UNIVERSIDADE DA BEIRA INTERIOR
Ciências Sociais e Humanas

Does the income inequality drive environmental degradation? Evidence from developed and developing countries

VERSÃO DEFINITIVA APÓS DEFESA PÚBLICA

Fábio Emanuel Valente de Almeida

Dissertação para obtenção do Grau de Mestre em
Economia
(2º ciclo de estudos)

Orientador: Prof. Doutor António Manuel Cardoso Marques

Covilhã, Julho de 2019

Resumo

Este estudo tem como objetivo analisar as consequências da desigualdade de rendimento na degradação ambiental em países desenvolvidos e países em desenvolvimento para o período de 1990-2014. As emissões de CO_2 é habitualmente o indicador utilizado para medir o impacto da humanidade no meio ambiente, no entanto, este não contabiliza os impactos totais da produção e consumo de bens e serviços. Recentemente, a pegada ecológica surge como um indicador alternativo. A pegada ecológica quantifica a procura da população, em termos de hectares per capita globais, de pecuária, peixe e laticínios, produtos alimentares e de fibra de base vegetal, madeira e outros produtos florestais, a área de terra usada para infraestruturas urbanas como prédios, estradas ou reservatórios criados por barragens, as emissões de CO_2 emitidas e a floresta necessária para absorver as emissões de dióxido de carbono das atividades humanas. Portanto, com a crescente degradação ambiental é importante entender se a desigualdade de renda tem desempenhado um papel neste caos. Então, o estimador Driscoll-Kraay com efeitos fixos foi escolhido para estimar a influência de curto e longo prazo de vários drivers na pegada ecológica. Os resultados sugerem que a desigualdade de renda não contribuiu para a pegada ecológica em curto prazo, mas, no longo prazo, a desigualdade diminui a pegada ecológica nos países em desenvolvimento enquanto que a amplia em países desenvolvidos.

Palavras-Chave

Desigualdade do rendimento, Degradação ambiental, Pegada Ecológica, ARDL

Resumo alargado

O atual estado do ambiente a nível global é alarmante. A temperatura global aumentou 1ºC desde a Revolução Industrial levando a sérias alterações no meio ambiente. As previsões existentes indicam que se, como previsto, atingirmos o aumento da temperatura global de 2ºC até 2050 um terço de planeta estará desertificado, resultará num degelo massivo de oceanos e numa drástica diminuição dos ecossistemas. Isto levará a que zonas costeiras se tornem praticamente inabitáveis e algumas irão mesmo desaparecer com o aumento do nível global do mar. Prevê-se que as temperaturas na zona central do globo estarão tão elevadas que será impossível o ser humano sobreviver com as mesmas sendo obrigado a abandonar o local em que sempre viveram e até mesmo os animais não terão tempo para se adaptar a estas alterações repentinas. Sem alterações drásticas e imediatas por parte de governos, empresas e comunidades não será possível garantir um futuro sustentável para as próximas gerações.

Nas últimas décadas, verificou-se que o rendimento tende a estar concentrado num número reduzido de pessoas levando a uma grande diferença entre os muitos ricos e os muitos pobres. Por essa razão, diversos estudos foram desenvolvidos com o objetivo de investigar a relação entre a desigualdade do rendimento e a degradação ambiental. Alguns estudos empíricos provam que um aumento da desigualdade do rendimento resulta num aumento das emissões poluentes enquanto que outros estudos encontram o efeito exatamente contrário. Geralmente, o efeito da desigualdade é positivo em economias desenvolvidas enquanto que em países com baixo rendimento per capita o efeito tende a ser negativo. Contudo, o efeito da desigualdade do rendimento na pegada ecológica não foi ainda empiricamente investigado. A pegada ecológica é caraterizada por contabilizar os efeitos do consumo e produção de bens e serviços necessários para satisfazer todas as necessidades da população.

Este estudo utiliza dados em painel para o horizonte temporal de 1990 a 2014. As variáveis utilizadas neste estudo são a pegada ecológica, a abertura do comércio, a desigualdade do rendimento, a energia utilizada e a biocapacidade. Com o objetivo de estudar se o efeito da desigualdade do rendimento na pegada ecológica varia consoante o nível do rendimento per capita, o painel foi dividido em países desenvolvidos e países em desenvolvimento. Para isso, a abordagem ARDL foi aplicada com o objetivo de analisar o efeito de curto e longo prazo de cada fator na pegada ecológica. Os resultados do teste de Wald modificado, do teste de Wooldridge e do teste de Pesaran indicam a presença de heterocedasticidade, autocorrelação temporânea e dependência entre países. Logo, o estimador Driscoll-Kraay com efeitos fixos foi usado nesta análise. Para corroborar os seus resultados, o estimador de efeitos fixos e o estimador robusto de efeitos fixos foram aplicados.

Os resultados demonstraram que o PIB per capita, a abertura do comércio, a desigualdade do rendimento e a energia utilizada são fatores que influenciam a pegada ecológica. O crescimento económico tem efeitos positivos na pegada ecológica tanto nos países desenvolvidos e em desenvolvimento. Mais ainda, este estudo mostra que a energia utilizada aumenta claramente a pegada ecológica para os dois conjuntos de países. A geração e produção de energia assente em combustíveis fósseis conduz a uma maior degradação ambiental como esperado. Relativamente a questão central do estudo, isto é, se a desigualdade do rendimento estará a conduzir a pegada ecológica, esta pode variar consoante a categoria dos países. Um aumento da desigualdade do rendimento provoca um aumento da pegada ecológica em países desenvolvidos, no entanto, para países em desenvolvimento um aumento resulta numa diminuição da pegada ecológica. Tendo em conta os resultados obtidos, países desenvolvidos e países em desenvolvimento devem se concentrar na diminuição da pegada ecológica ao reduzir a dependência de combustíveis fosseis no desenvolvimento das suas economias. Os países desenvolvidos devem apostar na redução da desigualdade de forma a reduzir a degradação ambiental enquanto que em os países em desenvolvimento, os governos devem aplicar medidas na redução da desigualdade e no mesmo sentido garantir que essa redução resulte num aumento da degradação ambiental. Concluindo, a redução da desigualdade do rendimento desempenha um papel crucial na preservação do meio ambiente.

Abstract

This study has the objective of examining the consequences of income inequality on environmental degradation for developed and developing countries for the period of 1990-2014. The CO_2 emissions are usually the indicator used to measure the impact of humanity on the environment, however, this does not account the total impacts of production and consumption of goods and services. Recently, Ecological Footprint emerges as an alternate indicator. Ecological Footprint quantify the population demand, in terms of global hectares per capita, of for livestock, fish and dairy products, plant-based food and fiber products, timber and other forest products, the land area used for urban infrastructure like buildings, roads or reservoirs created by dams, timber and other forest products, the CO_2 emissions emitted and the forest necessary to absorb carbon dioxide emissions from human activities. Moreover, as environmental degradation has increased worldwide, it is important to understand whether income inequality has played a role in this chaos. Therefore, the Driscoll-Kraay estimator with fixed effects was chosen to estimate the short and long-run effect of various drives in ecological footprint. The findings suggest that income inequality did not contributed to the ecological footprint in short-run but in long-run, inequality declines the ecological footprint in developing countries while expanding it in developed countries.

Keywords

Income Inequality, Environmental Degradation, Ecological Footprint, ARDL.

Contents

Figures list

Table List

Acronyms List

AMG	Augmented Mean Group
ARDL	Autoregressive Distributed Lag Model
BIO	Biocapacity per capita
CCEMG	Common Correlated Effect Mean Group
CO_2	Carbon Dioxide Emissions
CUP-BM	Continuously updated fully modified estimator
CUP-BC	Continuously updated bias corrected estimator
DCCE	Dynamic Common Correlated Effect Estimator
DIF-GMM	Difference Generalized Method of Moment
DK-FE	Driscoll-Kraay Fixed Effects
DOLS	Dynamic Ordinary Least Squares
ECT	Error Correction Term
EF	Ecological Footprint
ENER	Energy Use per capita
FE	Fixed Effects
FMOLS	Fully Modified Ordinary Least Squares
GDP	Gross Domestic Product
GINI	Gini Net Index
GHG	Greenhouse Gas emissions
GMM	Generalized Method of Moments
IPCC	Intergovernmental Panel on Climate Change
MG	Mean-Group
MG-DOLS	Group-mean Dynamic Ordinary Least Squares
MG-FMOLS	Group-mean Fully Modified Ordinary Least Squares
MPE	Marginal Propensity to Emit
OECD	Organisation for Economic Co-operation and Development
PMG	Pooled Mean-Group
RE	Random Effects
SYS-GMM	System Generalized Method of Moments
UBI	Universal Basic Income
UECM	Unrestricted Error Correction Model
TRADE	Trade Openness
VIF	Variance Inflation Factor
WMO	World Meteorological Organization

1.Introduction

According to the International Panel on Climate Change (IPCC) most recent report, humanity have approximately 11 years to stop an irreversible chain reaction on environment beyond human control (IPCC, 2018). Since the first industrial revolution in the 18^{th} century, enormous GHG emissions have been emitted into the atmosphere associated with the faster development of industries, the extensive use of fossil fuels, the population growth and economic growth. As a result, temperature have an increase already recorded at 1ºC above pre-industrial levels (IPCC, 2018; Steffen et al., 2018). In addition, Steffen et al. (2018) predicted that the temperature will expand 0,17ºC per decade with the current rate of emissions. Equally important, 2018 was the hottest year ever and along with 2015, 2016, 2017 were the warmest on record of history (WMO, 2019). As consequence, this increase has resulted in a higher ocean temperature and acidification, glaciers mass loss at global level and consequently, a global increase at mean sea level. Moreover, the strength and frequency of floods, droughts and storms are even greater than scientists expected (IPCC, 2018; Steffen et al., 2018; WMO, 2019).

