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The Impact of Non-Green Trade Openness on Environmental Degradation in Newly Industrialized Countries

Sil van Hek [1], Muhlis Can [2,*] and Jan Brusselaers [1]

[1] Department of Environmental Economics, Institute for Environmental Studies, Vrije Universiteit Amsterdam, Amsterdam 1081 HV, Netherlands; silvanhek@gmail.com (S.V.H.); janbrusselaers@hotmail.com (J.B.)
[2] Social Science Research Lab BETA Akademi, Istanbul, Turkey; muhliscan@yandex.com (M.C.)

* Correspondence: muhliscan@yandex.com

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Abstract

Environmental degradation due to human over-exploitation is one of the most pressing global issues. The ten Newly Industrialized Countries (NICs) have recently witnessed substantial economic growth and involvement in global trade. In the discussion on environmental degradation, trade has a crucial role. Scholars use trade openness to test the scale effect on the environment. This research investigates the effect of non-green trade openness, economic growth, and energy consumption on ecological footprint. Panel estimation techniques such as cross-sectional dependence, slope homogeneity, unit root, and cointegration analyses are applied to panel data of ten NICs between 2003 and 2016. The Fully Modified Ordinary Least Squares (FMOLS) method reveals that non-green trade openness increases environmental degradation in the panel. Energy consumption and economic growth are also found to increase environmental degradation. Moreover, the Environmental Kuznets Curve (EKC) hypothesis is validated. The research presents a few relevant policy implications. The NICs should invest in green energy and an energy-efficient economy and focus on stimulating green trade as a catalyst for sustainable economic development in order to improve the quality of their environment. This can be done by introducing higher tariffs on non-green products and investing in technological innovations for green production methods and renewable energy. Although local environmental pollution in the European Union (EU) decreases, an increase in pollution in the NICs threatens the global state of the environment. Therefore, non-green trade should be approached as an international problem that has detrimental effects on all countries in different phases of economic development.

1. Introduction

Environmental degradation, the deterioration of natural resources and ecosystems caused by human activities, is a pressing issue of global concern [1, 2]. In an extensive report, the Intergovernmental Panel on Climate Change (IPCC) [3] found that anthropogenic greenhouse gas (GHG) emissions are responsible for a warming of approximately 1.1°C since 1850-1900. Furthermore, a report from the World Economic Forum (WEF) [4] identified human-induced environmental damage as posing a very high likelihood and high impact risk. The report concluded that human over-exploitation and/or mismanagement of the environment is one of the key drivers of natural resource scarcity. Global economic growth since the Industrial Revolution has led to increasing energy consumption and demand for natural

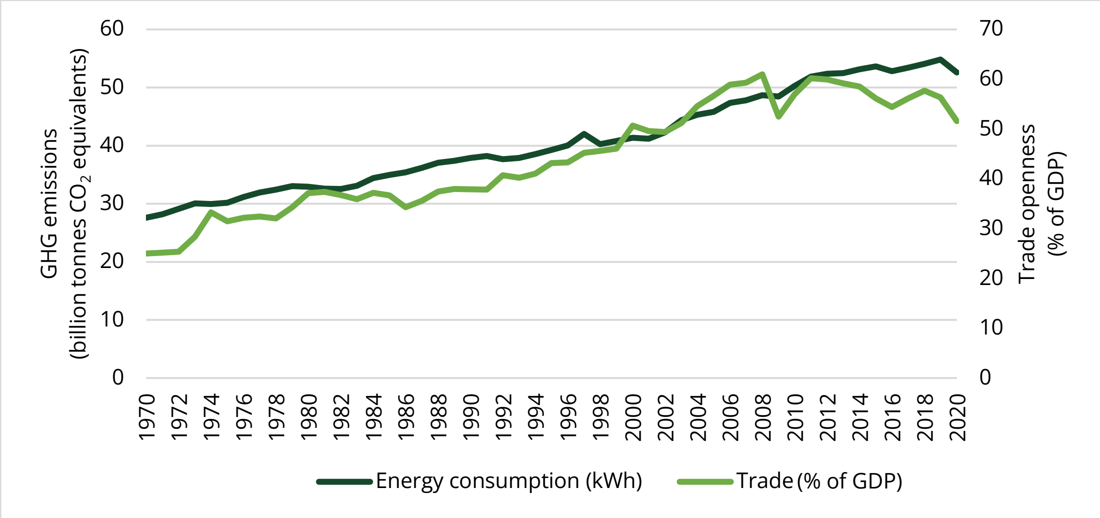

Figure 1. GHG emissions and trade openness in the World (1970-2020).
Note: Data retrieved from Our World in Data [5].

resources. This has led to threatened ecosystems, habitat destruction, deforestation, over-exploitation, and biodiversity loss. Total net anthropogenic GHG emissions have continued to rise between 2010 and 2019, and Climate Resilient Development is already challenging at current warming levels. It will become more limited if global warming exceeds 1.5°C [6].

Furthermore, the threat of climate change uncovers inequalities between countries. Whereas developed countries could create economic prosperity using carbon-intensive techniques and now have the means to decarbonize, developing countries did not have these opportunities [7]. Even though China, the United States, and India accounted for approximately 50% of global CO_2 emissions since 1960 [8], the consequences will fall disproportionately on poor countries [9].

In 2015, the United Nations (UN) adopted the 2030 Agenda for Sustainable Development with 17 corresponding Sustainable Development Goals (SDGs) to address various global challenges. Within these goals, world leaders expressed their determination to protect the planet from degradation through sustainable production and consumption and sustainably managing its natural resources [10]. Moreover, the Paris Climate Agreement established ambitious targets to limit global warming to below 2°C, above pre-industrial levels [11]. International trade is an important focus area for these targets to be reached. Trade has often been mentioned as a major contributor to environmental degradation. In fact, international trade alone accounts for approximately 20% of global CO_2 emissions [12]. Figure 1 illustrates the growth of GHG emissions (billion tonnes of CO_2 equivalents) and trade openness (value of imports and exports as a percentage of GDP) for the world between 1970 and 2020. Despite a drop around 2008 due to the global financial crisis and 2019 due to the COVID-19 pandemic, both indicators show a clear increasing trend.

The Newly Industrialized Countries (NICs) are increasingly important in global trade and have become important contributors to environmental degradation. Following Sawe [13], a NICs has surpassed the economic status of developing nations but is below that of developed nations. They can also be classified as middle-income nations. Brazil, China, India, Indonesia, Malaysia, Mexico, Philippines, South Africa, Thailand, and Turkiye are characterized by a prosperous market economy, trade openness, increasing environmental pollution, and high energy consumption [14]. In the past decades, the NICs saw a large increase in output, export, import, and value-added, highlighting their importance in global production and trade [15]. This high economic growth, energy use, and increase in trade openness also present a strain on the environment in the form of natural resource demand [16]. Furthermore, current production techniques in the NICs are often carbon- and energy-intensive. This shows that despite their recent economic development, the NICs have yet to benefit from new and innovative technologies that can help reduce pollution in the industrial sector.

