating more opportunities (Fang et al., 2019). Various studies argue that the type and quality of export goods that lead to economic growth and development are more important than the amount and volume of exports (Hausmann et al., 2014). The quality of exports increases the added value of export products and is related to characteristics such as human capital, the level of productivity of countries' resources (e.g., Fang et al., 2018; and Shahbaz et al., 2019).

In emerging economies, export quality occurs due to structural changes in the diversity of goods, so countries achieve high levels of export quality with a variety of export products. In addition, governments need labour based on better and newer knowledge and technologies to produce various export goods. Therefore, from this perspective, the quality of exports leads to an improved environment (e.g., Gozgor & Can, 2017; and Murshed & Dao, 2020). In some cases, product diversity leads to an overflow of productivity from one sector to another, leading to environmental damage. In addition, countries with higher export quality capture a larger share of global markets, leading to higher incomes for those countries. Wealthier communities also have higher energy demand. In this perspective, the quality of exports leads to environmental degradation (e.g., Fang et al., 2019; Dogan et al., 2020; and Wang et al., 2021). As mentioned above, few studies examined the impact of export quality on environmental degradation that did not reach a single conclusion. Therefore, exploring how the quality of exports affects the ecological footprint can be essential to achieve sustainable development for different communities.

This paper has selected the sample countries from the MSCI classification of emerging economies based on similar financial market structures (e.g., market size, liquidity, and accessibility). Emerging economies are in the middle stage of growth and focus on product diversity to achieve high economic growth. Diversifying export products can turn a developing country into a developed country (Apergis et al., 2018). So far, studies in the group of emerging economies have not received much attention, and therefore, studying these countries is essential to create effective policies for environmental protection.

The innovation and contribution of this research can be expressed in different aspects. First, the countries under study are emerging economies, and they pay more attention to economic growth than the environment, which negatively affects environmental quality. The difference between the recent study and previous studies is that first: to study the quality of the environment, it uses the ecological footprint index, which is more comprehensive than the CO<sub>2</sub>. Second: Previous studies have focused on the impact of trade on the ecological footprint, while exports quality has been considered in this study. Third, this study uses the SBM-DEA model to measure energy efficiency. This model eliminates the efficiency measurement deviation caused by the radial selection difference and thus achieves a more accurate efficiency assessment. Finally, after calculating the

energy efficiency, the effects of export quality and energy efficiency on the ecological footprint are computed using the quantile panel regression. To our knowledge, no studies have examined the impact of export quality and energy efficiency on the ecological footprint in emerging economies. Therefore, in this research, we seek to answer the following questions:

- 1. What is the energy efficiency rating of emerging economies relative to each other?**
- 2. Can moving towards energy efficiency in emerging economies improve the environment?**
- 3. Can increasing the quality of exports in the study group help improve the environment?**

In an attempt to answer these questions, the primary purpose of this study is to investigate the effect of export quality and energy efficiency on ecological footprint. Experimental models are analysed using the SBM-DEA technique and quantile regression. In addition to bridging the gap of existing studies, the empirical findings of this study present significant implications for the policy of emerging economies with quality and diversified export products in the field of environmental sustainability.

## **2. Literature review**

The new trade and economic development indicators have been used in the literature to explain the ecological footprint. Indeed, according to Fang et al. (2019), the main indicator used in the literature to explain the ecological footprint or environmental degradation are export diversification, economic globalisation, export quality, and economic complexity. In this investigation, the benchmark used is the export quality, an indicator widely explored by literature as mentioned by Fang et al. (2019), and the energy efficiency, which is few explored. In the light of this – **What are the main findings related to the effect of export quality and energy efficiency on the ecological footprint in the literature?**

When we approach the effect of export quality on CO<sub>2</sub> emissions or ecological footprint in literature, we find several authors that studied this topic (e.g., Gozgor & Can, 2017; Fang et al., 2019; Dogan et al., 2020; Murshed & Dao, 2020; and Wang et al., 2021). Indeed, inside this group, some authors found the export quality increases the ecological footprint of CO<sub>2</sub> emissions (e.g., Fang et al., 2019; Dogan et al., 2020; and Wang et al., 2021).

Therefore, Wang et al. (2021) explored the dynamic interdependence between CO<sub>2</sub> emissions, income per capita, renewable, non-renewable sources, the urbanisation process, and export quality for both the top ten renewable energy-producing countries and ten economically complex countries for the period between 1990-2014. The authors' methods were the fully modified ordinary least square (FMOLS), dynamic ordinary least square (DOLS), and Granger causality. The results showed that only renewable energy generation contributes to mitigating CO<sub>2</sub> emissions for the top ten renewable energy-producing countries, while the non-renewable energy, urbanisation, income per capita, and export quality lead to increased emissions levels in the long run. However, in leading complex economies, the empirics highlighted the significant role of renewable energy in carbon mitigation. Export quality decreases emissions levels, while the income per capita, non-renewable energy, and urbanisation contribute to the rise in emissions.

Dogan et al. (2020) studied the effect of export quality, urbanisation, trade openness, economic growth, and energy consumption on CO<sub>2</sub> emissions in 63 developed and developing countries from 1971 to 2014. The authors used the method of panel quantile estimators. The panel

quantile regression model results showed that economic growth, energy consumption, urbanisation, export quality, and trade openness increase CO<sub>2</sub> emissions. Finally, Fang et al. (2019) investigated the effects of the product quality of exports on CO<sub>2</sub> per capita. The authors focused on the panel dataset of 82 developing economies from 1970 to 2014 and used the fixed effects model as a method. The results showed that the exports quality, income per capita, and trade openness increase the CO<sub>2</sub> emissions.

Moreover, in this group of authors that studied the effect of export quality on ecological footprint or environmental degradation caused by CO<sub>2</sub> emissions, we found that some of them discovered that the export quality decreases the ecological footprint or environmental degradation caused by CO<sub>2</sub> emissions (e.g., Gozgor & Can, 2017; and Murshed & Dao, 2020). For example, Murshed & Dao (2020) investigated the impact of export quality on the economic growth-CO<sub>2</sub> emissions nexus in the context of selected South Asian economies, such as Bangladesh, India, Pakistan, Sri Lanka, and Nepal. The authors used annual data from 1972 to 2014 and used as a method the FMOLS model. Therefore, the results from panel data econometric analyses provide that the improvement in export quality led to lower levels of CO<sub>2</sub> emissions. Moreover, the statistical significance of the interaction term between economic growth and export quality implies that the overall impacts of economic growth on CO<sub>2</sub> emissions are conditional on the quality of the exports. Thus, enhancing the quality of the export products is pertinent concerning environmental sustainability across South Asia. Finally, Gozgor & Can (2017) explored the effect of the export product quality on CO<sub>2</sub> emissions in China from 1971 to 2010. The empirical results showed that economic growth and energy consumption increase the CO<sub>2</sub> emissions, while export quality decreases them.

Regarding the effect of energy efficiency on ecological footprint or environmental degradation (CO<sub>2</sub> emissions), some authors have studied this topic (e.g., Özbuğday et al., 2015; Kuittinen & Takano, 2017; Tajudeen et al., 2018; Ke et al., 2020; and Yao et al., 2021). However, inside this group of authors, we identified that some discovered energy efficiency decreases the ecological footprint or environmental degradation (e.g., Tajudeen et al., 2018; and Yao et al., 2021). Yao et al. (2021) studied the relationship between financial development, corruption, energy efficiency, and ecological footprint in Brazil, Russia, India, China, and South Africa (BRICS) countries and eleven countries from 1995 to 2014. The authors used the data envelopment analysis (DEA) method and generalised method of moments (GMM) models. They found that corruption is more likely to increase energy efficiency and decrease the ecological footprint. At the same time, natural resource rents and technological innovations can improve energy efficiency and environmental quality. The result of causality emphasises the feedback hypothesis between energy efficiency, ecological footprint, financial development, corruption control, natural resource rent, technological innovation, trade, and industrialisation. Tajudeen et al. (2018) investigated energy efficiency improvements on CO<sub>2</sub> emissions in 30 countries from the Organisation for Economic Cooperation and Development (OECD). The authors found that income has the most significant positive impact on CO<sub>2</sub> emissions but improving energy efficiency makes the most significant contribution to driving down CO<sub>2</sub> emissions.