Climate change is the present and future main problem of humanity. The creation of Kyoto Protocol in 1997 was born with the aim of combating climate change and limiting the global average temperature to less than 2ºC but it failed tremendously. When it was signed, only the emissions from the developed countries are covered, the emissions targets were not sufficient and only entering into force in 2005. In 2015, after the global emissions augmented by a one third since the Kyoto Protocol, 197 countries reached a consensus to create the Paris Agreement. Actions such as the decarbonization process through the development of forms of sequestration of GHG emissions such as carbon capture and storage, transformation of building and infrastructures with the objective of dealing with possible impacts of climate change and transparency and accountability of countries efforts to fight climate change are the foundation of Paris Agreement. However, the waiting time until these measures are effectively developed and implemented could result in possible environmental chaos. In fact, the latest GHG emissions are the highest registered in history and ocean heat content is also at a record level and obviously completely altering the surface of the Earth. Governments such as France, New Zealand and United Kingdom have already declared state of emergency due a climatic problem.

Moreover, the rise of temperature in historical numbers will entail greater pressure on ecosystems and human population. The world's richest 10% are responsible for half of carbon emissions, however, those who are more at risk from the effects of environmental degradation are the poor (Oxfam, 2015). Moreover, people living in tropical areas and islands will suffer most of the effects of climate change due the rising of ocean level and the species that are endangered or extinct are going to be a larger number (IPCC, 2014).

Furthermore, the rising of income and wealth inequality have attracted attention from leaders, governments and scholars. Greater income inequality could result in increased poverty and violence, reduced demand for goods and services and in a decrease in manufacturing production and consequently in productivity, which could affect the economic growth and employment levels (Fitoussi & Saraceno, 2014; Wolde-Rufael & Idowu, 2017). According to Oxfam, the gap between rich and poor is growing year after year and is stopping us from combating poverty. In 2019, 26 richest people on the planet possess the same as the poorest half of population and they are paying the lowest levels of tax in decades as the corporations they own. Despite the growing economic development of several countries over the past decades, governments have failed to assurance an equal distribution of income or to promote sustainability practices. In fact, Jorgenson et al. (2017) and Liu et al. (2019) arguments that the actual income distribution and the active and future effect of climate change must be two essential alarms by politics, leaders and scholars. Consequently, economists are studying the dynamic relationship between income inequality and environmental degradation (Hailemariam et al., 2019; Jorgenson et al., 2017) however, the lack of reliable data on the evolution of income inequality represent a major problem (Berthe & Elie, 2015). According to the existing literature, income inequality can influence environmental degradation in two ways: inequalities in contribution to pollution and inequalities in relation to the exposure to environmental degradation.

Therefore, is important explore the effect of income inequality on environmental degradation and identified if the result is altered by the level of income. The relationship between income inequality and environmental degradation is usually studied by mean of an indicator of emissions, such as GHG emissions or CO_2 emission, however, does not take into account the total effect of humanity on the atmosphere, land and water. In this way, the ecological footprint is used in this study as an indicator of environmental degradation. By using annual data for the time span from 1990 to 2014 employed through an Auto Regressive Distributed Lag (ARDL) approach, the empirical results have shown that an increase in income inequality will entail ecological footprint but, in contrast, will result in lower environmental degradation in developing countries.

The rest of this paper is organized as follow: Section 2.1 present the literature review of the relationship between income inequality and environmental degradation. Section 2.2 describes ecological footprint and respective literature review. Section 3 presents the data while Section 4 refers to the methodology used. The results and their discussion are presented in Section 4. Therefore, Section 5 provides the conclusions.

2. Literature Review

The present section is subdivided into: the literature review on the relationship between income inequality and environmental degradation and on the literature review on ecological footprint as an indicator of environmental degradation.

2.1 The Income Inequality and Environmental Degradation

The relationship between income inequality and environmental degradation is based on 3 theoretical perspectives. For more than three decades ago, Boyce (1994) proposed the firsts theoretical point of view about the effect of income inequality on environmental degradation. He advanced that with greater inequality of wealth and power the wealthy enforce their power to impose environmental costs on the poor. He proposed that there are winners and losers from degrading the environment. Winners are considered those who obtain liquid benefits with degradation and losers are those who feel the negative externalities of this action. Furthermore, Boyce (1994) questions why the losers don't imposed on the winners and explain three scenarios: 1) the losers doesn´t exist yet; 2) the losers exist but don't have enough information about the effects of environmental degradation; 3) the losers already exist but their power is useless. Therefore, purchasing power (differences in wealth) and / or political power (differences in influence) have a clear influence on the way we spoil the environment. Specifically, the influence of rich is reflected in avoiding the cost of environmental protection for after the poor suffer the cost of the environmental pollution. This effect was called as a "power-weighted social decision rule" by Boyce (1994). Moreover, Boyce (1994) formulates the "equality hypothesis" where greater inequalities of power and wealth will generate more environmental degradation. Equally important, Grossman & Krueger (1995) arguments that "vigilance and advocacy" are the two keys factors to control market failures. If greater inequality will generate more pollution due the wealth and power inequality as Boyce (1994) states, vigilance and advocacy are responsible for greater environmental control. Despite the arguments of Boyce (1994), Scruggs (1998) claims that income inequality has no influence on environmental degradation since, wealthy and powerful individuals do not necessarily choose to degrade more the environment than the poor. Whereas with the increase in income for the wealthy, the environment is seen as a "superior good", the rich tend to promote environmental regulation and consequently are willing to pay higher taxes because they prefer to live in a clean environment.

Nonetheless, Ravallion (2000) presents a difference approach, a marginal propensity to emit (MPE). The poor and rich have a marginal propensity to emit (MPE) since the consumption and production of goods results in CO_2 emissions directly or indirectly. If the poor have a low

MPE than the rich, reducing inequality will result in low emissions but if they have a higher MPE than the other superior classes, the emissions are going to be higher. Thus, Ravallion (2000) affirm that there is a trade-off between the reduction of inequality or the reduction the environmental degradation because the marginal propensity to emit and consume high-carbon goods and services may vary as the consumption patterns of individuals and households change. Furthermore, as appointed by Jorgenson et al. (2017), Veblen Effects (Veblen, 1899) is third and last point of view. According to Veblen (1899), the more equal the level of income distribution is, the greater the emissions from pollutants will be. In other words, when the poor move to the middle-class leads to an increase in energy consumed and consequently higher levels of emissions. The emulation theory, proposed by Veblen (1899) indicates that individuals who live in more unequal societies tend to imitate consumption patterns of their superior social class. This leads to increased demand for credit for higher consumption and consequently an increase of household debt and logically an increase in income inequality. The Veblen effects and politics who lead to more equal level of income distribution are the key factors responsible for more pollution according to Jorgenson et al. (2017).

From empirically perspective the effect of income inequality on environmental degradation could vary, considering whether it is a developed or developing country and whether we are analysing a panel of countries or only an individualized country. Firstly, while studying different panels Torras & Boyce (1998) produce the first results in relation to the impact of income inequality on environmental degradation. By using diverse types of pollution variables such as smoke, sulphur dioxide and heavy particles they do not found statistically signification connection with income inequality for high-income economies however they conclude that higher inequality in low income countries will lead higher pollution. Moreover, Ravallion (2000) while studying a panel data were the first to discover that higher inequality is correlated with lower CO_2 emissions for low-income economies. According to Magnani (2000), when a country growth in economic values, other social indicators such as income inequality must accompany its improvement to an effective reduction of pollution emissions. While examining the effect of income inequality on environmental protection for OECD countries, Magnani (2000) found out a negative correlation between both indicators. Similar to Magnani (2000), Heerink et al. (2001) found a significant negative effect of income inequality on CO_2 emissions. Additionally, discovered that higher inequality can lead in an increase in the population without access to safe water and sanitation. In the same way, Borghesi (2006) had found that higher inequality will decline CO_2 emissions for poor countries however it will increase emissions for rich countries.

Furthermore, using a quantile approach, Hübler (2017) concluded that income inequality has a negative influence on environmental degradation. In fact, Hübler arguments that characteristics present in developing countries such as foreign direct investment, weak trade techniques and the use of obsolete technologies can lead to a lower economic growth resulting in greater income inequality and the possibility of social tensions and poor-driven emigration. According to Grunewald et al. (2017), the relationship between income inequality and environmental degradation depends on the level of country income. In their study, income inequality has a negative effect on CO_2 emissions in low and middle-income countries, while for upper middle-income and high-income countries the impact is positive. Finally, Hailemariam et al. (2019) while analysing 17 OECD countries conclude that the Gini index is negatively correlated with carbon emissions, however, the richest 10% of population are the responsible for increasing CO_2 emissions.

Secondly, is crucial analyse the impact of income inequality on environmental degradation at national level. By studying the effect of Gini coefficient on CO_2 emissions through panel GMM for 23 Chinese provinces, Hao et al. (2016) proves that if income inequality expands, the carbon emissions will rise. Furthermore, Baek & Gweisah (2013) empirically find that higher equality in United States would reduce CO_2 emissions in short and long term. In addition, Jorgenson et al. (2017) analyse the effect of the income of the top 10% on CO_2 emissions in US state level data. They conclude that the top 10% of income share is responsible for the increase on emissions but the effect of Gini Coefficient was no statistically significant. Most recently, Liu et al. (2019) tested the effect of Gini coefficient and Global Moran's I against CO_2 emissions for 30 Chinese provinces and concluded that higher income inequality result in higher environmental degradation. In contrast, using an environmental pollution index for Chinese provinces, Q. Liu et al. (2018) determined that higher income inequality is associate with greater environmental quality. Moreover, Liu et al. (2019) uses an ARDL panel and a quantile regression to study the effect of income inequality on CO_2 emissions across United States of America. The conclusion is that higher income inequality reduces emissions in long-run, however, in short-term results show a rise in emissions. In addition, the result of quantile regression states that higher income inequality could reduce the CO_2 emissions in the most polluted states.

In conclusion, the impact of income inequality on environmental degradation is far from consensual. Nevertheless, note the dangerous impacts of income inequality on environment as the increase in the number of endangered species, as well as, has a negative effect on ecosystem maintenance and preservation (Holland et al., 2009; Mikkelson et al., 2007). According to Steffen et al. (2015), humans are the responsible for the actual global climate emergence since they destroy ecosystems, reduce biodiversity, pollute the air and the water and change landscapes for their infrastructures. In the next section, the ecological footprint and respective literature will be presented.