Figure 2 illustrates that, with the exception of Brazil, all the NICs currently experience a biological deficit [17]. This means that the ecological footprint exceeds the biological capacity of a specific country in Global Hectares (gha) per capita. These findings emphasize the need for an in-depth analysis of the relationship between trade, economic growth, energy use, and ecological footprint in the NICs. These parameters can help to explain the

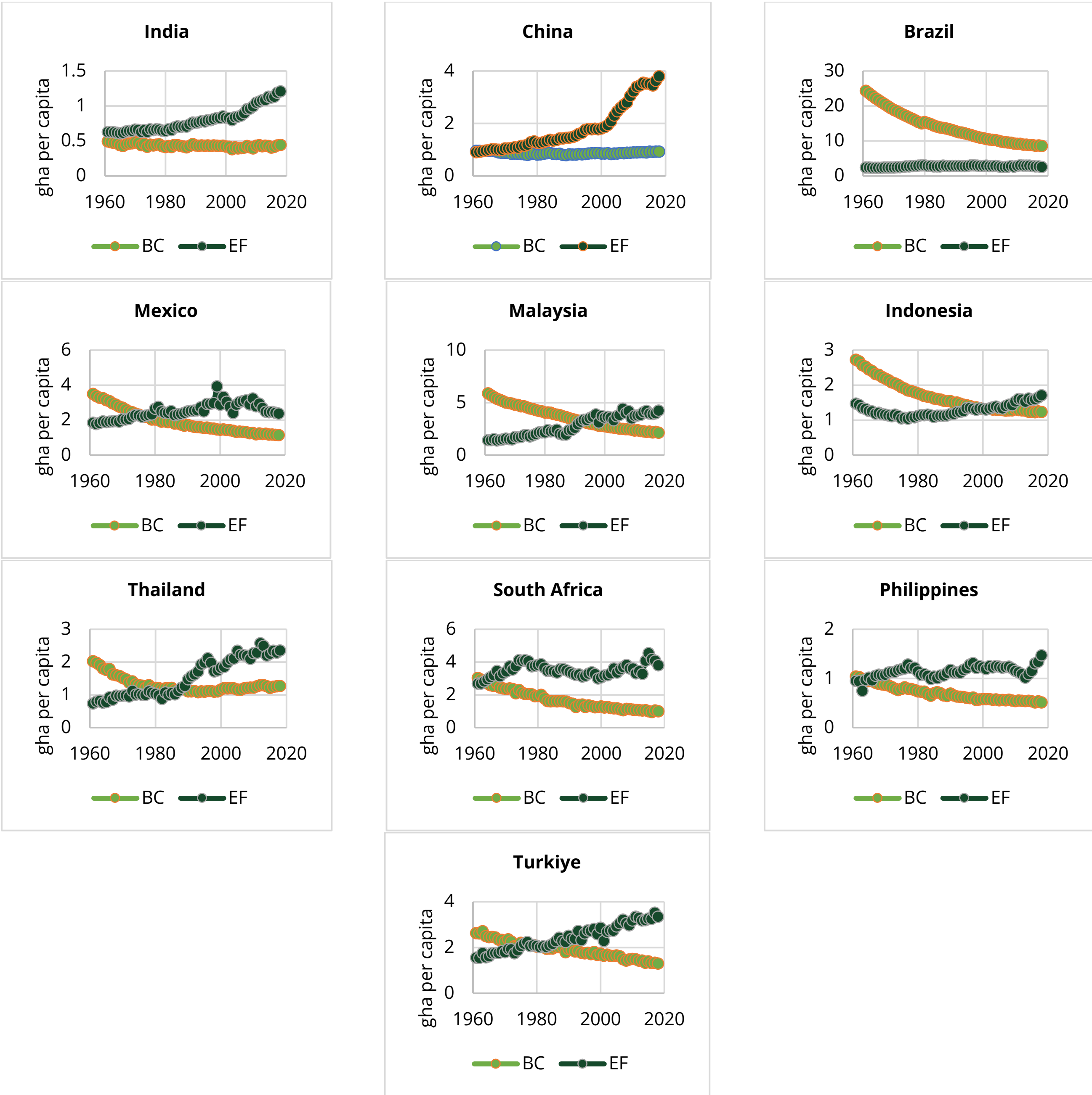

Figure 2. Biocapacity (BC) vs. Ecological Footprint (EF) in the 10 NICs (1961-2018).
Note: Data retrieved from the Global Footprint Network [17].

decreasing trend in biocapacity and the increasing trend in ecological footprint.

There is a general consensus in the literature that trade can exert a threefold effect on the environment. On one side, trade facilitates the relocation of green technologies from developed nations to developing nations, which can be linked to the composition effect and technique effect [18]. In addition, trade contributes to pollution increase through the scale effect [19]. According to the scale effect, growth in pollution is caused by scaling up economic activity, including both consumption and production [20]. Trade liberalization also facilitates a divide between 'clean' production in developed nations with stricter environmental regulations and 'dirty' industries moving to developing nations with weaker environmental regulations [21]. In other words, this process allows for lower and middle-income countries to become the industrial production centers for the rest of the world.

The scale effect of trade on the environment has generally been analyzed using trade openness as the principal explanatory variable [22]. Trade openness refers to the average value of a country's total exports and imports relative to its Gross Domestic Product (GDP) [23]. This index ignores the difference between green trade and non-green trade, and therefore, it does not capture the potential impact of different product groups.

