The European Journal of Comparative Economics
Vol. 17, no. 1, pp. 73-102
ISSN 1824-2979

Carbon emissions, income inequality and environmental degradation: the case of Mediterranean countries

Fateh Belaïd*, Sabri Boubaker**, Rajwane Kafrouni***

Abstract

This study examines the main driving forces affecting short- and long-term CO_2 emissions pattern due to changes in growth and income inequality for 11 Mediterranean economies over the period 1990—2012. It proposes an autoregressive dynamic distributive lag dynamic panel specification to (i) test for non-linearity between income inequality and CO_2 emissions, (ii) assess whether there is a differentiated effect of income inequality on CEO_2 emissions depending on the level of GDP, and (iii) test for other sources of non-linearity between income inequality and CO_2 emissions. The results indicate a negative and significant association between income inequality and carbon emissions which means that greater inequality leads to environmental degradation. However, in the short-run, the results show a positive and significant relationship between the income inequality and CO_2 emissions

JEL classifications: C2, O1, Q5, R1

Keywords: Income inequality, Environmental degradation, Economic growth, Heterogeneous panel

1. Introduction

Since 1950, environmental pressures have caused changes in ecosystems and contributed to the development of an environmental crisis that was followed in the 1980s by a social crisis and income inequalities in most countries around the world (Berthe and Elie, 2015). During the 1987 World Commission on Environment and Development, the Brundtland report suggests that poverty and income inequality are the major causes of global environmental problems. As a result, it would be useless to solve environmental problems without addressing poverty and international inequality. After the end of the Millennium Development Goals period, Goals for Sustainable Development (ODD) were announced in 2015 and mainly focus on the mitigation of climate change and the reduction of income inequalities. Thus, the objectives 10 and 13 of the ODD aim to reduce intra and inter country inequalities and to fight against climate change.

* Lille Catholic University, UMR 9221-LEM-Lille Économie Management, Paris School of Business, France, fateh.belaid@univ-catholille.fr / fateh.belaid@gmail.com

** EM Normandie Business School, Métis Lab, France, sboubaker@em-normandie.fr

*** Ph.D., University of Versailles, France, rajwane_kafrouni@hotmail.com

http://dx.doi.org/10.25428/1824-2979/202001-73-102

The environment-inequality-growth nexus has been widely studied in the literature without reaching any empirical or theoretical consensus[1]. Prior studies can be divided into two research stream. The first examines the relationship between economic growth and the environment quality using the Environmental Kuznets Curve (EKC) approach. The existing empirical studies led to divergent results where some present conclusions consistent with the EKC hypothesis (Selden and Song, 1994; Galeotti et al., 2008) whereas others find an N-shaped curve (Friedl and Getzner, 2003) or no significant relationship between economic growth and environmental pollutants (Agras and Chapman, 1999; Richmond and Kaufman, 2006). The second line of research examines the relationship between income inequalities and the environment quality using EKC approach by controlling for income inequalities using the Gini index. This strand of literature also leads to divergent results. On the one hand, Scruggs (1998), Ravallion (2001), and Heerink et al. (2001) suggest that income inequality is favorable for the environment. On the other hand, Boyce (1994) and Magnani (2000) suggest that income inequalities are harmful for the environment. Mixed results are provided by Torras and Boyce (1998) and Clément and Meunié (2010).

In light of these divergent results, we propose to test the presence of a nonlinear relationship between income inequality and environmental quality. In other words, we allow the presence of a threshold effect in the relationship between income inequality and environment quality. This potential non-linearity has been so far ignored in the literature, making the originality of this study. We also test whether this nonlinear relationship between income inequality and the environment depends on the level of Gross Domestic Product (GDP) in the country.

One major limitation of prior relevant studies is the use of simple econometric estimation techniques such as Ordinary Least Squares (OLS) and fixed effects (FE) regressions. They test for the causal relationship between income inequality and the environmental quality using the EKC approach. However, this approach allows us to

1 See, for instance, Boyce (1994), Scruggs (1998), Magnani (2000), Heerink et al. (2001), Bimonte (2002), Clement and Meunié (2011), Torras et al. (2011), and Grunewald et al. (2017).

have an insight only on the long-term relationship between economic growth, income inequality, and environment quality.

The aim of this study is to investigate the main driving forces that affect short- and long-term CO_2 emissions patterns due to changes in economic growth and income inequality for 18 Mediterranean countries over the period 1990—2012 by using the most appropriate panel econometric approach to overcome the issues of cross-sectional dependence and omitted common factor bias (i.e. the pooled mean group estimator (PMG).