2.2 Ecological Footprint as an indicator of environmental degradation

The ecological footprint, originally created and explored by Wackernagel & Rees (1996) is calculated over six types of productive lands: Cropland Footprint, Grazing Land Footprint, Fishing Grounds Footprint, Forest Land, Built-Up Land Footprint and Carbon Footprint. Cropland refers to the area needed to produce livestock, dairy products, fiber, animal feed, soy and oil; Grazing land consists on the area required to raise livestock for dairy products, wool and meat: Fishing Grounds is measured through primary production needed to support all captured fish and seafood, Forest land estimates the amount of forest area used to supply timber, pulp and fuel wood, Built-Up Land quantifies the area of land for built infrastructure like buildings, industrial structures, roads and reservoirs created by dams and Carbon Footprint takes into account the area necessary for CO_2 absorption. The ecological footprint of consumption is calculated as the sum of ecological footprint of production and imports minus exports. Biocapacity refer to total productive land and sea area available to supply the resources a country uses considering their current technology and political policies. It measures as the sum of cropland, grazing, fishing grounds, forest and built-up land. When an area or a country has the ecological footprint greater than biocapacity, lives with an ecological deficit.

Figure 1 displays the number of Earth used to supply human demands since 1961. Humanity is running in ecological deficit for more than 50 years. Since 2010, humankind is using approximately 1.7 Earths to afford all resources needed and to absorb our waste.

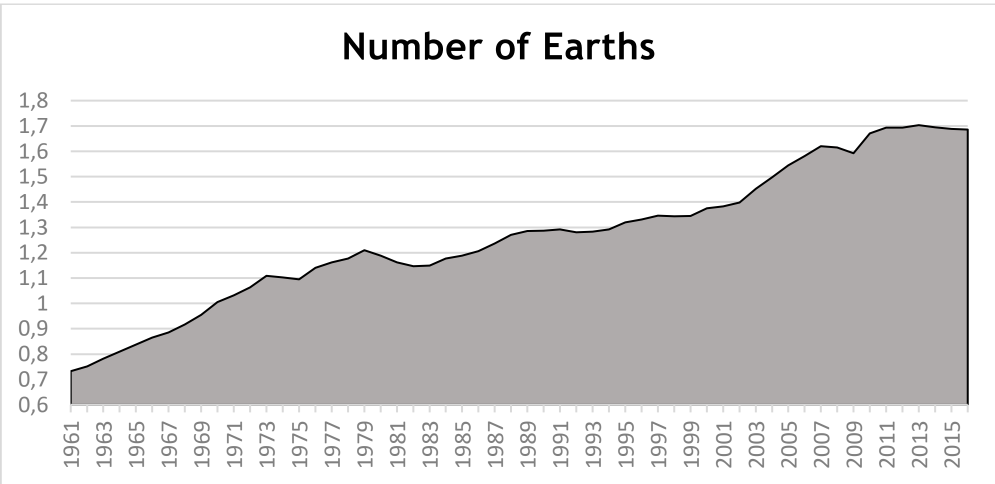

Figure 1. Number of Earth, Source: Global Footprint Network

Next, Figure 2 shows the evolution of the ecological footprint and biocapacity at the global level since 1961. Although the per capita ecological footprint keeps constant over the last decades, the big problem is that the biocapacity has declined dramatically. Clearly, we are destroying our biocapacity in order to sustain our consumption and life level.

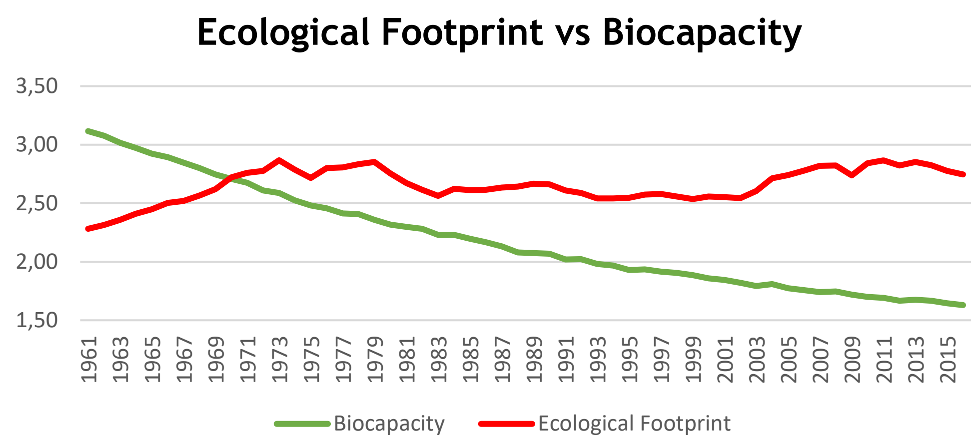

Figure 2. Ecological Footprint and Biocapacity by world (global hectares per capita), Source: Global Footprint Network

Furthermore, the evolution of the ecologic footprint and biocapacity of the countries under study are presented in Figures 3 and 4. It is highlighted that on developed countries, the ecological footprint has been higher than biocapacity since 1990 which confirms developed countries are the biggest culprits of environmental degradation. About the developing countries, the ecological footprint slowly increased over the years however the biocapacity decreased almost 1 global hectares per capita. It is predictable that for the next years, the ecological footprint will be higher than biocapacity on developing countries.

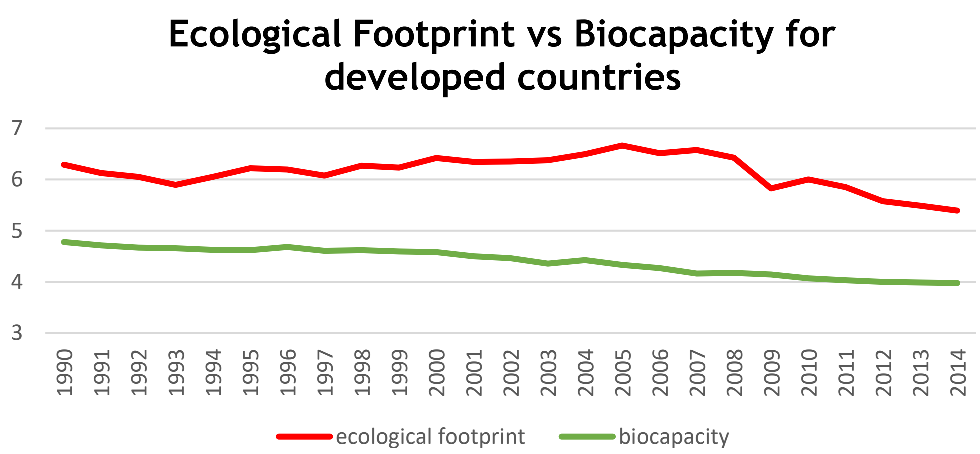

Figure 3. Mean per capita by year of ecological footprint and biocapacity for developed countries, Source: Global Footprint Network

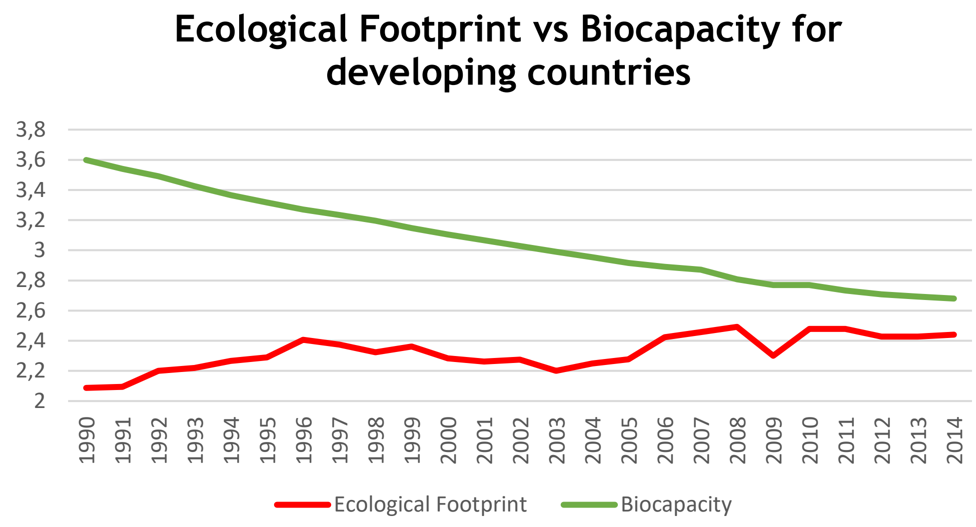

Figure 4. Mean per capita by year of ecological footprint and biocapacity for developing countries, Source: Global Footprint Network

In conclusion, is important analyse the relationship between income inequality and ecological footprint. Figure 5 show the ecological footprint and Gini index for the countries of the samples for the year 2014. Note that as the ecological footprint decreases, the income inequality increases.

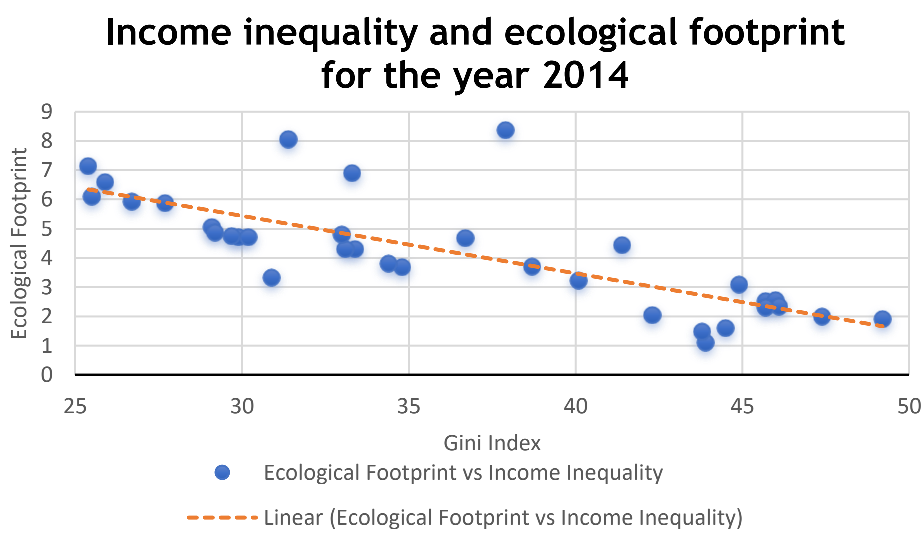

Figure 5. Ecological footprint per capita and Gini index, by country, in the year 2014, Source: Global Footprint Network and SWIID

The drivers of pollutants emissions depicted in the literature are the same as the ecological footprint such as economic growth, urbanization, trade openness and energy use. It is identified in the literature through Al-Mulali et al. (2015), Charfeddine & Mrabet (2017) and Ulucak & Bilgili (2018) that GDP per capita, Energy Consumption, Trade openness, domestic credit to private sector, urbanization and Industry value added increase ecological footprint while human capital and life expectancy at birth could reduce it. It is linked that, an increase in manufacturing and economic activity result in higher consumption of individuals and high energy demand generating higher CO_2 emissions (Pal & Mitra, 2017). Greater CO_2 emissions implies necessarily a higher ecological footprint since the carbon footprint represent 60% of total ecological footprint of the world (Global Footprint Network, 2018). Table 1 displays articles using the ecological footprint as an environmental indicator.