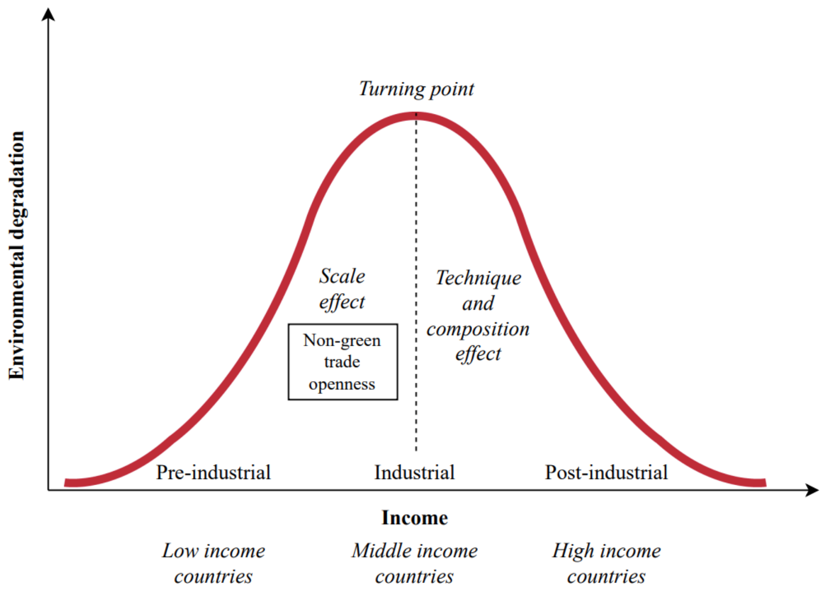

Figure 3. EKC hypothesis: income, non-green trade openness, and environmental degradation.
Note: Adapted from Mitić et al. [24].

Green trade openness was first proposed by Can et al. [22] to separate these two categories in the trade basket [25]. Paramati et al. [26] define green products as reducing environmental damage due to increased energy efficiency in production. This way, green trade can be a tool to minimize environmental degradation by reducing the use of fossil-based energy [27]. In addition, Can et al. [22] developed the Non-green Trade Openness Index. Non-green products are exposed to regulatory restrictions and pollution taxes in global trade. These goods are generally GHG intensive and are high in non-renewable energy consumption. Therefore, they cause a relatively high share of pollution and stimulate the use of fossil fuels. Examples of non-green products are pollution-intensive industries such as cement and steel [28], textiles, electricity, and energy production [29], as well as traditional fossil fuel vehicles [30].

In the literature, the Environmental Kuznets Curve (EKC) serves as a common framework to investigate the impact of various indicators on environmental deterioration. The EKC is based on an inverted U-shape relationship between economic growth and environmental deterioration, which was originally developed by Grossman & Krueger [31]. According to this hypothesis, environmental pollution first rises with economic growth. After a certain threshold of income is reached, environmental degradation declines. In other words, low and middle-income nations are expected to experience higher levels of environmental degradation than high-income nations. The EKC can also be linked to trade's scale, composition, and technique dimensions. As shown in Figure 3, scale has a dominant effect in the first phase of economic development, and technique and composition become more important in the second phase of economic development [24]. The NICs are middle-income countries with industrialized economies and are thus situated around the threshold of the inverted U-shape that represents the EKC hypothesis. Therefore, it is expected that the NICs will currently experience a dominant scale effect of (non-green) trade and high environmental degradation.

The NICs have not yet completed their structural economic transformation. As middle-income countries, they are generally focused on natural resource exploitation as the main source of income. With their increasing economic growth and structural change, the countries will likely pose an increasing threat to environmental quality. Oluc et al. [32] found that economic expansion and structural transformation increase environmental degradation in 94 middle-income countries. This coincided with the placement of middle-income countries in the EKC hypothesis. Following the EKC hypothesis, further structural change in the economy might decrease the negative impact of the NICs on the environment.

This study is relevant in the currently available literature base since it is the first study that applies the novel index of non-green trade openness to a group of developing nations. It will give a first insight into the relationship between the non-green trade openness of these nations and the environmental degradation in a respective country. Second, the EKC hypothesis will be used to analyze the relationship between income, non-green trade openness, and environmental degradation. Third, advanced panel estimation techniques will be used to analyze the empirical results. This will be followed by discussing the empirical model and the methodological techniques used. Next, the results of this empirical model will be discussed and placed into the existing theoretical context. Finally, research and policy recommendations will be provided based on the empirical findings.

2. Literature Review

Trade is an important parameter that can positively and negatively affect the environment. Generally, three different aspects of the trade are discussed in the literature. These are the technique, composition, and scale effect. The technique aspect of trade is often proxied by economic complexity. It refers to the changes in the sophistication of production methods resulting from trade liberalization. This has a twofold effect on the environment. New production technologies can increase energy consumption and carbon emissions, but green technologies can also provide opportunities to reduce pollution and produce cleaner energy [33]. Ahmad et al. [34], employing Cross-sectional Autoregressive Distributed Lag (CS-ARDL) analysis, found that economic complexity contributed to an expansion of the ecological footprint in 20 emerging economies from 1984 to 2017. By applying quantile estimation on panel data for 55 countries between 1971 and 2014, Dogan et al. [35] found that complexity increases carbon emissions in low- and middle-income countries and controls carbon emissions in high-income countries. Using the Fully Modified Ordinary Least Squares (FMOLS) method, Aluko et al. [36] discovered that economic complexity increased CO_2 emissions in Organisation for Economic Co-operation and Development (OECD) nations between 1971 and 2018. The researchers also validate the EKC hypothesis. Boleti et al. [33] applied pooled OLS to a world sample of 88 developed and developing economies between 2002 and 2012 and found that higher levels of economic complexity increase environmental quality. Finally, Nguyen & Doytch [37] compare the impact of economic complexity on the ecological footprint in 95 nations, which include low, middle, and high-income economies, from 1995 to 2013. Using the two-step Generalized Method of Mmoment (GMM) system, the researchers found an inverted U-shape relationship between economic complexity and the ecological footprints of consumption and production. Therefore, the general finding in the literature is that economic complexity has a deteriorating impact on the environment until a certain tipping point of economic development.

Proxies such as export diversification, import diversification, and import or export concentration are generally used to measure the composition effect of trade on the environment. The composition effect states that due to trade liberalization, the industrial structure of the economy changes as the country specializes in the goods on which it has a comparative advantage [38]. The dominant finding in the literature is that export diversification and concentration tend to decrease environmental degradation. Liu et al. [39] found that export market diversification and export product diversification decreased CO_2 emissions in a sample of 125 nations between 2000 and 2015, using the Driscoll-Kaay estimation method. The researchers also validate the EKC hypothesis in the sample. Shahzad et al. [40] found similar results for export product diversification in a world sample of 63 countries between 1971 and 2014, using a fixed effects model and system GMM. Apergis et al. [41] found that higher levels of export product concentration decreased CO_2 emissions for 19 high-income countries between 1962 and 2010, using panel ARDL and fixed effects quantile regression.