However, another group of authors finds that energy efficiency increases the ecological footprint or environmental degradation (CO<sub>2</sub> emissions) (e.g., Özbuğday et al., 2015; Kuittinen & Takano, 2017; and Ke et al., 2020). Kuittinen & Takano (2017) investigated the relationship between efficiency and the carbon footprint of temporary homes in Japan in 2011. The authors realised an energy simulation and life cycle assessment had been done for three alternative shelter models: prefabricated shelters, wooden log shelters and sea container shelters. The authors find that shelter materials have a very high share of life cycle emissions because of the short period of

temporary home use. Ke et al. (2020) explored the effect of innovation efficiency on the ecological footprint in 280 Chinese cities from 2014 to 2018. They used generalised spatial two-stage least squares (GS2SLS) and the threshold regression model to explore the threshold effect of innovation efficiency on the ecological footprint at different economic development levels. They find a relationship between innovation efficiency and the ecological footprint for cities across China and the Eastern and Central regions. That is, innovation efficiency promotes and then suppresses the ecological footprint.

Conversely, in Western and North-eastern China, improvements in innovation efficiency still raise the ecological footprint. Özbuğday et al. (2015) explored the effect of energy and renewable energy consumption on CO<sub>2</sub> emissions in thirty-six countries for the period between 1971 to 2009. The authors have used the method of the common correlated effects (CCE). The authors found that the energy efficiency increases the CO<sub>2</sub> emissions in the long run, while the renewable energy consumption decreases.

In this section, we realise a brief literature review indicating the prominent authors that studied the effect of export quality and energy efficiency on ecological footprint or environmental degradation (CO<sub>2</sub> emissions). In this literature review, we identified different conclusions attributed to the use of methodologies, different variables, time-spans, and countries or regions that lead the non-consensus about the impact of export quality and energy efficiency on ecological footprint or environmental degradation (CO<sub>2</sub> emissions). Indeed, due to this, it is essential to realise more studies about this topic.

Moreover, in this literature review, we found some gaps which need to be filled. The first and the most significant is the absence of studies investigating the impact of energy efficiency on the ecological footprint index. All reviewed studies solely explored this impact on CO<sub>2</sub> emissions. This scenario shows that the relationship between energy efficiency and the ecological footprint index remains unexplored and calls for further investigation. Another gap found is the non-use of the DEA and panel quantile models together, which will bring some advantages to the study of this topic. Moreover, we also noted a lack of studies focused on emerging countries, where only two studies were identified that approached the emerging economies. In the next section, we will present/explain the data and methods used in this article.

### **3. Data and Method**

This section consists of two sub-sections. The first part describes and introduces the database and variables, and in the second part, the mathematical models used in this research are given.

#### **3.1. Data**

This section shows the data used. The independent variables used in this study were selected through theoretical and experimental literature analysis. This dataset includes data for 16 emerging economies (e.g., **Brazil, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Morocco, Philippines, South Africa, Thailand, and Turkey**) from 1990 to 2014. Sixteen countries are selected from the Morgan Stanley Capital International (MSCI) Emerging Markets Classification \*. MSCI classifies countries as emerging economies based on the criterion that their financial markets meet access, size of liquidity, and market. The period selected

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\* <https://www.msci.com/our-solutions/index/emerging-markets>.

in this study is due to data availability for all countries. The following are the variables used in this research:

- Labour force total (**L**) based on 1000 persons;
- Total capital stock (**K**) based on constant 2010 million \$ (USD);
- Total energy consumption (**E**) based on tone of oil equivalent;
- Gross Domestic Product (**GDP (Y)**) based on constant 2010 million \$ (USD);
- Ecological footprint in a global hectare, named in this study as (**EFPG**);
- Export quality index (**EQ**);
- Energy efficiency calculated by SBM-DEA model (**EF**);
- Trade openness (**TO**);
- Urban population as a percentage of the total population, named in this study as (**URB**);
- Non-renewable energy consumption, named in this study as (**FOSSIL**).

**Table 1** describes the information about the variables and their databases.

**Table 1.** Variable acronyms, definitions, and sources (1990-2014)

Abbreviation	Variables	Sources
<b>L</b>	Labour force total (1000 person)	WBD (2020)
<b>K</b>	Total capital stock (constant 2010 million \$)	WBD (2020)
<b>E</b>	Total energy consumption (tone of oil equivalent)	WBD (2020)
<b>GDP(Y)</b>	Gross domestic product (GDP) (constant 2010 million \$)	WBD (2020)
<b>EFPG</b>	Ecological footprint (global hectares)	WBD (2020)
<b>EQ</b>	Export quality index	IMF (2020)
<b>EF</b>	Resources and energy efficiency	Calculated by the SBM-DEA model
<b>TO</b>	Trade openness = (import + export) / GDP	WBD (2020)
<b>URB</b>	Urban population = % of total population	WBD (2020)
<b>FOSSIL</b>	Consumption of fossil fuels (e.g., oil, gas, and coal) tone of oil equivalent	British Petroleum (BP) (2020)

**Notes:** This table was created by the authors.

After describing the databases, **Table 2** shows the statistical information of the variables, which includes the number of observations, mean, standard deviation, minimum and maximum.

**Table 2.** Descriptive statistics

Variables	Descriptive statistics				
	Obs.	Mean	Std.-Dev.	Min.	Max.
<b>L</b>	400	97878.53	190585	4011.205	783684.2
<b>K</b>	400	8053535	4.42e+07	9398.723	4.23e+08
<b>E</b>	400	1.94e+08	4.16e+08	7096905	2.97e+09
<b>GDP(Y)</b>	400	671740	1032651	43200	8320000
<b>EFPG</b>	400	4.08e+08	8.07e+08	2.85e+07	5.17e+09
<b>EQ</b>	400	0.872225	0.0832474	0.66	1.05
<b>EF</b>	400	0.6512339	0.3212756	0.02701	1
<b>POP</b>	400	209.4366	374.198	9.866468	1360
<b>TO</b>	400	67.04386	41.52926	15.16176	220.4068
<b>URB</b>	400	58.75274	17.90882	25.547	87.303
<b>FOSSIL</b>	400	1.75e+08	3.85e+08	6805529	2.65e+09

**Notes:** Obs. is the number of observations in the model, Std.-Dev. is the standard deviation, Min and Max are the minimum and maximum, respectively.

As can be seen, the number of observations is 400. The average of the main research variables such as **EQ** and **EF** are 0.872 and 0.651, respectively.

### 3.2. Method approach

In this research, we will use two different methods. In subsection **3.2.1**, we briefly show the SBM-DEA Model, and subsection **3.2.2** is the panel quantile regression model.

#### 3.2.1. SBM-DEA model

The DEA method is an effective tool for calculating energy efficiency. This method is based on linear programming and distance performance. The DEA model generally includes two types: (i) previous radial models (e.g., Charnes, Cooper & Rhodes (CCR); and Bankar, Charnes and Cooper (BCC)), and (ii) new non-radial models (e.g., SBM-DEA model) (e.g., Cook et al., 2000; Cook & Seiford, 2009; and Koengkan et al. 2021). Radial models do not consider input and output relaxation, which implies that an improvement direction of the inefficient decision-making unit (DMU) cannot be obtained. Thus, Tone proposed the SBM-DEA model (e.g., Tone, 2001; and Tone, 2004). In general, the principle of the SBM-DEA model is similar to the classical DEA model, which assumes that producing more favourable output than less input and poor output is a crucial factor for higher performance (e.g., Lozano & Gutiérrez, 2011; and Chang, 2013).