Table 1 - Literature on Ecological Footprint as an indicator of environmental degradation

Author	Period	Samples	Method	Variables	Main Findings
U. Al-Mulali et al. (2015)	1980-2008	93 countries divided by income	FE, GMM	EF, GDP, Energy Consumption, Trade, Urban Population, Domestic credit	GDP, Energy and Trade increase EF across all income groups
U. Al-Mulali et al. (2016)	1980-2009	58 developed and developing countries	FE, DIF-GMM, SYS-GMM	Water Footprint, Land Footprint, Renewable Energy, GDP, Urbanization, Trade, GDP2	GDP, Trade and Urbanization expand the land and water footprint
Charfeddine and Mrabet (2017)	1975-2007	15 MENA countries	FMOLS, DOLS, Granger causality	EF, GDP, Urban Pop., Political Index, Fertility Rate, Life expectancy at birth	Fertility Rate and Life Expectancy at birth diminish EF; Political Index increase EF
Masron and Subramaniam (2018)	2005-2013	64 Developing Countries	DIF-GMM, SYS-GMM	EF, CO_2, GDP, Renewable Energy Consumption, Control of Corruption, Trade, FDI, Manufacturing VA	Corrupt increase EF and CO_2; Renewable Energy hamper EF and CO_2
Ulucak and Bilgilli (2018)	1961-2013	45 countries divided by income	CUP-FM, CUP-BC	EF, GDP, GDP2, Trade, Human Capital, Biocapacity	GDP and Trade boost EF; Human Capital decrease EF
Solarin and U. Al-Mulali (2018)	1982-2013	20 Countries	CCEMG, AMG	EF, GDP, Urbanization, Energy Use, FDI	GDP, Urbanization and GDP increase EF
Destek et al. (2018)	1980-2013	15 EU countries	MG-FMOLS, MG-DOLS, DCCE-MG, DOLS, FMOLS	EF, GDP, GDP2, Renewable Energy, Non-Renewable Energy, Trade Openness	GDP and Non-Renewable Energy increment EF; Renewable Energy and Trade decline EF

Concluding, the ecological footprint by measuring the direct and indirect impacts of production and consumption of human activities on environment represents a better indicator of environmental degradation than CO_2 or GHG emissions.

3. Data

This study uses annual data from 1990 to 2014 for a panel of 34 countries. The dataset was divided into 20 developed and 14 developing countries in order to study the effect of income inequality on the ecological footprint by two distinct contexts. Following the World Development Indicators classification of the countries by income, it was considered as developed countries, countries that are High-Income Countries and as developing countries the set of groups of Upper Middle-Income and Lower Middle-Income countries. The countries were chosen considering the availability of data. The following countries were considered as developed countries: Australia, Austria, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Netherlands, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States of America. The developing countries are Argentina, Brazil, Colombia, Costa Rica, Dominican Republic, Ecuador, Egypt, Malaysia, Mexico, Panama, Peru, Philippines, Tanzania and Turkey. The variables used are ecological footprint, real gross domestic product per capita, trade openness, energy use, Gini index and biocapacity. These were chosen based on the existing literature however variables such as urbanization or foreign direct investment were not used due to a lack of data and stationarity problems. The econometric software used in this analysis was *Stata* 15. Therefore, Table 2 contains the variables, their definition and source.

Table 2 - Variable definition

Variable	Definition	Source
LNEF	Ecological footprint (global hectares per capita)	Global Footprint Network
LNGDP	Gross Domestic Product (per capita, constant LCU)	The World Bank, World Development Indicators (WDI)
LNGINI	Gini net index	Standardized World Income Inequality Database (SWIID)
LNTRADE	Trade Openness – Sum of export and imports (per capita, constant LCU)	The World Bank, World Development Indicators (WDI)
LNENER	Energy use (kg of oil consumption per capita)	Idem
LNBIO	Biocapacity (global hectares per capita)	Global Footprint Network

4. Methodology

To investigate the relationship between environmental degradation and income inequality in different frameworks it is fundamental to explore the dynamic effects of the short and long-run. Allowing different integration order of variables, I (0) and I (1), and dealing with cointegration and long memory behaviours the Unrestricted Error Correction Model (UECM) form of autoregressive distributed lag (ARDL) model was chosen for this analysis. The variables are both transformed in natural logarithms and in first differences. Moreover, natural logarithms are denoted by “L” and first differences by “D”.

The ARDL model specification is the following:

$$\begin{aligned} LEF_{it} = \alpha_i + b_{i1} LEF_{it-1} + b_{i2} LGDP_{it} + b_{i3} LGDP_{it-1} + b_{i4} LTRADE_{it} \\ + b_{i5} LTRADE_{it-1} + b_{i6} LGINI_{it} + b_{i7} LGINI_{it-1} + b_{i8} LENER_{it} \\ + b_{i9} LENER_{it-1} + b_{i9} LBIO_{it} + b_{i10} LBIO_{it-1} \end{aligned} \tag{1}$$

Furthermore, the ARDL can be transformed into to the general UECM:

$$\begin{aligned} DLEF_{it} = \alpha_i + \sum_{j=1}^{k} \beta_{1ij}\, DLGDP_{it-j} + \sum_{j=0}^{k} \beta_{2ij}\, DLTRADE_{it-j} + \sum_{j=0}^{k} \beta_{3ij}\, DLGINI_{it-j} \\ + \sum_{j=0}^{k} \beta_{4ij}\, DLNER_{it-j} + \sum_{j=0}^{k} \beta_{5ij}\, DLBIO_{it-j} + \lambda_{1j} LEF_{it-1} \\ + \lambda_{2j} LTRADE_{it-1} + \lambda_{3j} LGINI_{it-1} + \lambda_{4j} LENER_{it-1} + \lambda_{5j} LBIO_{it-1} \\ + \varepsilon_{it}. \end{aligned} \tag{2}$$

where α_i denotes the intercept, β_{ij} and λ_j the estimates parameters, ε_{it} the error term while the subscripts i, t and j express the country, time period and lag length.

When working upon macro panel data, it is imperative to observe the stationary properties of the variables, deal with slope heterogeneity of parameters in the short and long-run and with cross-section dependence on panel and in variables in order to choose the correct estimator to be used. Therefore, a preliminary data analysis of characteristics of series and crosses is applied. Firstly, the descriptive statistics of variables for developed and developing countries were presented in Table 3.

Table 3 – Descriptive Statistics

	Developed Countries					Developing countries				
Variable	Obs	Mean	S.D.	Min	Max	Obs	Mean	S.D.	Min	Max
LNEF	500	1.7918	0.2168	1.1995	2.3421	350	0,7849	0.3488	0.0823	1.5284
LNGDP	500	10.8384	1.2887	9.4414	15.2217	350	8.3980	0.7881	6.1242	9.4964
LNGINI	500	3.3972	0.1324	3.0445	3.6350	350	3.8419	0.0729	3.6558	3.9853
LNTRADE	500	26.6807	1.2125	23.3761	29.2208	350	24.8638	1.2488	21.6770	27.4058
LNENER	500	8.2457	0.3840	7.4271	9.0409	350	6.7526	0.5014	5.8753	7.9952
LNBIO	500	0.8343	1.1412	-1.4110	2.9468	350	0.7512	0.9015	-0.8041	2.4913
DLNEF	480	-0.0065	0.0629	-0.4221	0.2948	336	0.0058	0.0700	-0.3053	0.2808
DLNGDP	480	0.1311	0.0247	-0.0943	0.0896	336	0.0248	0.0331	-0.1264	0.1052
DLNGININ	480	0.0025	0.0096	-0.0305	0.0399	336	-0.0022	0.0080	-0.0297	0.0247
DLNTRADE	480	0.0451	0.0592	-0.2194	0.2241	336	0.0639	0.0830	-0.2134	0.3589
DLNENER	480	-0.0010	0.0380	-0.1504	0.1179	336	0.01567	0.4744	-0.1265	0.2301
DLNBIO	480	-0.0082	0.0644	-0.4162	0.3938	336	-0.0120	0.0263	-0.1452	0.1118

Notes: The prefix “L” denote natural logarithm and “D” denote first difference of the variable.

Moreover, the presence of cross-section dependence in variables is examined by the option of Pesaran CD-Test (Pesaran, 2004). Following the fact of the countries shares the same income, that is, common characteristics, is expected the presence of cross-sectional dependence in both samples. According to the literature two types of cross-section dependence can be present on panels (Menegaki et al., 2017). Geographical proximity between countries is considered as spatial dependence and long-range or global interdependence occurs when a country suffers an external shock on economy, and it is reflected to all countries regardless of the distance between them. Table 4 displays the Pesaran test for the presence of cross-section dependence.

Table 4 – Cross-section dependence test

	Developed Countries			Developing Countries		
Variables	CD-test	Corr	Abs (corr)	CD-test	Corr	Abs (corr)
LNEF	24.75***	0.359	0.433	6.70***	0.141	0.308
LNGDP	63.68***	0.924	0.924	44.80***	0.939	0.939
LNTRADE	67.32***	0.977	0.977	45.39***	0.952	0.952
LNGINI	10.49***	0.152	0.523	19.71***	0.413	0.710
LNENER	31.79***	0.461	0.529	21.45***	0.465	0.654
LNBIO	43.83***	0.636	0.709	29.55***	0.620	0.708
DLNEF	15.75***	0.233	0.263	6.26***	0.134	0.214
DLNGDP	39.29***	0.582	0.582	12.35***	0.264	0.292
DLNTRADE	45.49***	0.674	0.674	16.76***	0.359	0.374
DLNGINI	-1.35	-0.020	0.272	19.27***	0.412	0.427
DLNENER	19.01***	0.282	0.308	0.32	0.007	0.182
DLNBIO	4.07***	0.060	0.210	3.17***	0.079	0.198

Notes: ***, ** and * denote significance levels at 1%, 5% and 10% respectively; CD-test has N (0,1) distribution under the H0: cross-section dependence; The stata command xtcd was used.