Furthermore, Sharma et al. [42] found that a lower level of export diversification increased carbon emissions in the Brazil, Russia, India, and China (BRICS) nations between 1990 and 2018, using the CS-ARDL estimation method. In other words, higher export diversification is beneficial for the environment. For lower-income nations, Can et al. [43] found that export product diversification enhanced carbon emissions in 84 developing nations between 1971 and 2014, using Dynamic Ordinary Least Squares (DOLS), FMOLS and ARDL methods. This suggests diverging impacts of export diversification on the environment for countries in different stages of economic development. Jiang et al. [44] compare the impact of export and import diversification on the ecological footprint of 17 Asia-Pacific Economic Cooperation (APEC) nations between 1995 and 2019. Using FMOLS and DOLS techniques, the researchers found that whereas export diversification decreases the ecological footprint, import diversification has the opposite effect. Considering import, the general consensus is that import diversification or concentration increases environmental degradation. Sharma et al. [45] found that higher import diversification values increased the BRICS countries' ecological footprint from 1995 to 2018, using CS-ARDL. Hu et al. [28] compare the relationship between import diversification and environmental degradation in 35 developed and 93 developing countries between 1995 and 2014. Using Common Correlated Effects-Mean Group (CCE-MG) and Augmented Mean Group (AMG) estimation methods, the researchers found that import diversification decreases environmental degradation in developed countries and increases environmental degradation in developing countries.

The final aspect of the trade is the scale effect, which describes that as market access increases due to trade liberalization, a country will experience economic development and accelerated environmental degradation, all else being constant. Trade openness is mainly used as a proxy to measure the relationship between the scale of trade and environmental degradation. Literature on trade openness and the environment has presented different results for countries in different phases of economic growth [22]. The dominant finding for developed countries is that trade openness decreases environmental degradation. Several studies found a negative relationship between trade openness and environmental degradation for Central and Eastern European countries (CEECs) and the European Union (EU) [46–50]. Pata et al. [51] found similar results in six Association of Southeast Asian Nations (ASEAN) countries between 1995 and 2018, using panel ARDL. Two studies found a positive connection between trade openness and environmental degradation in EU countries [52, 53]. The disparity in these findings can be attributed to methodological variations and the empirical models employed across the studies. For developing countries, the dominant finding in the literature is that trade openness accelerates environmental degradation [16, 54–60]. Cole & Elliott [38] attribute this increase in environmental pollution to trade openness in lower-income countries to weaker environmental regulations. Lower environmental standards increase their comparative advantage in dirty production. In contrast, Zafar et al. [12] found that trade openness decreases carbon emissions for a sample of 18 emerging economies, including the NICs. The researchers conclude that the nations in the sample have invested in energy efficiency and environmental technologies to improve environmental quality, which might explain this relationship.

Trade openness is based on a trade basket with both environmental and non-environmental products. Can et al. [25] criticized this and presented the Green Openness Index. Green products consume less fossil-based energy in production, decreasing environmental degradation [26]. Can et al. [25] found that green trade openness decreased environmental degradation in 35 OECD nations from 2003 to 2016, using AMG and Mean Group/Pooled Mean Group (MG/PMG) ARDL techniques. Can et al. [27] found similar results for 31 OECD countries between 2007 and 2017 by using the FMOLS and DOLS estimation techniques. Using QR and Driscoll-Kraay fixed effect OLS, Lee et al. [61] found similar results in a negative relationship between green trade openness and the ecological footprint for 24 EU countries between 2000 and 2018. Other studies have also analyzed the connection between global environmental product trade and the environment. Ahmad et al. [62] found that green trade openness reduced environmental deterioration in BRICS between 2004 and 2018, using Continuously Updated Fully Modified (CUP-FM) and Continuously Updated Bias-Corrected (CUP-BC) techniques. Li et al. [63] applied a different regional green trade index with firm-level trade information on panel data between 2007 and 2016 in China. Using a SYS-GMM method, they found that increasing green trade can improve environmental quality by mitigating pollution emissions.

In addition to green trade openness, Can et al. [22] further analyzed the impact of non-green product trade on environmental degradation. The researchers discovered that non-green trade openness decreased environmental degradation in 25 EU member states between 2003 and 2016, using PMG estimation. This study will build on this finding and continue to investigate the influence of non-green trade openness on environmental degradation in a group of developing nations. Following the EKC hypothesis (refer to Figure 3), non-green trade openness is expected to increase environmental degradation in the NICs, which will be further explored in this research.

3. Materials and Methods

3.1. Model Specification and Data

In the discussion on environmental degradation, trade has a crucial role and can exert both positive and negative environmental impacts. Scholars use trade openness to test the scale effect on the environment, which includes green and non-green products. The non-green trade openness index measures the total value of non-green product exports and imports in the trade basket as a proportion of Gross Domestic Product (GDP). This empirical section aims to investigate the relationship between non-green trade openness (NGOP) and environmental degradation in a sample of developing countries for a time period between 2003 and 2016. This period was chosen due to a limitation in data availability from the non-green trade openness index based on data released by the OECD. The chosen sample consists of ten NICs, which can also be classified as middle-income nations. The NICs are suitable for this empirical model since they are expected to experience high environmental degradation due to a large industrial sector and the dominant scale effect of trade (refer to Figure 3). Figure 2 presents a list of the ten NICs included in the analysis.

Based on the studies of Can et al. [22], Idroes et al. [64], Destek et al. [49], and Lu [56], ecological footprint per capita (EF) will be used as the dependent variable for

Table 1. Dependent and independent variables of the empirical model.

Variable	Symbol	Measurement	Data Source
Ecological footprint per capita	EF	Ecological Footprint of Consumption (Global Hectares per capita)	Global Footprint Network [17]
Real Income per capita	GDP	Gross Domestic Product per capita (constant 2015 US$)	World Development Indicators [65]
Real Income per capita (squared)	GDP^2	Gross Domestic Product per capita (squared)	Author's own calculation
Energy Consumption per capita	EC	Energy Consumption per capita (kWh)	Our World in Data [5]
Non-Green Openness Index	NGOP	The sum of a country's non-green exports and imports as a share of that country's GDP (%)	BETA Akademi [66]

environmental degradation. A country's ecological footprint is defined as the area of land and water ecosystems that the population needs to generate resources that satisfy consumption levels and assimilate waste [67]. Using this as a proxy for environmental degradation gives a more complete estimation of environmental deterioration than, for example, CO_2 emissions [22, 56, 68, 69]. Table 1 outlines the dependent and independent variables and their respective data sources. These variables were chosen based on the model from [22]. This study also aims to validate the EKC hypothesis in the panel. The EKC is a hypothesized relationship between income per capita and environmental degradation, where environmental degradation first rises with income but decreases after a certain point in time [70, 71]. This implies an inverted U-shaped relationship between economic growth and environmental degradation. The logarithm of environmental degradation is typically computed as a quadratic function of the income indicator. Therefore, to test for the EKC hypothesis, the empirical Equations 1 and 2 are extended with GDP^2.

$$EF = f(GDP, GDP^2, EC, NGOP) \tag{1}$$

$$EF_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 GDP^2{}_{it} + \beta_3 EC_{it} + \beta_4 NGOP_{it} + \varepsilon_{it} \tag{2}$$

In Equation 2, EF represents the Ecological Footprint of Consumption (per capita) of a nation, measured by Global Hectares (gha) per capita. This represents the dependent variable. GDP denotes the Gross Domestic Product, which measures real income per capita. For the EKC hypothesis, GDP squared is added to the empirical model to capture its inverted U-shape [19, 31]. EC represents Energy Consumption per capita in kilowatt per hour. NGOP represents the Non-green Trade Openness Index as presented by Can et al. [22]. This index is calculated by excluding green products (based on OECD's Combined List of Environmental Goods (CLEG) list)) from the total trade basket of a country, which consists of 255 products. It is calculated annually from 2003 to 2016 for all nations [66].