The SBM model belongs to the non-radial distance function model. It considers the input and output slack variables and has no problem with input and output (e.g., Tone, 2001; and Song et al., 2019). The SBM model has three types: input-oriented, output-oriented, and non-oriented. The non-oriented model incorporates both input and output-oriented models, allowing the input surplus and output fraction (slack variables) to be estimated simultaneously. However, the SBM model differs from traditional DEA models such as CCR and BCC in that slack variables are added directly to the target function. In addition, another advantage of SBM models is that they are non-oriented and non-radial. Thus, the SBM model can prevent the deviation of radial or oriented models and reflect the nature of relative performance evaluation. In this study, we have used the three inputs of labour (L), energy (E) and capital (K) and one desirable output of GDP (Y). We



have used the SBM-DEA model based on CCR non-Oriented to calculate energy efficiency in 16 emerging countries. The SBM model is as follows **Equation (1)**.

$$\rho^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s_1} \left( \sum_{r=1}^{s_1} \frac{s_r^g}{y_{ro}} \right)} \quad (1)$$

$$\begin{aligned} \text{s.t} \quad & x_o = X\lambda + s^- \\ & y_o^g = Y^g\lambda - s^g \\ & s^- \geq 0, s^g \geq 0, \lambda \geq 0 \end{aligned}$$

where  $\rho^*$  value is the DMU<sub>0</sub> efficiency.  $s^-$ ,  $s^g$  are the slacks in inputs and desirable outputs. And  $m$ ,  $s_1$  stand for the number of inputs, and the desired output, respectively.  $\lambda$  is the intensity vector. These two factors are represented by the two vectors  $x \in R^m$  and  $y^g \in R^{s_1}$ , respectively. Two matrices  $X$  and  $Y^g$  are defined as  $X = [x_1 \dots x_n] \in R^{m \times n}$ ,  $Y^g = [y_1^g, \dots, y_n^g] \in R^{s_1 \times n}$ .

When  $\rho^* = 1$ ,  $s^- = 0$  and  $s^g = 0$  of a DMU, it means that the DMU is effective. When  $\rho^* < 1$  of a DMU, it means that the DMU is ineffective. DMU can be improved by reducing the surplus of inputs and increasing the shortage of desirable outputs. The relevant formulas are shown as **Equations (2)-(3)**.

$$x_o - s^- \rightarrow x_o \quad (2)$$

$$y_o^g + s^g \rightarrow y_o^g \quad (3)$$

### 3.2.2. Preliminary tests

Before estimating the model, it is crucial to perform a set of preliminary tests to assess the data properties. First, we test whether the data is normally distributed, using the Shapiro-Wilk (Royston, 1992) and the Shapiro-Francia (Royston, 1983) tests. Then, we check the degree of multicollinearity between the explanatory variables using the variance inflator factor (VIF). Multicollinearity is a serious problem as it renders the coefficient estimates unstable and prone to large variations driven by small changes in the data or model. The VIF for an explanatory variable can be computed as follows. First, we run an ordinary least square regression of this explanatory variable on all others. Next, we calculate the VIF with the formula below

$$VIF = \frac{1}{1 - R^2} \quad (4)$$

where  $R^2$  is the coefficient of determination of the regression.

Cross-sectional dependence is a highly prevalent feature of panel data, which arises when common shocks and unobserved components drive the behaviour of the variables in different countries. We assess its presence by resorting to the Breusch and Pagan (1980) LM test. To implement this test, we must estimate the following standard panel data model

$$y_{it} = \alpha_i + \beta' x_{it} + u_{it} \quad i = 1, \dots, N \text{ and } t = 1, \dots, T \quad (5)$$

where  $y_{it}$  represents the dependent variable for country  $i$  in year  $t$ ,  $x_{it}$  is a  $K \times 1$  vector of regressors,  $\alpha_i$  represents the time-invariant individual effects, and  $u_{it}$  is the idiosyncratic error term. Under the null hypothesis,  $u_{it}$  is i.i.d, which implies the errors are both serially and cross-sectionally uncorrelated. The alternative hypothesis of the Breusch-Pagan test states that the errors may be cross-sectionally correlated, but the assumption of serial independence is maintained. These authors proposed the following LM statistic to test for the presence of cross-sectional dependence

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2 \quad (6)$$

where  $\hat{\rho}_{ij}$  is the sample estimate of the correlation of the residuals

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^T \hat{u}_{it} \hat{u}_{jt}}{(\sum_{t=1}^T \hat{u}_{it}^2)^{0.5} (\sum_{t=1}^T \hat{u}_{jt}^2)^{0.5}} \quad (7)$$

Breusch and Pagan (1980) show that, under the null hypothesis, the LM statistic in **Equation (6)** is asymptotically distributed as a chi-squared with  $N(N - 1)/2$  degrees of freedom.

Estimations involving non-stationary variables lead to the well-known phenomenon of spurious regressions, i.e., the regression coefficients reveal a fictitious relationship between the data that is driven by the variables' trends. Thus, it is essential to test the data for stationarity. To achieve this goal, we use the Pesaran (2007) panel unit root test because it is robust to the presence of cross-sectional dependence. This test is based on an expanded version of the Dickey-Fuller regression, where the cross-sectional averages of the dependent and independent variables are added as regressors

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \delta_{0i} \overline{\Delta y}_t + \delta_{1i} \bar{y}_{t-1} + \epsilon_{it} \quad i = 1, \dots, N \text{ and } t = 1, \dots, T \quad (8)$$

where  $\overline{\Delta y}_t$  and  $\bar{y}_{t-1}$  represent the averages of the dependent variable and the regressor, respectively. Pesaran (2007) tests the null hypothesis  $\beta_i = 0$ , for all  $i$ , against the alternative  $\beta_i < 0$ , for at least one unit (that is, the variable is stationary for at least one country). The test is based on the average of the individual t-statistics for the null hypothesis  $\beta_i = 0$ , and follows a non-standard distribution.

### 3.2.3. The panel quantile regression

Panel quantile regression was introduced in 1978 by Kockner & Bast (1978). This model is based on a conditional quantitative function that minimises absolute error values in asymmetrically distributed variables. In addition to providing a completer and more comprehensive plot of data distribution, this model makes it possible to measure the relationship between the independent variable and the desired dependent variables even in the presence of outlier points (e.g., Buchinsky, 1998; and Koenker, 2004). Quantile regression has been used in various fields (such as economics, environment, climate) (e.g., Steers et al., 2011; Zhu et al., 2016; Xu et al., 2018; Paltasingh & Goyari, 2018; Buhari et al., 2020; and Gómez & Rodríguez, 2020). Therefore,

this study uses the panel quantile regression method to evaluate the impact of energy efficiency and export quality on the ecological footprint in emerging countries. The following is the mathematical formula of the quantile regression model **Equation (9)**

$$\begin{aligned} y_i &= x_i b_{\theta i} + \mu_{\theta i}, \quad 0 < \theta < 1 \\ \text{Quant}_{i\theta}(y_i/x_i) &= x_i \beta_{\theta}, \end{aligned} \quad (9)$$

where  $X$  and  $y$  represent the vectors of independent variables and dependent variables, respectively;  $\mu$  is a random error, whose conditional quantile distribution has a zero mean;  $\text{Quant}_{i\theta}(y_i/x_i)$  is the  $\theta$ th quantile of the explained variable; the  $\beta_{\theta}$  estimate shows the quantile regression  $\theta$ th and solves the **Equation (10)**

$$\min \sum_{y_i \geq x_i' \beta} \theta |y_t - x_i' \beta| + \sum_{y_i < x_i' \beta} (1 - \theta) |y_t - x_i' \beta| \quad (10)$$

As  $\theta$  is equal to different values, different parameter estimations are obtained. The median regression is a particular case of quantile regression under  $\theta = 0.5$  (Xu & Lin, 2018).