The results from Table 4 proved the presence of cross-section dependence for almost all variables. Cross-section dependence was not verified for the variable Gini in their first difference in developed countries and for the variable energy use in its first difference in developing countries. Overall, as expected, the countries chosen for the two different analysis shares the common characteristics. Considering the presence of cross section dependence, the traditional first-generation panel unit roots test such as ADF-Fisher (Maddala & Wu, 2003), Im Pesaran Shin (So, Pesaran, & Shin, 2003) and Levin Lin Chu (Levin, Lin, & Chu, 2002) were not applied to verify the order of integration of variables because it could generate erroneous outcomes due to not dealing with the presence of cross section dependence. Thus, second generation unit root CIPS tests (Pesaran, 2007) which controls cross-section dependence in variables, and it is robust to heterogeneity was applied. The null hypothesis of CIPS test is the non-stationary. Table 5 present 2nd generation unit root CIPS test for developed and developing countries.

Table 5 – 2nd Generation panel unit root test CIPS

	Developed Countries		**Developing Countries**	
Variables	No trend	Trend	No trend	Trend
LNEF	-1.773**	-1.869**	1.438	1.519
LNGDP	-0.300	-2.270**	-1.985**	-2.215**
LNTRADE	-0.953	-1.953**	-3.010***	-0.910
LNGINI	-1.390*	2.288	1.339	-0.674
LNENER	-3.685***	-2.974***	-0.151	0.651
LNBIO	-4.908***	-5.533***	0.456	0.962
DLNEF	-7.927***	-5.722***	-6.875***	-5.301***
DLNGDP	-5.526***	-3.151***	-5.708***	-4.390***
DLNTRADE	-8.316***	-6.709***	-5.997***	-4.526***
DLNGINI	-1.628*	-2.320**	-2.813***	-1.460*
DLNENER	-10.487***	-8.911***	-6.017***	-4.535***
DLNBIO	-14.666***	-12.919***	-7.669***	-7.297***

Notes: ***, ** and * denote significance levels at 1%, 5% and 10% respectively; The CIPS test has the null hypothesis of non-stationarity under non-standard distribution; The presented results include 1 lag; The stata command multipurt was used.

The results of CIPS test proved that all variables are I (0) and I(1) validating the use of an ARDL approach. Furthermore, VIF (Variance Inflation Factor) and correlation matrix were computed in order to test the presence of multicollinearity and collinearity among variables. Table 6 presents the correlation matrix and VIF of variables in their levels for developed and developing countries (see Appendix for the correlation matrix and VIF for the first difference variables).

Table 6 – Matrices of correlation and VIF statistics

Developed Countries	*LEF*	*LGDP*	*LTRADE*	*LGINI*	*LENE*	*LBIO*
LEF	1.0000					
LGDP	0.4888	1.0000				
LTRADE	0.2727	0.5120	1.0000			
LGINI	-0.1287	-0.4099	0.1166	1.0000		
LENE	0.7837	0.5795	0.5048	-0.2789	1.0000	
LBIO	0.6158	0.3536	0.1045	-0.3462	0.7046	1.0000
VIF		2.11	2.10	1.53	3.44	2.41
Mean VIF			2.32			
Developing Countries	*LEF*	*LGDP*	*LTRADE*	*LGINI*	*LENE*	*LBIO*
LEF	1.0000					
LGDP	0.8339	1.0000				
LTRADE	0.6015	0.6484	1.0000			
LGINI	-0.1505	0.0612	-0.0235	1.0000		
LENE	0.8847	0.7855	0.7102	-0.2661	1.0000	
LBIO	0.6058	0.5171	0.2057	0.2269	0.3406	1.0000
VIF		3.78	2.27	1.47	4.44	1.50
Mean VIF			2.69			

The low statistical values of correlation matrix and VIF indicates that multicollinearity and collinearity among variables will not represent a problem. For developed countries the highest value of individual VIF is 3.44 for the independent variable energy use (*LENER*) and the mean VIF is 2.32 and for developing countries independent variable GDP per capita have the highest value of individual VIF, 2.66, and the mean VIF is 1.69.

Consequently, before any estimation it is fundamental test the presence of individual effects. Thus, the Hausman Test which test the presence of random effects (RE) and fixed effects (FE) and has as null hypothesis that the best model is random effects was applied to both samples. The null is rejected for developed countries ($\chi^2 = 99.06^{***}$) and for developing countries ($\chi^2 = 49.84^{***}$) indicating the presence of fixed effects on panel structure. Furthermore, the presence of cointegration on panel data set was examined by Westerlund (2007) and Kao (1999) tests. The first generation cointegration tests developed by Kao assumes that the coefficients are homogenous and the null hypothesis for the tests are that the variables are not cointegrated in all panels. Taking in account the presence of cross-sectional dependence detected before, the second generation cointegration Westerlund test was computed. The Westerlund cointegration test distinguishes from the Kao test by dealing with dynamic structures instead of residuals. The null hypothesis of this test is no cointegration and is based on two statistical tests. Group-mean variance-ratio statistic test uses the alternative hypothesis that some of the panel are cointegrated and Panel VR statistic test use the alternative hypothesis that all the panel are cointegrated. The Pedroni (1999) cointegration test was not performed because this test considers independence between cross-section and could generate biased estimations. Next, table 7 displays Westerlund and Kao cointegration tests for developed and developing countries.

Table 7 – Cointegration tests

	Test	Developed Countries		Developing Countries	
		Statistic	P-Value	Statistic	P-value
Westerlund	GM-VR	-1.7903**	0.0367	0.0241**	0.0241
	Panel VR	-1.5934**	0.0555	-1.2500*	0.0957
Kao	Modified DF	0.9412	0.1733	-6.2234***	0.0000
	DF	1.0442	0.1482	-0.5096***	0.0000
	ADF	-1.7256**	0.0422	-2.5703***	0.0051
	U. Modified DF	1.7528**	0.0398	-7.9893***	0.0000
	U. DF	1.8371**	0.0331	-5.5475***	0.0000

Notes: ***, ** and * denote significance levels at 1%, 5% and 10% respectively; The null hypothesis of the Westerlund cointegration test and the Kao cointegration test is no co-integration; In the group-mean variance-ratio (GM-VR) of the Westerlund test, the alternative hypothesis is that the variables are cointegration in some of the panels and in the panel variance-ratio (Panel VR) of the Westerlund tests, the alternative hypothesis is that the variables are cointegrated in all the panels; the Stata command xtcointtest was performed.

The outcomes from Table 7 reveal the presence of cointegration in developed and developing countries. Kao and Westerlund tests clearly accepted the presence of cointegration by rejecting the null hypothesis for developing countries. For developed countries the presence of cointegration has only found for 3 of 5 tests of Kao test. Yet, the second generation Westerlund cointegration tests which deal the cross-sectional dependence present in variables proved the presence of cointegration for all panels.

5. Results and discussion

The two panels present in this study present a long time period and multiple countries thus it is recognized that we are working upon macro panels. The possibility of heterogeneity in macro panel is real and in order to test it, the panel Mean Group (MG), Pooled Mean Group (PMG) and Dynamic Fixed Effects (DFE) were estimated and then, the Hausman test was performed. If heterogeneity is found, Mean group and Pooled Mean groups must be applied. Table 8 presents the estimations of MG, PMG and DFE models, as well, the Hausman tests for developed and developing countries.

Table 8 – Heterogeneous estimators and Hausman test

	Developed Countries			Developing Countries		
Models	MG	PMG	FE	MG	PMG	FE
Constant	-4.2513	-3.6622***	-2.6473***	-7.2860	0.1757***	-0.4142
DLGDP	0.5988*	0.7299***	0.7533***	0.1491	0.2390	0.4334***
DLTRADE	0.6360	0.0437	0.0953	0.2293	0.1763**	0.1065*
DLGINI	-0.7079	-0.0384	-0.2093	1.3917	-0.1904	-0.0783
DLENER	0.5440***	0.5353***	0.4303***	0.4363***	0.3068***	0.3386***
DLBIO	0.2454***	0.3510***	0.1397***	1.0415***	1.2781***	0.5665***
ECT	-0.4595***	-0.4595***	-0.4649***	-0.8650***	-0.4051***	-0.3682***
LGDP	0.8410***	0.8410***	0.7408***	-0.3288	-0.1811*	-0.0649
LTRADE	-0.2887***	-0.2887***	-0.2706***	-0.0434	0.1375***	0.0641
LGINI	0.4467***	0.4467***	0.3782**	-0.3052	-1.1883***	-0.5904**
LENER	0.8463***	0.8463***	0.6548***	0.4152*	0.3628***	0.3978***
LBIO	0.0243	0.0243	0.2189***	-0.0967	0.7169***	0.5516***
Hausman tests	MG vs PMG	PMG vs FE	MG vs FE	MG vs PMG	PMG vs FE	MG vs FE
Chi2(5)	1.78	0.00	0.00	2.58	0.00	0.00
Prob>chi2	0.8783	1.0000	1.0000	0.7648	1.0000	1.0000

Notes: ***, ** and * denote statistically significance at 1%, 5% and 10% level, respectively; ECT denotes error correction term; the Stata command *xtpmg* was used. Hausman results for H0: difference in coefficient is not systematic including the constant; the Stata command xtpmg was used.

Following the outcomes from Table 8, the null hypothesis is rejected in all Hausman tests. The Hausman statistic between MG and PMG for developed countries is 1.78 and is distributed $\chi^2(5)$. The conclusion is the PMG estimator is preferred. Additionally, the Hausman test was performed between PMG and MG against DFE estimators and it is concluded that the DFE model is the most suitable estimator. For developing countries, the Hausman statistic is 2.58 and the PMG is chosen over MG. Moreover, as developed countries, DFE model is chosen instead of PMG and MG models. This result determines that the two panels are homogeneous since the DFE models implies that all parameters, except intercepts, are constrained to be equal across panels.