β_0 is the constant term, and β_1 to β_4 presents the long-run coefficients of the independent variables. Furthermore, i and t represent the country and the year, respectively. Finally, ε represents the stochastic error term of the empirical model. Descriptive statistics of the variables will be provided before starting data analysis with the empirical model. Based on the EKC hypothesis and the findings presented in the previous section, it is expected that $\beta_1 > 0$ (GDP) and $\beta_2 < 0$ (GDP^2). For the EKC hypothesis to be confirmed, it is required that the coefficients for GDP and GDP^2 are statistically significant. Furthermore, it is expected that energy consumption increases the ecological footprint, in other words, $\beta_3 > 0$. Finally, for the NICs, it is expected that NGOP increases the ecological footprint, or $\beta_4 > 0$.

3.2. Econometric Methodology

Panel data estimation techniques will be used for the empirical analysis. This method was chosen mainly because data for non-green trade openness was only available between 2003 and 2016. This time limitation makes panel data estimation more suitable for this model than time series analysis [64, 72]. The empirical analysis will be conducted according to a predefined number of steps. The order of these steps is crucial since the choice of several tests depends on the result of the preceding test. Data analysis will be performed using a combination of STATA and R. Prior to conducting the data analysis, all variables will undergo logarithmic transformation to account for the different units of measurement (refer to Table 1).

3.2.1. Cross-sectional Dependence (CD) Test

First, three cross-sectional dependence tests will be conducted to assess robustness. These are the LM test (CDLM1) of Breusch & Pagan [73], as well as the CD tests (CDLM2, CDLM3) developed by Pesaran [74]. These tests aim to assess the presence of cross-sectional dependence in the dataset. In the NICs, cross-sectional dependence is expected since the countries trade, and events in one country can impact another. Moreover, the selection of the unit root test will be decided by the outcomes of the cross-sectional dependence tests. The null hypothesis is 'there is no cross-sectional dependence in the data,' and the alternative hypothesis is 'there is cross-sectional dependence in the data.'

3.2.2. Slope Homogeneity Test

Before conducting the empirical analysis, testing for homogeneity of slope coefficients (β_i) is relevant. When slope coefficients are heterogeneous, the impact of an explanatory variable on the dependent variable varies based on the values of another variable. Not all empirical methods are suitable for panel data with heterogeneous slopes. The homogeneity test developed by Pesaran & Yamagata [75] assesses whether the panel data shows homogeneity or heterogeneity. The null hypothesis is 'the slope coefficients are homogeneous,' and the alternative hypothesis is 'the slope coefficients are heterogeneous.'

3.2.3. Unit Root Test

Panel data unit root analysis examines the stationarity of the panel by assessing the presence of a unit root, which would indicate non-stationarity. In a stationary panel, the mean and variance remain constant over time. Two types of unit root tests are usually employed for panel data: first-generation and second-generation tests. Whereas the first generation unit root test assumes independence of cross-sectional units, the second generation unit root test allows for cross-sectional dependence. Given the results from the CD test and the expectation of interrelatedness and shared economic events among the NICs, the second-generation unit root test is more appropriate. Therefore, the cross-sectionally augmented Im, Pesaran, and Shin (CIPS) unit root test from Pesaran [76] will be used to test the stationarity of the variables. It also allows for cross-sectional dependence and heterogeneity. For this test, the null hypothesis is 'the variable presents a unit root,' and the alternative hypothesis is 'the variable does not present a unit root.'

3.2.4. Cointegration Test

Following the unit root analysis, cointegration analysis will be employed to investigate the presence of a long-run correlation between the independent and dependent variables. The presence of cointegration shows that these variables share a common trend. Cointegration analysis involves running a regression model that includes the panel data variables and their first differences to account for non-stationarity. The Durbin-H approach by Westerlund [77] will be primarily used for this analysis. This approach accommodates heterogeneity and cross-sectional dependence within the panel data. For robustness, an additional Pedroni cointegration test is employed [78]. For both these tests, the null hypothesis is 'there is no cointegration between the variables', and the alternative hypothesis is 'there is cointegration between the variables.'

3.2.5. Long-run Estimation Techniques

After the cointegration analysis, the long-run coefficients of the independent variables will be estimated. This analysis shows whether the independent variables have a negative or positive effect on the dependent variable. First, the Fully Modified Ordinary Least Squares (FMOLS) method by Pedroni [79] will be used. This method is an extension of Ordinary Least Squares (OLS) and is considered most suitable when the panel data shows non-stationarity and cointegration [80]. The FMOLS method is also employed to solve endogeneity and serial correlation issues.

For robustness, the Pooled Mean Group Estimation (PMG) by Pesaran et al. [81] will be conducted. This method is suitable for dynamic and heterogeneous panels. It allows for capturing heterogeneous short-run dynamics across individual entities while simultaneously assuming a common long-run equilibrium.

4. Results and Discussion

4.1. Descriptive Statistics

Table 2 presents each variable's relevant statistics in the previous Equation 1. These findings are computed using the logarithmic forms of the variables. First, EF has a mean of 0.830 and a standard deviation of 0.465. The distribution of this variable is slightly negatively skewed and is platykurtic. This means the distribution has a relatively short tail due to few outliers. Second, GDP has a mean of 8.471 and a standard deviation of 0.670. Its distribution is also slightly negatively skewed and platykurtic. Third, NGOP has a mean of 3.948 and a standard deviation of 0.566. This is the only distribution that is slightly positively skewed, and it is also platykurtic. Finally, EC has a mean of 9.503 and a standard deviation of 0.705. This distribution is slightly negatively skewed and platykurtic.

4.2. Cross-sectional Dependence (CD) Test

Cross-sectional dependence is a common feature of panel data. Therefore, it is important to first evaluate if the variables in the empirical model are cross-sectionally dependent. Three different CD tests with different approaches are employed to test the null hypothesis of 'no cross-sectional dependence' for robustness. Table 3 shows the results of this analysis. From these results for all three tests, we can reject the null hypothesis for GDP and NGOP at the 1% significance level. For EF and EC,

Table 2. Descriptive statistics.