Econometric theory points out that model variables must be logarithmic to eliminate possible heterogeneity phenomena. Therefore, it was logarithmised, and our model follows **Equation (11)** below

$$\text{LEFPG}_{it} = a_i + \beta_1 \text{LGDP}_{it} + \beta_2 \text{LEQ}_{it} + \beta_3 \text{LEF}_{it} + \beta_4 \text{LFOSSIL}_{it} + \beta_5 \text{LPOP}_{it} + \beta_6 \text{LURB}_{it} + \beta_7 \text{LTO}_{it} + \delta_{it}. \quad (11)$$

where the prefix  $L$  denotes the logarithm of the variable,  $a_i$  is the individual effect, **EFPG** represents ecological footprint measured in global hectares, **GDP** is Gross Domestic Product, **EQ** is export quality, **EF** is energy efficiency that the SBM-DEA model calculates, **FOSSIL** is the fossil fuels consumption (e.g., oil, gas, and coal) calculated in tonnes of oil equivalent, **POP** is total population, **URB** is urban population (in % of the total population), and **TO** is trade openness that measures the sum of exports and imports in GDP.

Given that this study used panel quantile regression to measure ecological footprint, **Equation (11)** is converted to the following form **Equation (12)**

$$Q_{\tau}(\text{LEFPG}_{it}|x_{it}) = a_i + \beta_{1\tau} \text{LGDP}_{it} + \beta_{2\tau} \text{LEQ}_{it} + \beta_{3\tau} \text{LEF}_{it} + \beta_{4\tau} \text{LFOSSIL}_{it} + \beta_{5\tau} \text{LPOP}_{it} + \beta_{6\tau} \text{LURB}_{it} + \beta_{7\tau} \text{LTO}_{it} \quad (12)$$

In this regard,  $Q_{\tau}(\text{LEFPG}_{it}|x_{it})$  is the  $\tau^{\text{th}}$  quantile of the ecological footprint for country  $i$  in year  $t$  conditional on the covariates. The coefficients  $\beta_{1\tau}, \beta_{2\tau}, \beta_{3\tau}, \beta_{4\tau}, \beta_{5\tau}, \beta_{6\tau}, \beta_{7\tau}$  are the quantile regression parameters and show the influencing factors.

#### 4. Empirical results

This section consists of two subsections. Using the SBM-DEA model, the first part calculates energy efficiency for 16 emerging countries. The second part uses panel quantile regression to estimate the effects of energy efficiency and export quality on the ecological footprint.

#### 4.1. SBM-DEA model results

The period used for the research is 1990-2014. **Table 3** shows the energy efficiency results using the SBM-DEA model (1990, 1995, 2000, 2005, 2010, and 2014). As can be seen, Brazil and Chile have the highest energy efficiency scores during this period. On the other hand, China and India have the lowest scores in energy efficiency in these years. Mexico's energy efficiency score was 1 in 1990, but energy efficiency in this country has declined over time. Hungary, South Korea, and Turkey's efficiency scores in 1990 were 0.78853, 0.60763 and 0.88455, respectively. In other years, their efficiency score has increased to an energy efficiency score of 1. The SBM-DEA model for all years (1990-2014) is in the Appendix (see **Tables A1, A2, and A3**).

**Table 3.** Resources and energy efficiency from SBM-DEA model (1990-2014)

Country	1990	1995	2000	2005	2010	2014
Brazil	1	1	1	1	1	1
Chile	1	1	1	1	1	1
China	0.12701	0.14462	0.15468	0.16552	0.19547	0.22675
Colombia	0.67496	0.62376	1	0.70891	0.68124	0.69209
Egypt	0.42449	0.56726	0.44871	1	1	1
Hungary	0.78853	1	1	1	1	1
India	0.21544	0.27798	0.25237	0.25027	0.26246	0.29492
Indonesia	0.27062	0.28541	0.29179	0.32137	0.33897	0.36864
Malaysia	0.49172	0.54747	0.59257	0.65377	0.68324	0.65274
Mexico	1	1	0.921	0.84518	0.825	0.84236
Morocco	0.41602	0.38995	0.35102	0.3805	0.40346	0.44611
Philippines	0.34101	0.36049	0.34566	0.43352	0.42935	0.4428
South Africa	1	1	0.74368	0.69681	1	0.71297
South Korea	0.60763	1	1	1	1	1
Thailand	0.23932	0.27319	0.36278	0.37468	0.43123	0.46511
Turkey	0.88455	1	1	1	1	1

**Notes:** Authors' calculations.

**Table 4** shows the average energy efficiency of countries and their ranking compared to other countries. As can be seen, Turkey ranks 1st among other countries with an average of 0.9922, and Hungary (0.99154) and Chile (0.9905) are second and third, respectively. The lowest energy efficiency is in China (0.165345). The low energy efficiency in this country can be explained as China, on the one hand, is the largest consumer of energy in the world in 2010 and on the other hand, a large part of the energy used in China is coal, which is the most crucial factor affecting CO<sub>2</sub> emissions (e.g., British Petroleum (BP), 2020; and Apergis & Payne, 2010). The average efficiency of all these countries is 0.6515.

**Table 4.** Resources and energy efficiency mean and rank from the SBM-DEA model

Country	SBM-DEA	Rank
Brazil	0.9891444	(4)
Chile	0.9904928	(3)
China	0.1653452	(16)
Colombia	0.7218904	(8)
Egypt	0.695288	(9)
Hungary	0.9915412	(2)
India	0.2525976	(15)
Indonesia	0.3067644	(14)
Malaysia	0.5989848	(10)
Mexico	0.8905656	(6)
Morocco	0.391036	(12)
Philippines	0.4101652	(11)
South Africa	0.817084	(7)
South Korea	0.959934	(5)
Thailand	0.351036	(13)
Turkey	0.99217875	(1)
Mean	0.65150302	-

**Notes:** Author's calculations.

#### *4.2. Panel quantile regression results*

After calculating the energy efficiency using the SBM-DEA model, in this section, we estimate the effect of energy efficiency and trade quality on the ecological footprint using the panel quantile regression. Before performing econometric models, a preliminary test is required for the results to be valid. The initial condition for using the panel quantile regression is the non-normal data distribution. This section examines the normality of variables before performing the panel quantile estimation. Then, the multicollinearity between the independent variables is evaluated. In the following, cross-sectional dependence and stationarity of variables are investigated.

##### *4.2.1. Preliminary tests*

When data are distributed non-normally, quantile regression results are more robust than the OLS estimation results (Koenker & Xiao, 2002). This study used Shapiro-Wilk (Royston, 1992) and Shapiro-Francia (Royston, 1983) tests to measure data normality. **Table 5** shows the results of the normality test. As can be seen, the results of Shapiro-Wilk and Shapiro-Francia normality tests indicate the non-normal distribution of data in all variables.