Considering that the DFE model is the most suitable estimator, it is necessary to implement additional specifications tests, namely: the Pesaran test for contemporaneous correlation between cross sections; the modified Wald test to verify the presence of groupwise heteroscedasticity of fixed effects regression; and the Wooldridge test to check the presence of serial correlation. The specifications tests results can be observed in Table 9.

Table 9 - Specification tests

	Developed Countries	Developing Countries
	Statistics	
Pesaran's test	2.544**	2.369**
Modified Wald test	1272.84***	331.48***
Wooldridge test	9.847***	25.623***

Notes: ***, ** and * denote significance levels at 1%, 5% and 10% respectively; the modified Wald test has χ^2 distribution and tests the null hypothesis of $\sigma_C^2 = \sigma^2$, for c = 1, …, N; the Wooldridge test is normally distributed N(0,1) and tests the null hypothesis of no serial correlation; The Pesaran's test has a null hypothesis of cross-section dependence;

The Table 9 show similar outcomes for developed and developing countries. The results of the modified Wald Test show the presence of group-wise heteroscedasticity by rejecting the null hypothesis. Also, the presence of contemporaneous correlation was detected on Pesaran test. Lastly, the null hypothesis of Wooldridge test was rejected indicating the presence of first order autocorrelation.

Consequently, with the presence of heteroscedasticity, cross-sectional dependence and first order correlation in the two panels the Driscoll and Kraay estimator was chosen. The Driscoll & Kraay (2002) estimator has the error structure heteroscedastic and it is autocorrelated up to some lag. The standard errors of this estimator are robust to spatial and temporal cross-sectional dependence independently of the time dimension. Thus, the Driscoll-Kraay FE estimator was applied in this paper and the FE estimator and the FE estimator with robust standard errors were also computed to corroborate the results. The results for developed and developing countries are present in Table 10.

Table 10 - Estimation Results

	Developed Countries			Developing Countries		
Models	FE	FE-rob	DK-FE	FE	FE-rob	DK-FE
Constant	-2.6473***	-2.6473***	-2.6473***	-0.4142	-0.4142	-0.4142
DLGDP	0.7533***	0.7533***	0.7533***	0.4335***	0.4335***	0.4335***
DLTRADE	0.0953	0.0953	0.0953*	0.1065*	0.1065**	0.1065**
DLGINI	-0.2093	-0.2093	-0.2093	-0.0783	-0.0783	-0.0783
DLENER	0.4302***	0.4302***	0.4302***	0.3386***	0.3386***	0.3386***
DLBIO	0.1397***	0.1397***	0.1397***	0.5665***	0.5665***	0.5665***
LEFC (-1)	-0.4649***	-0.4649***	-0.4649***	-0.3682***	-0.3682***	-0.3682***
LGDP (-1)	0.3444***	0.3444***	0.3444***	-0.2391	-0.2391	-0.2391
LTRADE (-1)	-0.1258***	-0.1258***	-0.1258***	0.0236	0.0236	0.0236**
LGINI (-1)	0.1758**	0.1758	0.1758**	-0.2174***	-0.2174	-0.2174**
LENER (-1)	0.3044***	0.3044***	0.3044***	0.1465***	0.1465***	0.1465***
LBIO (-1)	0.1018***	0.1018***	0.1018***	0.2038***	0.2038***	0.2038***
Diagnostic Statistics						
N	480	480	480	336	336	336
R2	0.4432	0.4432	0.4432	0.4498	0.4498	0.4498
R2_a	0.4060	0.4301		0.4073	0.4311	
F	F(11,449) = 32.49***	F(11,19) = 40.59***	F(11,23) = 72.38***	F(11,311)= 23.11***	F(11,13) = 114.45***	F(11,23) = 64.12***

Notes: ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively; FE denotes Fixed Effect; FE-rob denotes Fixed Effects estimator with robust standard error; DK-FE denotes Driscoll-Kraay estimator with the option fixed effects; The Stata commands *xtreg* and *stscc* were computed.

Subsequently, Table 11 and Table 12 displays the short- and long-run elasticities of FE, FE Rob, DK-FE models for developed and developing countries respectively. Note that the long-run elasticities were obtained by dividing the coefficient of the variables by the coefficient of LEF, both lagged once and multiplying the ratio by -1.

Table 11 - Elasticities, Semi-elasticities, impacts, and adjustment speed for developed countries

Models	Coefficients	FE	FE Robust	DK - FE
Short-run elasticities		Significance level		
Constant	-2.6472	***	***	***
DLGDP	0.7534	***	***	***
DLTRADE	0.0952			**
DLGINI	-0.2093			
DLENER	0.4303	***	***	***
DLBIO	0.1397	***	***	***
Long-run elasticities				
LGDP (-1)	0.7407	***	***	***
LTRADE (-1)	-0.2706	***	***	***
LGINI (-1)	0.3782	***	***	***
LENER (-1)	0.6547	***	***	***
LBIO (-1)	0.2188786	**	**	**
Speed of adjustment				
ECT	0.4649	***	***	***

Notes: ***, ** and * denote statistically significance at 1%, 5% and 10% level, respectively; ECT means Error Correction Term; the long-run parameters are computed elasticities; FE denotes Fixed Effect; FE Robust denotes Fixed Effects estimator with robust standard error; DK-FE denotes Driscoll-Kraay estimator with the option fixed effects; the Stata command *xtreg* and *xtscc* were used.

Table 12 – Elasticities, Semi-elasticities, impacts, and adjustment speed for developing countries

Models	Coefficients	FE	FE Robust	FE D.K.
Short-run elasticities			Significance level	
Constant	-0.4142			
DLGDP	0.4335	***	***	***
DLTRADE	0.1065	***	***	***
DLGINI	-0.0783			
DLENER	0.3386	***	***	***
DLBIO	0.5665	***	***	***
Long-run elasticities				
LGDP (-1)	-0.0649			
LTRADE (-1)	0.0642	**	**	***
LGINI (-1)	-0.5904	**	**	***
LENER (-1)	0.3978	***	***	***
LBIO (-1)	0.5516	***	***	***
Speed of adjustment				
ECT	0.3681	***	***	***

Notes: ***, ** and * denote statistically significance at 1%, 5% and 10% level, respectively; ECT means Error Correction Term; FE denotes Fixed Effect; FE-rob denotes Fixed Effects estimator with robust standard error; DK-FE denotes Driscoll-Kraay estimator with the option fixed effects; the long-run parameters are computed elasticities; the Stata command *xtreg* and *xtscc* were used.

The results of short- and long-run elasticities presented in Table 10 show a consistency at significance levels and signs between models. Moreover, the presence of cointegration described before is consistent with the results obtained since the error correction terms (ECT) is negative and statistically significant for both samples, revealing the presence of long memory between ecological footprint and the variables. The ECT is 46% for developed countries and 36% for developing countries. The results reveal that developed countries are quicker than developing countries to recover the equilibrium after a shock in the ecological footprint.

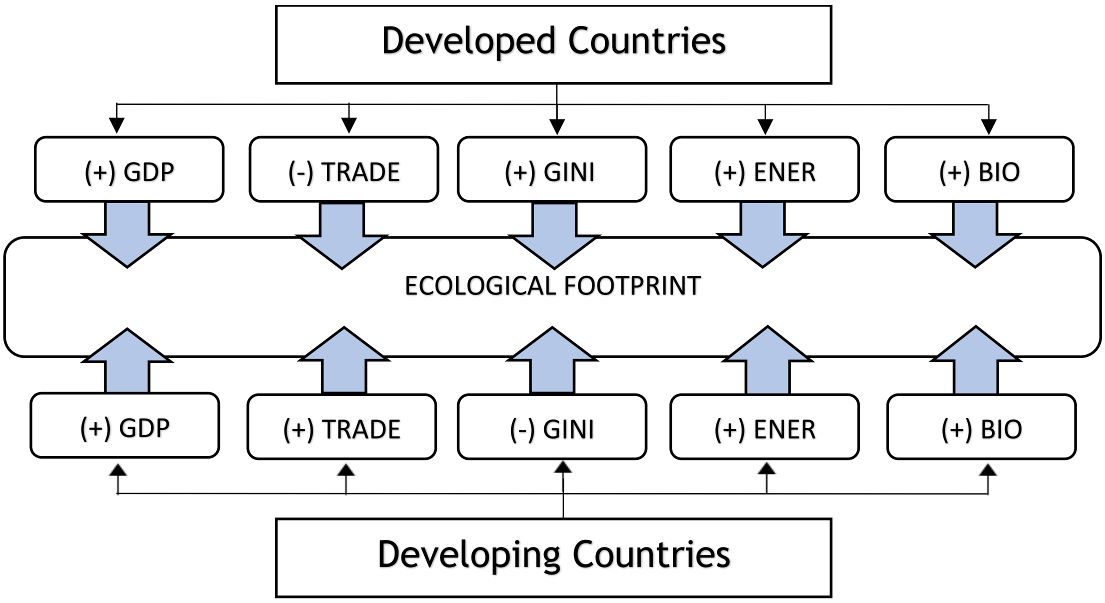

Figure 6. Summary of the estimated effect of variables on ecological footprint.

The main finding is that the effect of income inequality varies by the level of country income. The relationship is highly statistically significant at 1% level for both samples in long-run. In developed countries if income inequality rises the ecological footprint will increase. However, for developing countries if income inequality increases the ecological footprint will be smaller. Nevertheless, it is highlighted that both panels have a particularity in the outcomes since the income inequality does not have a significant statistical relationship with ecological footprint in short-run.