Variable	Min.	Max.	Mean	Std. dev.	Skewness	Kurtosis	Obs.
EF	-0.174	1.513	0.830	0.465	-0.643	2.087	140
GDP	6.734	9.308	8.471	0.670	-0.858	2.672	140
EC	8.152	10.524	9.503	0.705	-0.630	2.125	140
NGOP	2.845	5.225	3.948	0.566	0.361	2.678	140

Table 3. The results of cross-sectional dependence test.

Variable	CDLM1	Prob.	CDLM2	Prob.	CDLM3	Prob.
EF	68.69	0.013**	2.49	0.006***	1.94	0.026**
GDP	186.92	0.000***	14.96	0.000***	11.32	0.000***
EC	59.92	0.067*	1.57	0.058*	2.38	0.008***
NGOP	139.78	0.000***	9.99	0.000***	10.09	0.000***

Note: ***, **, and * indicate the rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively; CDLM1 test is based on Breusch-Pagan [73], CDLM2 and CDLM3 tests are based on Pesaran [74].

Table 4. The results of the homogeneity test.

Name of the Test	t-stat.	Prob.
Delta	3.446	0.001***
Adjusted Delta	4.559	0.000***

Note: ***, **, and * indicate the rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively, based on the homogeneity test of slopes from Pesaran & Yamagata [75].

Table 5. The results of unit root test.

Variable	Level	1st Diff.	Critical Value	
			1%	5%
EF	-1.87	-2.66***	-2.66	-2.37
GDP	-0.70	-2.92***	-2.66	-2.37
EC	-1.34	-2.92***	-2.66	-2.37
NGOP	-0.77	-2.74***	-2.66	-2.37

Note: ***, **, and * indicate the rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively; the CIPS test is based on Pesaran [76].

Table 6. The results of Durbin-H panel cointegration test.

Variable	t-stat.	Prob.
Durbin-H Group stat	2.671	0.004***
Durbin-H Panel stat	3.228	0.001***

Note: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. H_0: No Cointegration. The cointegration test is based on Westerlund [77].

Table 7. The results of Pedroni panel cointegration test.

Variable	t-stat.	Prob.
Modified Philips-Perron t	3.094	0.001***
Phillips-Perron t	-2.691	0.004***
Augmented Dickey-Fuller t	-2.655	0.004***

Note: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. The cointegration test is based on Pedroni [78].

mixed results were found, with the rejection of the null hypothesis at the significance levels of 1%, 5%, and 10%. From these findings, it can be concluded that all variables are cross-section-dependent.

4.3. Slope Homogeneity Test

In the next step, the slope homogeneity test of Pesaran & Yamagata [75] will be applied to the panel. These tests assess the presence of cross-sectional dependence in the dataset. From the findings presented in Table 4, we can reject the null hypothesis of 'homogeneous slopes' at the 1% significance level. In other words, slope heterogeneity can be assumed in the panel.

4.4. Unit Root Test

The appropriate second-generation unit root test is chosen based on the findings from the cross-sectional dependence tests and the slope homogeneity test. The unit root analysis investigates the stationarity of the series, which is the case when the variables do not vary over time. Since the data presents cross-sectional dependence and heterogeneity, the Im, Pesaran, and Shin (CIPS) test by Pesaran [76] will be used. As illustrated in Table 5, EF, GDP, EC, and NGOP present a unit root at their level value. Furthermore, the variables become stationary at first difference a 1% significance level. These results show that cointegration analysis can be performed as the subsequent step.

4.5. Cointegration Test

The next step entails cointegration analysis to examine the existence of long-term relationships among the variables in the empirical model. Since the previous unit root analysis illustrated that all variables become stationary at I(1), the cointegration analysis can be performed. This means that the variables are correlated and share a long-run common trend. For this purpose, the Durbin-H panel cointegration analysis of Westerlund [77] is used. This analysis is based on two tests: the

Table 8. The results of FMOLS estimation.

Model: $EF = f(GDP, GDP^2, EC, NGOP)$			
Variable	**Coeff.**	**t-stat.**	**Prob.**
GDP	0.130	12.14	0.000***
GDP^2	-0.064	-2.26	0.0252**
EC	0.569	25.60	0.000***
NGOP	0.142	9.91	0.000***

Note: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. Panel cointegration coefficients were estimated using FMOLS [79].

Durbin-H Group stat (assuming panel heterogeneity) and the Durbin-H Panel stat (assuming panel homogeneity). Based on the findings in Table 6, we reject the null hypothesis of 'there is no cointegration' at a 1% significance level for both test statistics. For robustness, the panel cointegration test from Pedroni [78] was performed to confirm the previous results. This analysis is based on three different tests: the Modified Phillips-Perron t, the Phillips-Perron t, and the Augmented Dickey-Fuller t. The findings in Table 7 indicate that we can reject the null hypothesis at a 1% significance level for all three test statistics. This means that variables are cointegrated. In other words, the difference between their means remains constant in the long run. Based on the findings from both cointegration results, it can be confirmed that the variables in the panel have a long-run common trend.

4.6. Long-run Estimation

4.6.1. Fully Modified Ordinary Least Squares (FMOLS)

After finding evidence of long-run cointegration between the variables in the model, the next step is to compute the long-run coefficients of GDP, GDP^2, EC, and NGOP. For the main analysis, the FMOLS method is utilized [79]. Table 8 presents the results of the FMOLS regression. These results demonstrate that the long-run coefficients of GDP, EC, and NGOP are statistically significant at a 1% level. Similarly, the long-run coefficient of GDP^2 is statistically significant at a 5% level.

The coefficient for GDP is positive, which indicates that a 1% increase in real GDP per capita leads to a 0.130% increase in the ecological footprint. The coefficient for GDP^2 is negative (-0.064) and statistically significant, so the EKC hypothesis can be confirmed in the panel. These findings align with the research conducted by Zhang et al. [14] in relation to NICs and Zafar et al. [12] in the context of a broader sample of emerging economies. In other words, during the initial stages of economic development, environmental degradation tends to rise in NICs. Once a certain threshold of economic development is surpassed, this trend is reversed, and environmental degradation declines.

Next, the coefficient for EC is positively significant at a 1% level of significance. A 1% increase in energy consumption corresponds to a 0.569% increase in the ecological footprint. These results corroborate the findings of studies conducted by Destek & Okumus [82] and Kongbuamai et al. [83], which also highlight a positive association between energy consumption and ecological footprint within the NICs and BRICS country groups, respectively.