**Table 5.** Normal distribution test

Variables	Shapiro-Wilk test		Shapiro-Francia test		Obs
	Statistic	Prob.	Statistic	Prob.	
<b>EFPG</b>	0.45885	0.00000	0.45688	0.00001	400
<b>GDP</b>	0.54850	0.00000	0.54520	0.00001	400
<b>EQ</b>	0.98112	0.00004	0.98255	0.00019	400
<b>EF</b>	0.96039	0.00000	0.95782	0.00001	400
<b>POP</b>	0.52104	0.00000	0.52112	0.00001	400
<b>TO</b>	0.81749	0.00000	0.81810	0.00001	400
<b>URB</b>	0.95003	0.00000	0.95308	0.00001	400
<b>FOSSIL</b>	0.40540	0.00000	0.40293	0.00001	400

After performing the data normality test, we examine the multicollinearity test of dependent variables. For this purpose, the variance inflation factor (VIF) is used to investigate the multicollinearity of variables (Belsley et al., 2005). As shown in **Table 6**, the VIF score for all variables is less than 10, and the average VIF score is 2.90, which is less than the accepted value of 6. It can be concluded that there is no severe multicollinearity problem. In addition, since the number of periods (T) is more than the number of countries (N), so to examine the cross-sectional dependence in the panel data, the Breusch-Pagan LM test was used (Breusch & Pagan, 1980). The null hypothesis in this test is the existence of cross-sectional independence. As shown in **Table 6**, the results of the LM test reject the null hypothesis, which indicates the presence of cross-sectional dependence in all variables.

**Table 6.** VIF test and Breusch- Pagan (LM test)

Variables	VIF-test		Breusch- Pagan (LM test)	
	VIF	Mean VIF	$\chi^2$ - statistic	Prob.
<b>EFPG</b>	n.a.	2.90	390.908	0.0000
<b>GDP</b>	3.95			
<b>EQ</b>	1.78			
<b>EF</b>	2.72			
<b>POP</b>	2.94			
<b>TO</b>	1.54			
<b>URB</b>	3.51			
<b>FOSSIL</b>	3.85			

**Notes:** n.a. denotes not available.

According to the results of the LM test, which confirmed the existence of cross-sectional dependence in panel data, so in this section, the Panel Unit Root test (CIPS) prepared by Pesaran (2007) is used to perform the stationary test. Therefore, the null hypothesis is the unit root in all series. The results of the CIPS test in **Table 7** show that only the variables of EFPG, EQ, and FOSSIL are stationary at the level; however, all variables are stationary in logs.

**Table 7.** Panel unit root test (CIPS)

CIPS			CIPS		
Variables	Lags	(Zt-bar)	Variables	Lags	(Zt-bar)
EFPG	0	-4.978***	LEFPG	0	-4.151***
	1	-3.305***		1	-2.523***
GDP	0	1.343	LGDP	0	-2.669***
	1	0.631		1	-2.442***
EQ	0	-2.675***	LEQ	0	-2.686***
	1	-0.877		1	-0.887
EF	0	0.247	LEF	0	-2.340***
	1	0.764		1	-0.612
POP	0	3.704	LPOP	0	1.222
	1	0.608		1	-2.878***
TO	0	0.591	LTO	0	-1.114
	1	-0.455		1	-2.017**
URB	0	0.150	LURB	0	-2.312***
	1	-0.092		1	-0.597
FOSSIL	0	-1.933**	LFOSSIL	0	-2.362***
	1	-1.456*		1	-3.350***

**Notes:** "L" variables in the natural logarithms, \*\*\*, and \*\* denote statistical significance at (1%) and (5%) levels, respectively; Panel unit root test (CIPS) assumes that cross-sectional dependence is in the form of a single unobserved common factor and  $H_0$ : series is  $I(1)$ .

The panel unit root test results showed that all variables are stationary in logarithms. These results support the adequacy of performing the analysis in natural logarithms, thus avoiding a spurious regression.

#### 4.2.2. Panel quantile regression results

After the preliminary tests, the panel quantile regression is done in this section. For this purpose, quantiles of 10th, 25th, 50th, 75th and 90th are considered. In **Table 8**, countries are divided into six groups based on their average ecological footprint.

**Table 8.** Country distribution in terms of ecological footprint (gha)

Quantile	Country
The lower 10th quantile group	Morocco, Hungary
The 10th-25th quantile group	Colombia, Chile
The 25th-50th quantile group	Thailand, Egypt, Philippines, Malaysia
The 50th-75th quantile group	Mexico, South Korea, Turkey, South Africa
The 75th-90th quantile group	Brazil, Indonesia
The upper 90th quantile group	China, India

**Notes:** According to the level of EFPG, we divided 16 countries into six groups.

As shown in **Table 9**, panel quantile and panel fixed effects regression results are given. Here, the panel fixed effects are used to evaluate the robustness checks of the results. In addition, **Figure 1** shows the graphical results of the panel quantile regression. The results of the panel fixed

effects show that the export quality (EQ) at the level of (10%) has a positive and significant impact on the ecological footprint. Also, the variables of GDP, FOSSIL, POP, and URB have positive and significant effects on ecological footprint at the (1%) level.

In comparison, energy efficiency (EF) and trade openness (TO) have negative and significant effects on the ecological footprint at the (1%) level. As can be seen, the panel fixed effects confirm the panel quantile regression results. In the following paragraphs, we will review the results of panel quantile regression.

**Table 9.** Estimation results from panel quantile regression model and panel fixed effects

Variables	Quantiles						OLS	
	10th	25th	50th	75th	90th	Fixed Effects		
<b>LGDP</b>	0.2419 ***	0.2441 ***	0.2613 ***	0.2148 ***	0.2528 ***	0.2515 ***		
<b>LEQ</b>	0.2177 **	0.3441 ***	0.1157 ***	0.1609	0.0534	0.1256 *		
<b>LEF</b>	-0.148 ***	-0.130 ***	-0.154 ***	-0.128 ***	-0.142 ***	-0.1157 ***		
<b>LFOSSIL</b>	0.4153 ***	0.3748 ***	0.3511 ***	0.3365 ***	0.3288 ***	0.3421 ***		
<b>LPOP</b>	0.2854 ***	0.3224 ***	0.3259 ***	0.4063 ***	0.3656 ***	0.3868 ***		
<b>LURB</b>	0.0775	0.1149 **	0.2034 ***	0.3113 ***	0.3328 ***	0.2863 ***		
<b>LTO</b>	-0.129 ***	-0.129 ***	-0.128 ***	-0.074 ***	-0.098 ***	-0.0467 ***		
<b>Constant</b>	1.2415 ***	1.6622 ***	1.5091 ***	1.4459 ***	1.3368 ***	1.5514 ***		
<b>Pseudo R<sup>2</sup></b>	0.8996	0.9069	0.9083	0.9258	0.9324	0.9604		