Since this analysis is a pioneer in the study of the effect of inequality in the ecological footprint, it is important to compare our results with studies, previously described, on the effect of inequality on emissions indicators such as CO_2 and GHG emissions. The positive effect of income inequality on ecological footprint for developed countries is in line with studies about the effect of income inequality and CO_2 emissions such as Grunewald et al. (2017), Hao et al. (2016) and Q. Liu et al. (2019). According to Boyce (1994), higher income inequality contributes to degradation in environmental quality. Thus, if the inequality increases the rich will create more environmental pollution, by the companies they own and their high carbon-consumption, through imposing their political and economic power while redirecting the cost of environmental degradation for the poor. In addition, Veblen Effects can explain the positive influence of inequality in ecological footprint on developed countries. When income inequality increases, the social structure based on income is naturally altered. Hence, certain group of households tend to over-consumption high polluted goods and services in order to gain status or maintain the consume patterns of high-income households (Veblen, 1899). Therefore, other possible explanation is suggested by Bowles & Park (2005) and Jorgenson et al. (2017) more Inequality on developed countries could lead to a higher number of hours of work which lead to more energy consumed, and consequently, a higher ecological footprint. The results of income inequality in developing countries are similar to Ravallion (2000), Heerink et al. (2001) and Hübler (2017) . For this group, an increase in economic inequality will result in a smaller environmental degradation. Since the mean of the ecological footprint in developing countries is clearly lower than that of developed countries, the results suggest that part of the population, after increasing inequality, fails to have or cannot afford the use of pollutant goods and services leading to a reduction in footprint. Notwithstanding, note that more than 70% of the overall growth of carbon dioxide emissions during the last 35 years came from upper-middle-income economies (Dong et al., 2018).

Considering economic growth as a main driver of the actual climate emergency, *GDP* in short-run show a positive and statistically significant association at 1% level with ecological footprint for developed and developing countries. In the long term, *GDP* per capita is only statistically significant in developed countries. Considering the results of the Semi-elasticities of short-run, trade openness rises ecological footprint in developed and developing countries. This effect is similar with the studies of Al-Mulali et al. (2015), Destek et al. (2018) and Ulucak & Bilgili (2018). The effect in long-run of trade on ecological footprint is negative in developed economies and positive in developing economies. Globalization factors such as foreign direct investment and trade openness allow developed countries to shift the production of goods and land use to non-developed countries. This necessarily implies a smallest use of land and a greater import of goods to support the needs of the population of developed countries. Therefore, the effect of long run of trade is expected to be positive in developing countries, since if the use of the land increases due to the displacement of land use, the ecological footprint also increases. In fact, the short-run positive impact of trade in ecological footprint on developed countries can be explained for the big imports necessary to sustain the high-demands of carbon goods for the population. The impact is only significant at 10% and only in DK-FE estimator which proves the consistency of the estimator chosen to this study.

Energy use, as expected, harms ecological in short-and long-run in the two groups. Producing and using energy causes depletion of natural resources and emissions of various pollutants. It is recognized empirically as a main driver of ecological footprint (Charfeddine & Mrabet, 2017). Finally, the effect of biocapacity on ecological footprint is positive for both samples however is rather superior in developing countries. According to Bagliani et al. (2008), Wang et al. (2013) and Hervieux & Darné (2016) the ecological footprint is positively affected by biocapacity. This means that if biocapacity increases, the ecological footprint will also increase because people who live in areas with a large amount of resources tend to have a lower environmental concern than those who live in areas with pollution and scarcity of resources. Equally important, the lower level of education and the low awareness about the actual state of climate are important to explain the superior effect. For Boyce (1994) the poor have a tendency to overexploit natural resources if inequality rise since they perceive that is the only way to obtain income to secure their survival. Concluding, the effect is greater in developing countries and can be explained due to powerless policies in the preservation of resources and biodiversity and lower educational level.

In brief, GDP, Energy Use, Trade Openness, Biocapacity and Income Inequality are driving ecological footprint. The climate breakdown that the world faces now represents a time of change in the way the humankind lives, consume and develop. Measure are strictly necessary without postponing the problem anymore since there are no planet B. The deforestation, overfishing, global development, massive construction of infrastructures associated with changes in the land, pollution, climate change and invasive alien species took nature to the limit. According to Intergovernmental Science-policy platform on biodiversity and ecosystem services (IPBES), one million species are at risk of extinction (IPBES, 2019). In addition, humans are responsible for a serious change in more than 75% of the Earth's lands area (IPBES, 2019). Thus, our actions are slowly destroying our health, food security and economies.

Considering the current climate crisis is essential mitigate our pollutants emissions. The energy sector was and is severely sustained in fossil fuels which generates 25% of total GHG emissions. Obviously, energy production should be adapted in order to reduce pollutants emissions. If the energy generation comes from a carbon-free source, this will imply that the other sectors responsible for generating the other 75% of GHG emissions are able to reduce their emissions. Another objective is the massive use of renewable energies associated with low carbon cost to supply the needs from the population. Consequently, investment policies in renewable energies are being applied, such as the minimum quota of renewable energies currently used in several countries. Indeed, Afonso, Marques, & Fuinhas (2017) argues that a maximum quota of fossil fuel sources should be tested instead of minimum quota of renewable. In addition, according to Boyce (2018) a mandated limit (a cap) in the use of fossil fuel will result in higher prices and logically, higher prices lead to a decrease in the quantity demand. By placing a limit on the consumption/production of fossil fuels, a limit is placed on the emissions. The annual cap should be decreased over time to reach the numbers of Paris Agreement and the carbon price should be calculated by demand for permits as the use of fossil fuel source like coal or oil declines. In addition to the emission cap, Boyce (2018) added a carbon tax that regulates automatically in function of emissions emitted and quantity targets. In short term, carbon pricing generates incentives for cost-effective emissions reductions and reduce the cost of innovation in the long-run. Moreover, Boyce (2018) defends that part of the revenue obtained from pricing carbon or carbon rent should return to the population via equal per capita dividends. This could change the way people think, creating an "ethical" premise that can lead to more active environmental changes.

Finally, the bet on energy sources such as the sun and the wind must continue on a larger scale and even the energy storage systems of these energies must be improved. This can be achieved through technologies such as lithium-ion batteries or thermal-powered storage technologies. Moreover, the innovation of nuclear energy is essential as well the investment in tidal and wave energy from oceans. Similarly, is crucial a global scale investment and development of technologies of carbon capture and storage. Furthermore, policies such as, investment in education about the climate change, increase the forest area at a global level and conservation of biodiversity must be a target by leaders and government. But, as defended by Steffen et al. (2018), these policies can not only be taken at national level. If the countries considered the nature as the basis of our economies and our development will be easier change the current situation. However, only with a joint effort at global level to combat climate change we will be able to reverse this emergence.

6. Conclusion and policy implications

This study examined the influence of income inequality in ecological footprint in developed and developing countries. Using drives of ecological footprint such as GDP, Trade and Energy Use, the Driscoll-Kraay estimator with fixed effect was performed to observe the short and long effects. Considering the presence of cross-sectional dependence, first-order autocorrelation and heteroscedasticity the Driscoll-Kraay estimator with fixed estimator was employed. Additionally, Fixed Effects and Fixed Effects Robust were applied in order to ensure the results of robustness of results. The results point out that economic growth, trade openness, energy, Gini index and biocapacity are key determinants of ecological footprint.

The effect of income inequality in ecological footprint is positive in developed economies and negative in developing economies. These findings are important for political decisions. High-income countries need to create or redefine policies aimed at reducing inequality, knowing that a reduction in inequality will lead to a decline in environmental degradation. In contrast, the solution for developing countries it's not that simple. It is necessary policies to reduce inequality, while at the same time worrying about the potential problem of economic growth in environmental degradation. Possibly, when developing countries achieve higher income per capita, the inequality will diminish, and the ecological footprint will increase consequently as a result of better distribution of wealth, evolution of technology and access to a larger number of goods. That's represent clearly a trade-off for developed countries between reducing ecological footprint or Income Inequality.

In order to reduce income inequality, various policies can be applied. At education level, a more equitable access to education is essential to ensure a fairest distribution of income. Moreover, at labour level a higher minimum wage could lead in more equal income distribution. In addition, a more egalitarian tax level where rich pay their taxes instead of avoiding them as it happens now and a more redistribute tax level at labour. Lastly, an alternative hypothesis is the Universal Basic Income (UBI) based on taxes and fees on luxuries and financial transactions, as well, carbon pricing. This could be generated two effects, mitigate climate change and reducing income inequality. UBI can be defined as a monthly cash payment provided by state regardless of race, gender or need and it is enough to cover basic needs.

Finally, our empirical findings contribute to the literature by being the first to empirically investigate the relationship between income inequality and ecological footprint. For future research, a proxy of the quality of institutions and a proxy of educational level must be used to study the effect of politics and education on relationship between income inequality and ecological footprint. Moreover, dividing the countries considering their ecological footprint will permit identify the real flow between income inequality and ecological footprint. It is also useful investigate the effect of inequality on the carbon footprint since 60% of the total ecological footprint of globe is the carbon footprint, as well as, investigate the other footprints.

In addition, the use of variables of income inequality such as the richest 10% of population and the Palma Ratio could provide different results from those obtained with the Gini Index.

References

Afonso, T. L., Marques, A. C., & Fuinhas, J. A. (2017). Strategies to make renewable energy sources compatible with economic growth, *18*, 121–126. https://doi.org/10.1016/j.esr.2017.09.014

Al-Mulali, U., Weng-Wai, C., Sheau-Ting, L., & Mohammed, A. H. (2015). Investigating the environmental Kuznets curve (EKC) hypothesis by utilizing the ecological footprint as an indicator of environmental degradation. *Ecological Indicators*, *48*, 315–323. https://doi.org/10.1016/j.ecolind.2014.08.029

Baek, J., & Gweisah, G. (2013). Does income inequality harm the environment?: Empirical evidence from the United States. *Energy Policy*, *62*, 1434–1437. https://doi.org/10.1016/j.enpol.2013.07.097

Bagliani, M., Bravo, G., & Dalmazzone, S. (2008). ANALYSIS A consumption-based approach to environmental Kuznets curves using the ecological footprint indicator, *5*(1955). https://doi.org/10.1016/j.ecolecon.2008.01.010

Berthe, A., & Elie, L. (2015). Mechanisms explaining the impact of economic inequality on environmental deterioration. *Ecological Economics*, *116*, 191–200. https://doi.org/10.1016/j.ecolecon.2015.04.026

Borghesi, S. (2006). Income Inequality and the Environmental Kuznets Curve. *Fondazione Eni Enrico Mattei, Nota de La*.

Bowles, S., & Park, Y. (2005). Emulation, inequality and work hours: was throsten veblen right?, *115*(1996), 397–412.