Finally, the focal variable of this model is NGOP. The coefficient of NGOP is positive and statistically significant at a 1% significance level. This implies that a 1% increase in non-green trade openness leads to a 0.142% increase in the ecological footprint. Thus, more trade of non-green products contributes to a higher ecological footprint per capita in NICs. Since non-green products are those subject to carbon taxes and cause relatively high pollution, it aligns with the initial expectations that an increased trade in non-green products increases ecological footprint. This result complements the findings of Can et al. [22], where the researchers found a negative relationship between NGOP and EF in 25 EU countries. In this context, this result is the first in the literature. The empirical findings show that non-green trade increases environmental degradation in the NICs country group.

4.6.2. Pooled Mean Group (PMG)

To ensure the robustness of the findings, the model is also estimated using the Pooled Mean Group/Autoregressive Distributed Lag (PMG/ARDL) method. This approach enables the estimation of both the long-run and short-run coefficients. The PMG/ARDL method is chosen because it suits panel data with heterogeneity and cross-sectional dependence. It first estimates a separate model for each unit (country) and then pools the individual estimates to estimate the short-run coefficients. The ARDL method is used for the long-run coefficients. Figure 4 visualizes the long-run results of the estimations. Based on the results in Table 9, the long-run coefficient of GDP is positive (8.714), and the long-run coefficient of GDP^2 is negative (-1.114). Both coefficients for GDP and GDP^2 are statistically significant at a 1% significance level, confirming the panel's EKC hypothesis.

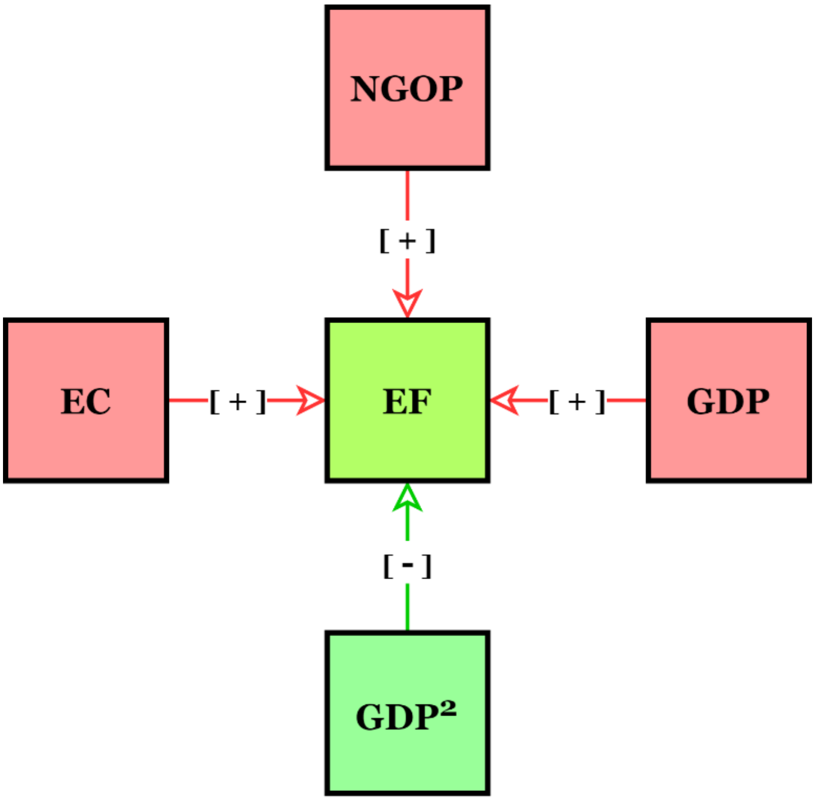

Figure 4. Overview of Long-run estimation results.

Table 9. The results of PMG/ARDL (1,1,1,1,1) estimation.

Model: $EF = f(GDP, GDP^2, EC, NGOP)$			
Variable	**Coeff.**	**t-stat.**	**Prob.**
Long-run estimation			
GDP	8.714	11.589	0.000***
GDP^2	-1.114	-11.835	0.000***
EC	0.898	47.810	0.000***
NGOP	0.239	20.425	0.000***
Short-run estimation			
ECT	-0.819	-2.858	0.006***
D(GDP)	43.757	0.648	0.519
D(GDP^2)	-5.469	-0.627	0.533
D(EC)	-0.249	-0.843	0.402
D(NGOP)	0.015	0.337	0.737

Note: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. Panel short-run and long-run coefficients were estimated using the PMG [81].

This is consistent with the results from the FMOLS model. The long-run coefficient EC (0.898) is positive and statistically significant at a 1% significance level, which also fits with our results from the FMOLS estimation. Furthermore, the coefficient of NGOP (0.239) is positive and statistically significant at a 1% significance level. Consequently, an increase of 1% in NGOP is associated with a long-run increase of 0.239% of the ecological footprint.

Looking at the results from the short-run estimation in Table 9, a negative error correction term (-0.819) is found, which is also statistically significant at a 1% level. This indicates that following shocks, the series reverts back to its original long-run equilibrium within approximately 1.3 years (calculated as 1/0.819), which indicates that the panel is stable in the long run.

5. Discussion and Policy Implications

5.1 Discussion

Trade plays a significant role in potentially influencing the environmental conditions of a nation. In this research, the goal was to analyze the influence of non-green trade openness on the ecological footprint of ten NICs between the years 2003 and 2016. The findings add to a small literature base on green and non-green trade openness.

For developing nations, the group in which the NICs fall, the results suggest that economic development and participation in global non-green trade are paired with a problematic deteriorating effect on the environment. First, the main finding of this research is that non-green trade openness has a deteriorating effect on the environment in the ten NICs measured by ecological footprint. This result is in line with other articles that found a positive relationship between trade openness and environmental degradation in samples of developing nations [55, 57, 59]. The article by Can et al. [22] was the first to study non-green trade openness and found that non-green trade openness decreases the ecological footprint of 25 EU members. Comparing the results reveals opposite environmental effects between high and middle-income countries. Can et al. [22] suggest that the decrease in environmental degradation due to non-green trade can be attributed to the Pollution Haven Hypothesis (PHH). This indicates that pollution is pushed to countries outside the EU with weaker environmental regulations, which mainly includes the trade of non-green products. Combining these findings suggests that the transfer of industrial activity for non-green trade from higher-income countries to middle-income countries increased the ecological footprint of the NICs.