The study of Mediterranean economies is motivated by the importance of income inequalities and CO_2 emission differences between these countries. Moreover, to the best of our knowledge, there are no empirical studies so far that have focused on these countries. According to Daniele and Malanima (2013), income inequality, proxied by the Gini Index, has grown since the mid-1980s and Mediterranean countries have gone through a phase of economic divergence. Some of these countries exhibit low levels of income inequality, whereas others exhibit higher levels of inequality. The same divergence can be seen for their CO_2 emissions. According to the Climate Change Data explorer, CO_2 emissions in the northern Mediterranean countries are extremely diverse and range from 1.3 tons per capita in Albania to 7.6 in Greece in 2012. Similarly, in the southern and eastern Mediterranean countries, differences in CO_2 emissions vary from 1.6 tons per capita in Morocco to 8.3 tons in Libya.

This paper contributes to the literature in several ways. First, it adds to the empirical literature on the effect of income inequality on CO_2 emissions by using the most recent inequality database, Standardized World Income Inequality Database (SWIID) dataset (version 5.1), proposed by Solt (2016) that offers wider coverage, especially for Mediterranean countries. Second, while previous studies rely on simple estimation methods such as OLS and FE regressions, this study relies on recent advances in non-stationary heterogeneous panel literature and uses pooled mean group estimation (PMG) regressions. PMG estimation technique allows for the short-run coefficients, intercept, and error variances to differ across the groups while it constrains the long-run coefficients to be equal across the groups[2]. Third, to the best of our

2 Unlike the most previous studies, we perform (i) a cross-section dependence test to decide which unit root test would be appropriate (ii) Westerlund 's cointegration test that allows for cross-sectional dependence; (iii) Pesaran's Common Correlated Effects Mean Group estimator (CCEMG) to assess the

knowledge, none of the prior empirical studies has investigated the dynamic link between income inequality, economic growth, and environmental degradation in the Mediterranean region.

The rest of the paper is organized as follows. Section 2 presents the theoretical background, conceptual framework and research hypotheses. Section 3 describes the data and the modelling approach. Section 4 reports the empirical finding. Section 5 draws the conclusions and provides policy implications.

2. Inequality and the environment: A literature review

2.1. The Environmental Kuznets Curve (EKC)

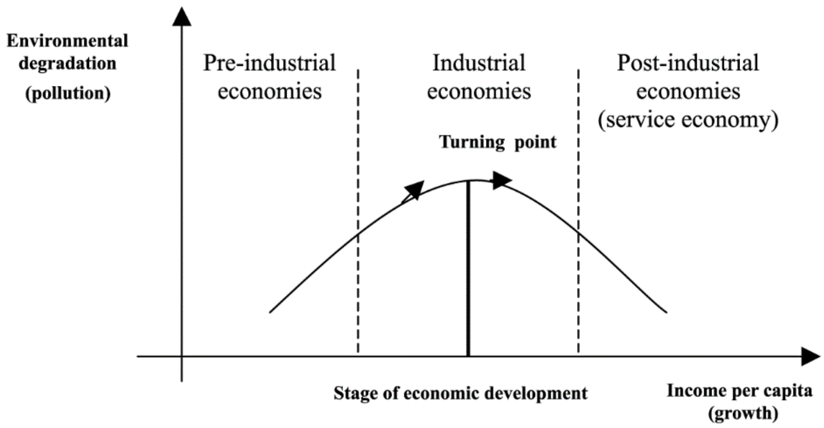
Introduced in 1995 by Grossman and Krueger, the Environmental Kuznets Curve (EKC) shows an inverted U-shaped relationship between economic growth and environmental degradation (see, Figure 1). This shape was documented for 12 of the 14 indicators of air and water pollution that were used by Grossman and Krueger (1995). According to this curve, the level of environmental degradation decreases after reaching a certain level of economic development. This is mainly explained by three effects: the *scale effect*, the *technical effect*, and the *composition effect*.