Boyce, J. K. (1994). Inequality as a cause of environmental degradation. *Ecological Economics*, *11*(3), 169–178. https://doi.org/10.1016/0921-8009(94)90198-8

Boyce, J. K. (2018). Carbon Pricing: Effectiveness and Equity. *Ecological Economics*, *150*(April), 52–61. https://doi.org/10.1016/j.ecolecon.2018.03.030

Charfeddine, L., & Mrabet, Z. (2017). The impact of economic development and social-political factors on ecological footprint: A panel data analysis for 15 MENA countries. *Renewable and Sustainable Energy Reviews*, *76*(August 2015), 138–154. https://doi.org/10.1016/j.rser.2017.03.031

Destek, M. A., Ulucak, R., & Dogan, E. (2018). Analyzing the environmental Kuznets curve for the EU countries: the role of ecological footprint. *Environmental Science and Pollution Research*, *25*(29), 29387–29396. https://doi.org/10.1007/s11356-018-2911-4

Dong, K., Timilsina, G. R., & Hochman, G. (2018). Are Driving Forces of CO 2 Emissions Different across Countries ? Insights from Identity and Econometric Analyses. *World Bank. Policy Research Working Paper*, *8477*(June).

Driscoll, J. C., & Kraay, A. C. (2002). Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Review of Economics and Statistics*, *80*(4), 549–560. https://doi.org/10.1162/003465398557825

Fitoussi, J., & Saraceno, F. (2014). Inequality and macroeconomic performance OFCE / POLHIA N ° 2010-13 J ULY 2010.

Grossman, G. M. ., & Krueger, A. B. . (1995). Economic growth and the environment. *Q. J. Econ.*, *110*, 353–377. https://doi.org/10.2307/2977834

Grunewald, N., Klasen, S., Martínez-Zarzoso, I., & Muris, C. (2017). The Trade-off Between Income Inequality and Carbon Dioxide Emissions. *Ecological Economics*, *142*, 249–256. https://doi.org/10.1016/j.ecolecon.2017.06.034

Hailemariam, A., Dzhumashev, R., & Shahbaz, M. (2019). Carbon emissions, income inequality and economic development. *Empirical Economics*. https://doi.org/10.1007/s00181-019-01664-x

Hao, Y., Chen, H., & Zhang, Q. (2016). Will income inequality affect environmental quality? Analysis based on China's provincial panel data. *Ecological Indicators*, *67*, 533–542. https://doi.org/10.1016/j.ecolind.2016.03.025

Heerink, N., Mulatu, A., & Bulte, E. (2001). Income inequality and the environment: Aggregation bias in environmental Kuznets curves. *Ecological Economics*, *38*(3), 359–367. https://doi.org/10.1016/S0921-8009(01)00171-9

Hervieux, M. S., & Darné, O. (2016). Production and consumption-based approaches for the environmental Kuznets curve using ecological footprint. *Journal of Environmental Economics and Policy*, *5*(3), 318–334. https://doi.org/10.1080/21606544.2015.1090346

Holland, T. I. M. G., Peterson, G. D., & Gonzalez, A. (2009). A Cross-National Analysis of How Economic Inequality Predicts Biodiversity Loss, *23*(5), 1304–1313. https://doi.org/10.1111/j.1523-1739.2009.01207.x

Hübler, M. (2017). The inequality-emissions nexus in the context of trade and development: A quantile regression approach. *Ecological Economics*, *134*, 174–185. https://doi.org/10.1016/j.ecolecon.2016.12.015

IPBES. (2019). Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services - ADVANCE UNEDITED VERSION – assessment Key messages, (May 2019).

IPCC. (2014). *Climate change 2014: mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. Climate change 2014: mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.* (Vol. 218). https://doi.org/10.1016/S0022-0248(00)00575-3

IPCC. (2018). *Global warming of 1.5°C-IPCC*. Retrieved from https://report.ipcc.ch/sr15/pdf/sr15_spm_final.pdf

Jorgenson, A., Schor, J., & Huang, X. (2017). Income Inequality and Carbon Emissions in the United States: A State-level Analysis, 1997–2012. *Ecological Economics*, *134*, 40–48. https://doi.org/10.1016/j.ecolecon.2016.12.016

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data, *90*.

Levin, A., Lin, C., & Chu, C. J. (2002). Unit root tests in panel data : asymptotic and ÿnite-sample properties, *108*, 1–24.

Liu, C., Jiang, Y., & Xie, R. (2019). Does income inequality facilitate carbon emission reduction in the US? *Journal of Cleaner Production*, *217*, 380–387. https://doi.org/10.1016/j.jclepro.2019.01.242

Liu, Q., Wang, S., Zhang, W., & Li, J. (2018). Income distribution and environmental quality in China: A spatial econometric perspective. *Journal of Cleaner Production*, *205*, 14–26. https://doi.org/10.1016/j.jclepro.2018.09.090

Liu, Q., Wang, S., Zhang, W., Li, J., & Kong, Y. (2019). Examining the effects of income inequality on CO 2 emissions: Evidence from non-spatial and spatial perspectives. *Applied Energy*, *236*(October 2018), 163–171. https://doi.org/10.1016/j.apenergy.2018.11.082

Maddala, G. S., & Wu, S. (2003). A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test. *Oxford Bulletin of Economics and Statistics*, *61*(s1), 631–652. https://doi.org/10.1111/1468-0084.0610s1631

Magnani, E. (2000). The Environmental Kuznets Curve, environmental protection policy and income distribution, *32*, 431–443.

Menegaki, A. N., Marques, A. C., & Fuinhas, J. A. (2017). Redefining the energy-growth nexus with an index for sustainable economic welfare in Europe. *Energy*, *141*, 1254–1268. https://doi.org/10.1016/j.energy.2017.09.056

Mikkelson, G. M., Gonzalez, A., & Peterson, G. D. (2007). Economic inequality predicts biodiversity loss. *PLoS ONE*, *2*(5), 3–7. https://doi.org/10.1371/journal.pone.0000444

Oxfam. (2015). Oxfam Media Briefing Extreme Carbon Inequality, (December).

Pal, D., & Mitra, S. K. (2017). The environmental Kuznets curve for carbon dioxide in India and China: Growth and pollution at crossroad. *Journal of Policy Modeling*, *39*(2), 371–385. https://doi.org/10.1016/j.jpolmod.2017.03.005

Pedroni, P. (1999). Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple of Economics and Statistics, Vol. No. 0, pp. . *Oxford Bulletin of Economics and Statistics*, *61*(SPECIAL ISSUE (1999)), 653–670.

Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels General Diagnostic Tests for Cross Section Dependence in Panels ∗, (1229).

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence, *312*, 265–312. https://doi.org/10.1002/jae

Ravallion, M. (2000). Carbon emissions and income inequality. *Oxford Economic Papers*, *52*(4), 651–669. https://doi.org/10.1093/oep/52.4.651

Scruggs, L. A. (1998). Political and economic inequality and the environment. *Ecological Economics*, *26*(3), 259–275. https://doi.org/10.1016/S0921-8009(97)00118-3

So, K., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels, *115*(9526), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7

Steffen, W., Broadgate, W., Deutsch, L., Gaffney, O., & Ludwig, C. (2015). The trajectory of the anthropocene: The great acceleration. *Anthropocene Review*, *2*(1), 81–98. https://doi.org/10.1177/2053019614564785

Steffen, W., Rockström, J., Richardson, K., Lenton, T. M., Folke, C., Liverman, D., … Schellnhuber, H. J. (2018). Trajectories of the Earth System in the Anthropocene. *Proceedings of the National Academy of Sciences*, *115*(33), 8252–8259. https://doi.org/10.1073/pnas.1810141115

Torras, M., & Boyce, J. K. (1998). Income, inequality, and pollution: A reassessment of the environmental Kuznets curve. *Ecological Economics*, *25*(2), 147–160.

https://doi.org/10.1016/S0921-8009(97)00177-8

Ulucak, R., & Bilgili, F. (2018). A reinvestigation of EKC model by ecological footprint measurement for high, middle and low income countries. *Journal of Cleaner Production*, *188*, 144–157. https://doi.org/10.1016/j.jclepro.2018.03.191

Veblen, T. (1899). The Theory of the Leisure Class: an economic study of institutions. *Journal of Political Economy*, *7*(4), 265. https://doi.org/10.1086/250610

Wackernagel, M., & Rees, W. (1996). Our ecological footprint: reducing human impact on the earth. In *New Society Publishers, The New Catalyst Bioregional Series*.

Wang, Y., Kang, L., Wu, X., & Xiao, Y. (2013). Estimating the environmental Kuznets curve for ecological footprint at the global level : A spatial econometric approach. *Ecological Indicators*, *34*, 15–21. https://doi.org/10.1016/j.ecolind.2013.03.021

Westerlund, J. (2007). New Simple Tests for Panel Cointegration, (June 2013), 37–41. https://doi.org/10.1080/07474930500243019

WMO. (2019). *WMO Provisional statement on the State of the Global Climate in 2018*. https://doi.org/10.1029/2018GL079362

Wolde-Rufael, Y., & Idowu, S. (2017). Income distribution and CO2 emission: A comparative analysis for China and India. *Renewable and Sustainable Energy Reviews*, *74*(November), 1336–1345. https://doi.org/10.1016/j.rser.2016.11.149

Appendix

Table A1. Matrices of correlation and VIF statistics

Developed Countries	*DLEF*	*DLGDP*	*DLTRADE*	*DLGINI*	*DLENE*	*DLBIO*
DLEF	1.0000					
DLGDP	0.4314	1.0000				
DLTRADE	0.4348	0.7784	1.0000			
DLGINI	-0.0579	-0.0616	-0.0026	1.0000		
DLENE	0.3427	0.3882	0.3515	-0.0474	1.0000	
DLBIO	0.1122	0.0480	0.0414	-0.0344	0.0176	1.0000
VIF		2.66	2.57	1.01	1.19	1.00
Mean VIF				1.69		
Developing Countries	*DLEF*	*DLGDP*	*DLTRADE*	*DLGINI*	*DLENE*	*DLBIO*
DLEF	1.0000					
DLGDP	0.4231	1.0000				
DLTRADE	0.4132	0.6400	1.0000			
DLGINI	-0.0818	-0.2131	0.0031	1.0000		
DLENE	0.3823	0.3915	0.3147	-0.1072	1.0000	
DLBIO	0.2780	0.1756	0.1598	-0.0036	0.0281	1.0000
VIF		1.97	1.78	1.09	1.20	1.04
Mean VIF				1.41		