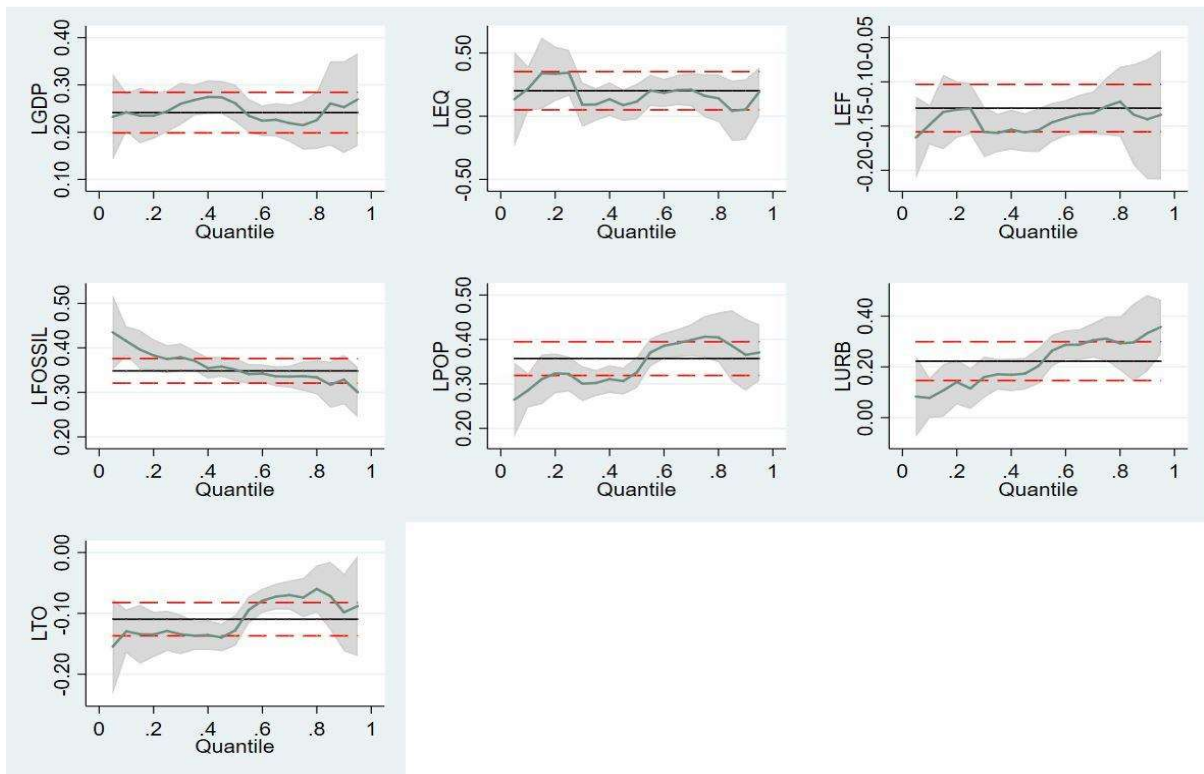
**Notes:** \*\*\*, \*\*, \* denote statistically significant at the (1%), (5%), (10%), levels, respectively; “L” denotes variables in natural logarithms.

It is essential to note that the relationship of the independent variables with the dependent one is conditioned by the variables included in the model we are examining. As shown in **Table 9**, GDP at all quantile levels has a positive and significant effect on the ecological footprint at the (1%) level. These results show that increasing economic growth increases the ecological footprint and further degrades the environment. These coefficients also indicate that these effects are more significant in quantile 50th than in other levels. On the other hand, the export quality (EQ) results on ecological footprint show that this variable has positive and significant effects only in quantiles 10th and 25th. Export quality produces environmental degradation in countries that have a low ecological footprint. On the other hand, energy efficiency (EF) significantly negatively affects the ecological footprint at the (1%) level in all quantiles. As can be seen, the higher effect of this variable is also in the quantile 50th (-0.154). These results indicate that increasing energy efficiency reduces the ecological footprint and improves environmental quality.

Fossil energy consumption at all quantile levels has positive and significant effects on ecological footprint. These results confirm that the consumption of fossil fuels causes environmental degradation. The population at all levels of quantiles has a positive and significant effect on the ecological footprint at the (1%) level. This result states that population growth has a negative impact on environmental quality. The coefficients of this variable show that the most significant effect of this variable on the ecological footprint is in quantile 75th (0.4063). Except in quantile 10th, urbanisation (URB) at other quantile levels has a significant positive impact on environmental footprint. These results show that increasing urbanisation increases the ecological footprint and further degrades the environment. As shown in **Table 9**, as quantile levels rise, the impact of urbanisation on the ecological footprint increases. The trade openness results indicate that it has a negative and significant effect on the ecological footprint at all levels of quantiles. As



can be seen, this effect is more significant in quantiles 10th and 25th than other levels of quantiles on ecological footprint. It states that trade openness through technology transfer can improve environmental quality.



**Figure 1.** Quantile estimate: Shaded areas are (95%) confidence bands for the quantile regression estimates. The vertical axis shows the elasticities of the explanatory variables, and the red horizontal lines depict the conventional (95%) confidence intervals for the OLS coefficient.

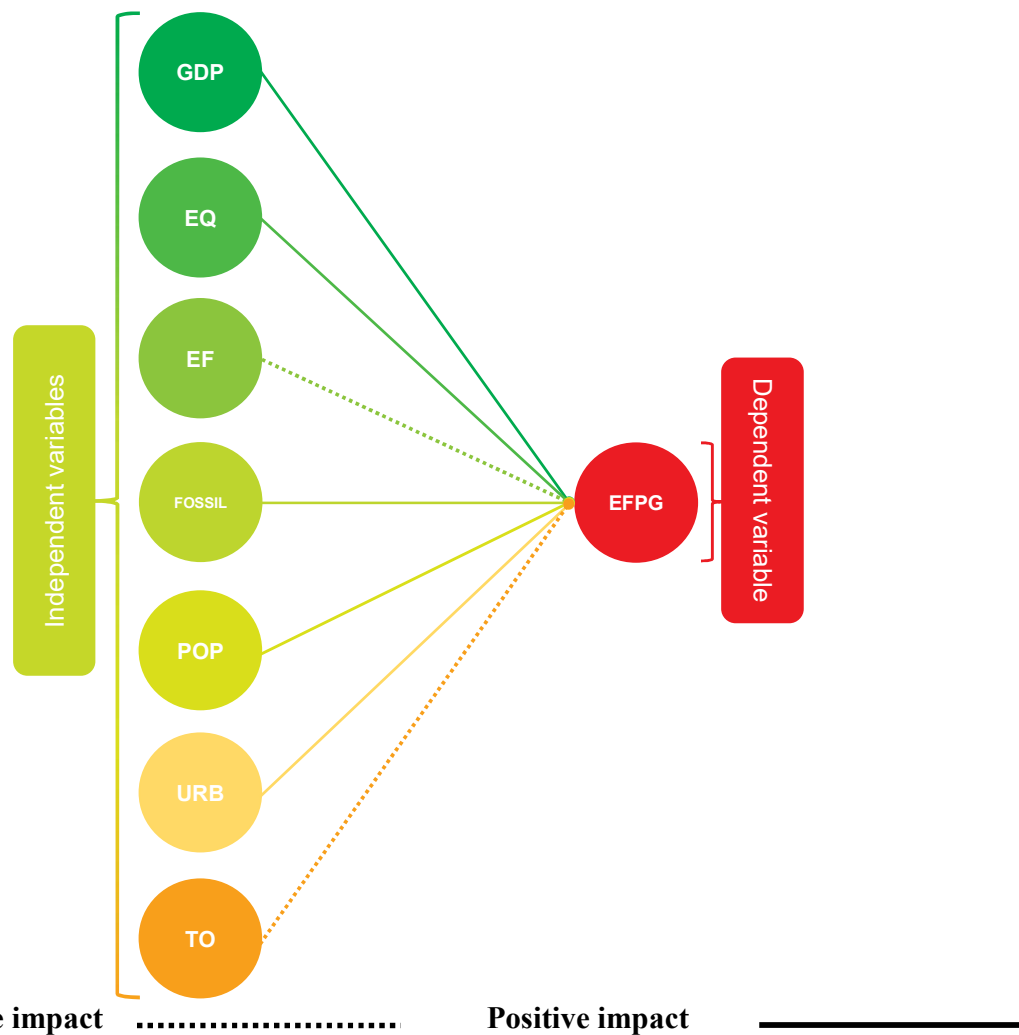
## 5. Discussion

Throughout history, economic growth across countries has been accompanied by an ever-increasing consumption of energy and other natural resources that pressure environmental sustainability. As a result, governments in emerging countries face the challenge of reducing poverty and fulfilling their populations' legitimate aspirations of improving their living standards without degrading the environment and compromising the well-being of future generations. To achieve this dual goal, they must transition their economies to higher value-added goods and, simultaneously, implement more efficient production processes that contribute to preserving natural resources.