Grossman and Krueger claim that in the early stages of development, the production of more outputs requires more inputs, leading to an increase in the level of pollution (the "*scale effect*"). However, this effect has a more or less serious impact on the environment depending on the technological progress ("*technical effect*"). Finally, the "*composition effect*" refers to the changing composition of an economy. At the later stage of the development, the growth level reaches a turning point beyond which any rise in living standards leads to a reduction in pollution. This can be explained by the structural changes in the composition of the economy by moving from an industrial economy where pollution is expected to increase to a more service-oriented economy which is supposed to be less polluting given the non-materialistic nature of services. Another

long-run relationship that accounts for cross sectional dependence; and (iv) PMG estimator proposed by Pesaran to identify the sources of causality and distinguish between short-run and long-run relationships. This estimation technique is robust to outliers and the choice of lag orders. To the best of our knowledge, none of the related empirical studies has investigated the non-linearity that can exist between inequalities and the environment, which makes the originality of this work.

possible explanation of this inverted U shape is related to the concept of post-materialism of Inglehart (1981). Demand for environmental quality increases with the level of development and exceeds the demand for consumer goods (Scruggs, 1998; Heerink et al., 2001). Indeed, after a certain level of income per capita, individuals give more importance to the environment as the primary needs are filled.

Figure 1. The Environmental Kuznets Curve. Source. Panayotou (1993)



2.2. Revisited EKC: The importance of income inequalities

The validity of the environmental curve of Kuznets was widely criticized by economists. Cho and Li (2014) argue that the validation of the EKC hypothesis is highly dependent on studied countries, sample size, and the econometric approach. Most importantly, several relevant explanatory variables were omitted from the analyses. Many authors such as Unruh and Moomaw (1998), Kaufmann et al., (1998), and Suri and Chapman (1998) argue that GDP alone is not enough to explain the environmental degradation Thus, additional explanatory variables were added to the EKC model to increase its explanatory power and to avoid omitted variable concerns such as population density (Selden and Song, 1994, Cropper and Griffiths, 1994), openness to trade (Suri and Chapman, 1998), industrial production composition (Grossman and Krueger, 1995), environmental regulations (Shafik, 1994; Baldwin, 1995), and income inequalities (Torras and Boyce, 1998; Scruggs, 1998; Heerink et al., 2001; Magnani, 2000, Bimonte, 2002, Borghesi, 2006, Clément and Meunié, 2010, Baek and Gweisah, 2013, Grunewald et al., 2017).

This paper focuses on the effect of income inequality on environmental quality. Boyce (1994) was the first to argue that inequalities cause environmental degradation through political choices. He distinguishes between the winners (the rich) and the losers (the poor) of the polluting economic activity and hypothesizes that there is a game of power between these two groups. The dominant social group has the power to tackle environmental problems and translate them into policy decisions. If the power of the winners (rich) is greater than that of the losers (poor), environmental degradation will be greater than in the reverse situation. These outcomes termed by Boyce (1994) the Power Weighted Social Decision Rule, which means that wealth is positively correlated with power and social choices regarding environmental policies that are mainly determined by rich individuals who have no interest in preserving the environment as long as its degradation brings them private returns. As a result, environmental policies are expected to be virtually non-existent and the quality of the environment is low in unequal societies.

Magnani (2000) shows that in inequitable societies, internal governmental concerns are centered on growth policies rather than environmental policies. Using a panel of 19 OECD countries covered from 1980 to 1992, the author argues that the marginal rate of substitution between consumer goods and the quality of the environment depends on income distribution. Indeed, if inequalities increase, the difference between average and median income increases, and the median voter becomes relatively poor. Therefore, the median voter is expected to rethink his economic choices and to spend more money on the purchase of economic goods rather than public goods (such as environmental quality).

Scruggs (1998) criticizes the equality hypothesis of Boyce (1994). First, Boyce (1994) assumes that not all rich people have an interest in preserving the environment, while prior studies, theoretical and empirical alike, suggest that rich households are more interested in preserving the environment than poor households (Milbrath, 1984). Second, the equality hypothesis assumes that democratic societies have better environmental performance than other societies. However, literature on social choices shows that democratic institutions can produce divergent results in terms of environmental performance (Li and Reuveny, 2006). Scruggs (1998) explains that the impact of income inequalities on the quality of the environment depends on the effect of the individual income on the environmental pressure that it exerts. He presents three types of possible relationships between individual income and individual environmental pressure. In almost all three situations, environmental pressure increases with income. However, each situation adopts a different assumption regarding the marginal variation in environmental pressure. In the first situation, the curve is concave, which means a marginal decrease in environmental pressure. In other words, income inequality results lead to the reduction of environmental pressure. According to Scruggs (1998), this situation is the closest to reality. In the second situation, Scruggs (1998) assumes a convex relationship between income and environmental pressure and therefore an increase in marginal environmental pressure. In other words, in an egalitarian society, environmental degradation is weak. Finally, in the third situation, income distribution has no impact on environmental degradation as long as overall income remains stable.