Furthermore, the relationship between economic development and ecological footprint in the NICs shows a non-linear pattern, providing empirical support for the EKC hypothesis. Zhang et al. [14] found similar results for CO_2 emissions. This provides strong evidence for the EKC hypothesis in the NICs based on different proxies for environmental degradation. It suggests that the increased industrialization as a form of economic growth in the NICs increased environmental degradation. This finding also links to the growth in output, exports, imports, and value-added that the NICs experienced due to high economic development [15]. The resulting economic prosperity increases the biologically productive area required to provide the population with the resources it needs, thus increasing the ecological footprint. The confirmed EKC hypothesis also suggests that further economic growth in the NICs could potentially decrease environmental degradation in the future.

Third, the empirical analysis reveals a positive relationship between energy consumption and environmental degradation in the NICs. This finding builds on previous literature that discovered a positive relationship between energy consumption and environmental deterioration in high- and middle-income countries [14, 47, 53, 56]. The dominant share of energy consumption in the NICs stems from non-renewable sources [84]. Since non-renewable energy relies on fossil fuels, this increases the demand for natural resources and negatively impacts the environment. Furthermore, increased energy consumption leads to more GHG emissions, both in industry and household consumption.

5.2. Policy Implications

From the empirical findings of this research, it is possible to suggest a few relevant policy implications. These implications pertain to both governments and companies in and outside the NICs. The nations in this sample have experienced increased participation in global trade and economic growth, increasing their energy consumption and environmental degradation. All NICs, except Brazil, are currently in a biological deficit, suggesting that their natural resource reserves are decreasing. This indicates that their trade and growth strategy is not sustainable in the long run. Research showed that while non-renewable energy use enhances the ecological footprint of emerging economies, green energy has the opposite effect [34]. Therefore, the first policy recommendation for policymakers and companies in the NICs is to invest in green energy and an energy-efficient economy. By reducing the use of fossil fuels, the countries can also reduce their demand for natural resources, thus limiting the biological deficit. Policymakers can discourage the consumption of fossil fuels by subsidizing energy from renewable sources. Renewable energy can even increase economic growth in the short term [12]. Furthermore, the verification of the EKC hypothesis suggests that the ten NIC governments should still stimulate economic growth to eventually decrease environmental degradation. This also increases the available financial resources that can be put into environmental protection. The empirical findings of this research show that non-green trade has a detrimental impact on the environment in the NICs, while Ahmad et al. [62] found a positive impact on the environment of green trade in Brazil, India, China, and South Africa.

Furthermore, importing environmental goods tends to lower carbon emissions in developing nations [85]. Thus, NIC governments should focus on stimulating green trade as a catalyst for sustainable economic development in order to improve the quality of their environment. This can be done by introducing higher tariffs on non-green products and investing in technological innovations for green production methods and renewable energy.

Second, the empirical results suggest policy recommendations for the NICs and higher-income nations and regions such as the EU. The decrease in ecological footprint for EU countries due to non-green trade contrasts sharply with the increase in ecological footprint in the NICs [22]. Although local environmental pollution in the EU decreases, an increase in pollution in the NICs threatens the global state of the environment. Therefore, non-green trade should be approached as an international problem that has detrimental effects on all countries in different phases of economic development. Higher-income regions can implement restrictions on the import of non-green goods to stimulate the growth of green production technologies in highly industrialized regions.

Finally, it must be considered that the nations in the panel are heterogeneous in terms of the structure of their economy and their comparative advantages. This also demands tailored policies. For example, while 50% of India's exports stem from the service sector, China's focus lies on manufacturing products [15]. The NICs have very different positions in the global value chain, ranging from raw material and primary product exporter, producer of intermediates, or final assembly location. Therefore, the trade basket of these nations consists of different products and services, which requires different kinds of policies for sustainable growth. For example, primary product exporters such as Indonesia and Brazil can focus on limiting their exports of biological resources and finding sustainable alternatives. As a global producer of intermediates and final products, China can, for example, focus on implementing technological innovations for greener production and energy efficiency.

6. Conclusions

The degradation of the environment due to human actions poses a global hazard to the ecosystems required to sustain life on this planet. Economic growth, increased energy consumption, and trade liberalization have caused many large environmental issues, such as climate change and decreased biological diversity. All NICs are currently experiencing a biological deficit, except for Brazil, due to their recent economic development. An important reason for this is their increased participation in world trade. To analyze the net impact of trade on the environment, it is important to differentiate between green and non-green trade. Whereas green trade tends to promote energy efficiency and sustainable production methods, non-green trade is mainly fossil fuel-based and causes a relatively high share of GHG emissions.

This study aimed to validate the EKC hypothesis and analyze the influence of non-green trade on the environment in the NICs between 2003 and 2016, using various panel estimation techniques such as the Durbin-H and Pedroni cointegration analysis, FMOLS, and PMG methods. Income, energy consumption, and non-green trade openness were chosen as the independent variables, with ecological footprint as the dependent variable. Before estimating the long-run coefficients, the relevant cross-sectional dependence tests, slope homogeneity tests, and unit root analysis were completed. The coefficients of the empirical model present a long-run relationship between the variables in the model. The significant income and square of income results confirm the EKC hypothesis in the panel.

Furthermore, a positive relationship between energy consumption and ecological footprint was found. The main finding of this study is the positive relationship between non-green trade and ecological footprint. Non-green products are generally fossil fuel based and are therefore GHG intensive. The NICs experienced increased participation in non-green trade due to the shift of industrial production from developed to developing countries, presenting a strain on their environment. To mitigate the negative environmental influence of non-green trade, the NICs need to focus on shifting to green trade, investing in renewable energy, and conserving their natural resources.

There are a few limitations to this research that are important to mention. First, the data for calculating non-green trade openness was only available between 2003 and 2016. This limited the empirical section to panel data estimation instead of time series analysis. Second, other variables might influence the relationship between non-environmental trade and the environment, which were not fully considered in this study. For example, the strength of environmental regulations, or institutional quality, can affect the extent to which a country engages in non-green trade.

These limitations also present opportunities for future research. It would, for example, be relevant to check for the Pollution Haven Hypothesis (PHH) in the sample of NICs to complement the small literature base on non-green trade openness. This could reveal whether Foreign Direct Investment (FDI) plays a role in trade and environmental degradation in the NICs. Furthermore, research could continue to investigate the relationship between non-green trade openness and the environment for different country groups and other forms of pollution. For example, carbon emissions, local air pollution such as sulfur dioxide, the Air Quality Index (AQI), or a broader environmental quality index. Previous findings also suggest creating two separate empirical models, one of which is energy from fossil fuel sources and the other from green energy, to assess the different effects of environmental degradation. Investigating the impact of institutional strength on the relationship between non-green trade openness and ecological footprint could also be relevant. Finally, to complement this study and provide better policy recommendations, the influence of green trade imports and exports on the environment in the NICs specifically could be investigated.

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