In the first part of this study, we analysed resource use efficiency in sixteen emerging markets economies. According to that criterium, our findings show that South-Asian countries exhibit the worst performances. In particular, China, India, and Indonesia occupy the last three positions in this ranking. The underperformance of these countries may be related to their large populations, which provide a vast supply of cheap labour and curtails the incentives to adopt more efficient production technologies. Furthermore, these economies rely heavily on the manufacturing

and agricultural sectors, and the weight of the resource-light services sector is lower than in the other emerging countries (WBD, 2020). Over the years, these economies managed to close the gap relative to the best-performing ones partially, as they shifted the structure of their economies. However, they remain amongst the least efficient countries in resource utilisation.

**Figure 2** below summarises the impact of independent variables on dependent ones. This figure was created based on **Table 10** above.



**Figure 2.** Summary of the variable's effect. The authors created this figure.

Economic growth, measured by GDP, positively affects the ecological footprint. This finding is consistent with most studies involving developing countries (e.g., Fang et al., 2019; and Dogan et al., 2020; Yang and Usman (2021); Usman et al. (2021b); Usman and Hammar (2021), among many others), which reveal they have not yet reached a stage where economic growth does not cause environmental degradation. However, the response of the ecological footprint to economic growth is inelastic, which suggests these economies experienced structural changes during their development process and, over time, produced higher-value goods and services using more efficient processes, thus mitigating the environmental impact of economic growth. Danish et

al. (2019) proved the research results, and they stated that economic growth increases the ecological footprint.

As Fang et al. (2019), Dogan et al. (2020), Wang et al. (2021), and Kazemzadeh et al. (2021) found that increasing export quality leads to increased environmental degradation, our results support their findings. This positive relationship between export quality and increasing environmental degradation in emerging economies can be attributed to the fact that emerging economies strive to achieve high levels of economic growth as their primary goal through increasing their international competitiveness by improving the quality and variety of export products. So environmental protection is a secondary goal for them. On the other hand, the production of various export products requires complex assembly lines that incorporate components from all over the country and abroad. In this context, modern transport and communication infrastructures are essential to ensure the global competitiveness of domestic firms. Thus, governments may inadvertently augment the ecological footprint to build the needed infrastructures to increase export quality. However, studies also argue that improving the quality of exports due to increased revenue for environmentally friendly technologies will reduce environmental degradation (e.g., Gozgor & Can, 2017; and Murshed & Dao, 2020).

Fossil fuel consumption raises the ecological footprint, mainly in the minor level of countries (10th), while reducing the ecological footprint caused by energy efficiency is broadly stable across quantiles. These countries rely heavily on fossil fuels to satisfy their primary energy needs, and the weight of non-renewable energy sources in the total primary energy consumption ranges between (59%) for Brazil and (98%) for Egypt (WBD, 2020). Thus, these countries must improve energy efficiency by adopting modern production techniques, effective transport systems and adequate building standards, and switching to renewable energy sources to ensure the environment can regenerate itself. Ulucak et al. (2020), in a study for OECD countries, confirmed that the use of non-renewable energy has devastating effects on ecological footprint. Results of the study for 20 Asian economies by Usman et al. (2021) confirmed that non-renewable energy consumption negatively affects the ecological footprint. Usman and Makhdom (2021) also confirmed these results in a study for BRICS countries.

The population has an inelastic impact on the ecological footprint, which implies that its per capita value decreases as the population grows. Curiously, the urbanisation process associated with population growth and the structural change in economies from the agricultural sector to the manufacturing and services sectors exerts differing effects on the ecological footprint across countries: it increases it on the most populous ones but has no impact on smaller countries. The reasons beneath this heterogeneous impact deserve further research through a detailed study of the urbanisation process in the various countries. Ahmed et al. (2020), in a survey for Group of Seven (G7) countries, confirmed that urbanisation has a positive effect on ecological footprint. Danish & Wang (2019) also confirmed the research results in another study for emerging countries. Usman et al. (2021c), in a study for 52 countries, confirmed that urbanisation increases environmental pollution. Whereas, Danish & Khan (2019), in a survey for BRICS countries, found that urbanisation reduces the ecological footprint.

We also find that trade openness contributes to the mitigation of the ecological footprint. This result is consistent with Dogan et al. (2020), but it is at odds with Gozgor & Can (2017) and Fang et al. (2020), who show trade openness increases carbon dioxide emissions. Khalid et al. (2021), in a study for the South Asian Association for Regional Cooperation (SAARC) countries, stated that trade openness only improves the ecological footprint in Nepal. In another study for 105 countries, Kamal et al. (2021) also confirmed that trade openness improves the quality of the environment. While Usman et al. (2020a), in a study of 33 upper-middle-income countries, they

found the negative relationship of trade on the ecological footprint of Africa and the United States. The traditional explanation for the beneficial impact of trade openness on the environment is its contribution to fostering modern production techniques from abroad. However, we offer a complementary explanation based on the nature of trade realised by these countries. Usually, developing countries export low-to-middle value resource-intensive goods and import high-value resource-light products from developed countries. Thus, trade has a negative net effect on the ecological footprint of consumption in emerging countries, and a higher trade openness results in a lower ecological footprint.

## 6. Conclusion and policy implications

This research contributes to the literature on emerging countries in two ways. First, using an optimisation technique to evaluate an augmented rank of countries' resource efficiency, including energy jointly with labour and capital. Second assessing this former variable and exports quality along with traditional variables on the ecological footprint. Indeed, the research focuses on capturing the contribution of countries' resources and energy efficiency on mitigating/reducing the pressure over the environment, here approached by the ecological footprint (global hectares), in emerging countries.

The empirical analysis was carried out for a panel of sixteen emerging countries from 1990 to 2014, and the estimations were based on a two-step approach. First, a slacks-based measure (SBM) - data envelopment analysis (DEA) model, known as the SBM-DEA model, was used to estimate countries' resources and energy efficiency by year. In the second step, a panel quantile regression was used to assess the impacts of resources and energy efficiency, export quality, and the other variables on the ecological footprint.

From the SBM-DEA model (1990-2014), it can be concluded that Turkey and Hungary were the countries that got the better rank on resources and energy efficiency mean with 0.992 and 0.991, respectively. In contrast, with 0.165, China and India, with 0.253, were the countries with the worst rank on resources and energy efficiency.

The analysis of results from quantile regression allows us to conclude that resources, energy efficiency, and trade openness contribute to reducing the ecological footprint. On the other hand, GDP, consumption of fossil fuels, and population contribute to deteriorating the environmental footprint. Export quality and urban population contribute to deteriorating the environmental footprint but only in some quantiles. Export quality in 10th and 25th quantiles and the case of the urban population in all quantiles except the 10th one aggravates the ecological footprint.

Some variables are especially worrying and deserve close monitoring. The consumption of fossil fuels is the variable with the highest coefficient (elasticity), in particular in the 10th quantile, indicating that a percentage variation in the consumption of this type of energy is the one that most contributes to environmental deterioration. Population ranks second as environmental damage, especially in the 75th and 90th quantiles. The urban population also deserves attention mainly on the quantiles 75th and 90th. GDP also is an essential source of deterioration of the environmental footprint, being its effect independent of the quantile analysed.

Thus, from a policy perspective, we have variables that require different kinds of intervention to mitigate/reduce the ecological footprint. The ecological footprint is the environmental damage that results from the production of goods and services to satisfy the necessities of human beings. More often than not, there are several ways that one can pursue to satisfy them. For example, different lifestyles exert distinct pressures on ecological footprint and,

consequently, Earth sustainability. Hence, policymakers should facilitate people to become aware of the implications of using scarce resources throughout the economy and become more and more conscious of the sustainability of their lifestyles and prone to change the mixture of goods and services they consume.

A practical action to mitigate/reduce the ecological footprint, given its great extension, requires many policy measures and the active collaboration of citizens. The first step is for authorities to identify and appraise the impact on the ecological footprint of the production/consumption of goods and services. The intervention must simultaneously consider the demand and the supply side of economics to be ecologically effective. The results of our study suggest that consumption of fossil fuels must be replaced as soon as possible for renewable sources of energy speeding the energy transition already underway. Governments should also support the transition of the productive structure of the economies from the manufacturing to the services sector, as the latter requires less energy consumption and has a higher value-added. Furthermore, since the planet's ecological capacity is minimal, additional efforts should control human fertility. Finally, the adverse effect of the urban population infers that the policymakers ought to support the development of informational and communicational infrastructure that can enhance the power of policies in developing peoples' ecological consciousness.

On the one hand, the finding that, in the lower quantiles, export quality is a solid factor for the harm the ecological footprint requires attention from policymakers. The deepening of the sophistication of transition economies must be accompanied by economic policy measures that mitigate their environmental impact. On the other hand, a result with critical environmental implications is that the efficient use of resources (labour, capital, and energy) in emerging countries reduces their ecological footprint. Thus, policies favouring resources and energy efficiency beyond ameliorating the output also help to reduce the ecological footprint. Finally, trade openness also can be promoted as it has a favourable impact on ecological footprint.

In short, the main policy recommendations of this research for emerging countries are by one hand directed to restrain human actions that aggravate ecological footprint (i) accelerate the energy transition from fossil fuels to renewables ones, (ii) develop birth control policies that regulate population growth, (iii) stimulate economic growth less environmentally aggressive, and (iv) promote urban lifestyles environmentally responsibly. On the other hand, promote human actions that improve ecological footprint (v) resources and energy efficiency, (vi) increase trade openness, and (vii) promote export quality in countries where the ecological footprint global hectares are low. Future research can assess the effects of trade quality or trade products diversification on PM<sub>2.5</sub> emissions.

### **Ethical Approval**

This article does not contain any studies with human participants performed by any of the authors.

### **Authors Contributions**

*Emad Kazemzadeh* Investigation, Methodology, Data curation, Writing - original draft; *José Alberto Fuinhas* Supervision, Visualisation, Writing - review & editing, Funding acquisition; *Matheus Koengkan* Investigation, Formal analysis; *Nuno Silva* Investigation, Validation; *Fariba Osmani* Introduction. All authors have read and approved the final manuscript.

### **Conflict of Interest Statement**

*Emad Kazemzadeh* declares that he has no conflict of interest. *José Alberto Fuinhas* declares that he has no conflict of interest. *Matheus Koengkan* declares that he has no conflict of interest. *Nuno*

Silva declares that he has no conflict of interest. *Fariba Osmani* declares that he has no conflict of interest.

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## Appendix

**Table A1.** Resources and energy efficiency from SBM-DEA model (1990-1998)

Country	1990	1991	1992	1993	1994	1995	1996	1997	1998
Brazil	1	1	1	1	1	1	1	1	0.9397
Chile	1	1	1	1	1	1	1	1	1
China	0.12701	0.12917	0.13245	0.13497	0.13996	0.14462	0.14608	0.14696	0.15039
Colombia	0.67496	0.68725	0.66564	0.60595	0.59544	0.62376	0.62591	0.6579	0.6479
Egypt	0.42449	0.4049	0.43212	1	0.53436	0.56726	0.44388	0.4113	1
Hungary	0.7885	1	1	1	1	1	1	1	1
India	0.21544	0.21431	0.22332	0.25283	0.25783	0.27798	0.28993	0.28929	0.27708
Indonesia	0.27062	0.25618	0.26489	0.27589	0.27584	0.28541	0.28301	0.28435	0.29718
Malaysia	0.49172	0.49153	0.50579	0.50948	0.53486	0.54747	0.56513	0.55634	0.59668
Mexico	1	1	1	1	1	1	0.95666	0.9326	0.90555
Morocco	0.41602	0.41314	0.38707	0.38361	0.42513	0.38995	0.43548	0.41145	0.40341
Philippines	0.34101	0.34145	0.33707	0.33879	0.33548	0.36049	0.35091	0.34823	0.36611
South Africa	1	0.7844	0.7508	1	1	1	1	1	1
South Korea	0.60763	0.66883	0.72189	1	1	1	1	1	1
Thailand	0.23932	0.24286	0.24918	0.26063	0.26429	0.27319	0.27031	0.28763	0.35728
Turkey	0.88455	0.91313	0.9586	1	0.94056	1	1	1	1

Notes: Authors' calculations

**Table A2.** Resources and energy efficiency from SBM-DEA model (1999-2006)

Country	1999	2000	2001	2002	2003	2004	2005	2006
Brazil	0.94265	1	1	0.92428	1	0.92194	1	1
Chile	1	1	1	1	1	1	1	1
China	0.15343	0.15468	0.15715	0.15813	0.1599	0.162	0.16552	0.17025
Colombia	1	1	1	1	0.67192	0.67907	0.70891	0.68036
Egypt	0.44379	0.44871	0.45851	0.44435	1	1	1	0.47544
Hungary	1	1	1	1	1	1	1	1
India	0.23543	0.25237	0.22223	0.23125	0.24754	0.25134	0.25027	0.24747
Indonesia	0.30993	0.29179	0.28685	0.29006	0.30968	0.29934	0.32137	0.33195
Malaysia	0.62516	0.59257	0.56711	0.58313	0.60036	0.61518	0.65377	0.65436
Mexico	0.94724	0.921	0.89639	0.87886	0.85746	0.84793	0.84518	0.82436
Morocco	0.35765	0.35102	0.36542	0.35928	0.37237	0.36039	0.3805	0.38272
Philippines	0.35779	0.34566	0.36562	0.36729	0.36739	0.39133	0.43352	0.44074
South Africa	0.67669	0.74368	0.7819	1	1	0.63952	0.69681	0.67192
South Korea	1	1	1	1	1	1	1	1
Thailand	0.35579	0.36278	0.3638	0.36677	0.36906	0.36027	0.37468	0.3821
Turkey	1	1	1	1	1	1	1	1

Notes: Authors' calculations

**Table A3.** Resources and energy efficiency from SBM-DEA model (2007-2014)

Country	2007	2008	2009	2010	2011	2012	2013	2014
Brazil	1	1	1	1	1	1	1	1
Chile	1	0.97488	1	1	0.94904	0.9125	0.9259	1
China	0.17676	0.18275	0.18947	0.19547	0.20284	0.20979	0.21713	0.22675
Colombia	0.68465	0.72679	0.66369	0.68124	0.68589	0.6937	0.69424	0.69209
Egypt	0.44543	0.44766	1	1	1	1	1	1
Hungary	1	1	1	1	1	1	1	1
India	0.24527	0.25642	0.25838	0.26246	0.24306	0.24579	0.27273	0.29492
Indonesia	0.33505	0.33966	0.34186	0.33897	0.33145	0.32936	0.34978	0.36864
Malaysia	0.65912	0.69728	0.66617	0.68324	0.66038	0.63618	0.62887	0.65274
Mexico	0.81997	0.81117	0.77101	0.825	0.79137	0.7874	0.80263	0.84236
Morocco	0.37145	0.37709	0.38565	0.40346	0.38634	0.38904	0.42215	0.44611
Philippines	0.44747	1	0.44634	0.42935	0.43933	0.42335	0.43661	0.4428
South Africa	0.65721	0.64782	0.6527	1	0.65843	0.65738	0.69484	0.71297
South Korea	1	1	1	1	1	1	1	1
Thailand	0.4049	0.41577	0.43713	0.43123	0.40341	0.40342	0.43499	0.46511
Turkey	1	1	1	1	1	1	1	1

Notes: Authors' calculations