Torras and Boyce (1998) find that in low-income countries, air pollution increases, and water pollution decreases with increasing inequality. In high-income countries, their Gini index shows a negative coefficient for all pollutants tested, except for fine particles. Ravallion et al. (2000) argue that the marginal propensity to emit (MPE) is a decreasing function of income (Holtz-Eakin and Selden, 1995, Heil and Selden, 2001; Grunewald et al., 2017). Consequently, income inequalities must be added to the model because, if not, the estimates will be biased. Using a panel dataset of 42 countries for the period 1975—1992, Ravallion et al. (2000) they find that an increase in income inequality implies a lower level of CO_2 emissions. However, this impact is conditioned by the level of income. In poor countries, there is a trade-off between policies aiming to reduce inequalities and environmental policies. However, in rich countries, this arbitration does not exist.

Borghesi (2006) criticizes the empirical studies using the OLS regression method and explains that this method does not take into account countries heterogeneity. He uses a panel dataset for 37 countries over 1988—1995 and compares the OLS estimator to the fixed effects estimator (FE). With OLS, an increase in inequalities leads to a reduction in CO_2 emissions. However, using FE estimation technique, income inequalities do not show a significant effect on income inequality.

Grunewald et al. (2017) also assert that cross-section estimates based on OLS estimators are not appropriate and can yield erroneous results. Therefore, they adopt the group fixed effects estimator for a sample of 158 countries over the period 1980—2008. They also test for the conditional effect of GDP on the relationship between income inequalities and CO_2 emissions by adding an interaction term between the Gini index, proxy for income inequality, and GDP. They conclude that in poor (rich) countries, income inequalities result in low (high) levels of CO_2 emissions. They explain that in poor countries, most of the population does not have access to modern energy sources and are outside the carbon economy, whereas in rich countries income equality weakens the relative power of the rich. Therefore, the median voter, considered favorable for environmental policies, opts for political choices that favor environmental policies.

The existing empirical studies do not provide a consensus on the nature of the relationship between income inequalities and environment quality. The results vary depending on the environmental indicators (Berthe and Elie, 2015) and on the level of income in the sampled countries (Torras and Boyce, 1998, Ravallion et al. 2000, Borghesi 2006, Grunewald et al., 2017). These divergent conclusions lead us to believe that the impact of income inequalities on the environment is not linear and depends on other factors, including the country's average income level, governance, and the nature of the political system, among other. Moreover, prior studies, use simple econometric estimations approaches such as OLS or FE estimation techniques (see, Table 1) that do not account for the short-term relationship between economic growth, income inequality and environment quality. Therefore, we use a multilevel co-integration panel technique that allows short-and long-run relationships among these variables.

Table 1. Summary of the existing literature on environment-growth-inequality nexus

Authors	Periods	Geographic region	Methodology	Conclusion on the relationship between income inequality and environmental indicator
Torraset al. (2011)	1961-2000	180 countries	OLS	(-)
Scruggs (1998)	1980	17 OECD countries	OLS	(+)
Heerinket al. (2001)	1985	64 countries	OLS	(-)
Clément et Meunié (2010)	1988-2003	83 developing and transition economies	Fixed effect (FE)	Dependent on environmental indicator used
Torras and Boyce (1998)	1977-1991	18-52 cities / 19-42 countries	OLS	+ (low income) - (high income)
Magnani(2000)	1980-1991	19 OECD countries	Random effect (RE), Fixed effect (FE) and pooled cross section (PCS)	(-)
Bimonte (2002)	1996	24 European countries	OLS	NS
Vona and Patriarca(2011)	1980-2000	OECD countries	Fixed effect (FE) and Random effect (RE)	(-)
Mikkelson et al. (2007)	1966-2005	45 American states	OLS	(+)
Ravallion et al. (2000)	1975-1992	42 countries	OLS and FE	(+)
Borghesi (2006)	1988-1995	37 countries	OLS, FE, RE	(-)
Grunewald et al. (2017)	1980-2008	158 countries	Group fixed effects	(+) rich countries (-) poor countries
Baek & Gweisah (2013)	1967-2008	United States	Auto Regressive Distributed Lag (ARDL)	(+)

3. Data and modeling approach

3.1. Data

Our unbalanced panel data covers the period 1980—2012 for 11 Mediterranean countries, namely, Algeria, Cyprus, Egypt, France, Greece, Italy, Lebanon, Morocco, Spain, Tunisia, and Turkey (242 observations). The choice of these countries depends on the availability of income inequality data.

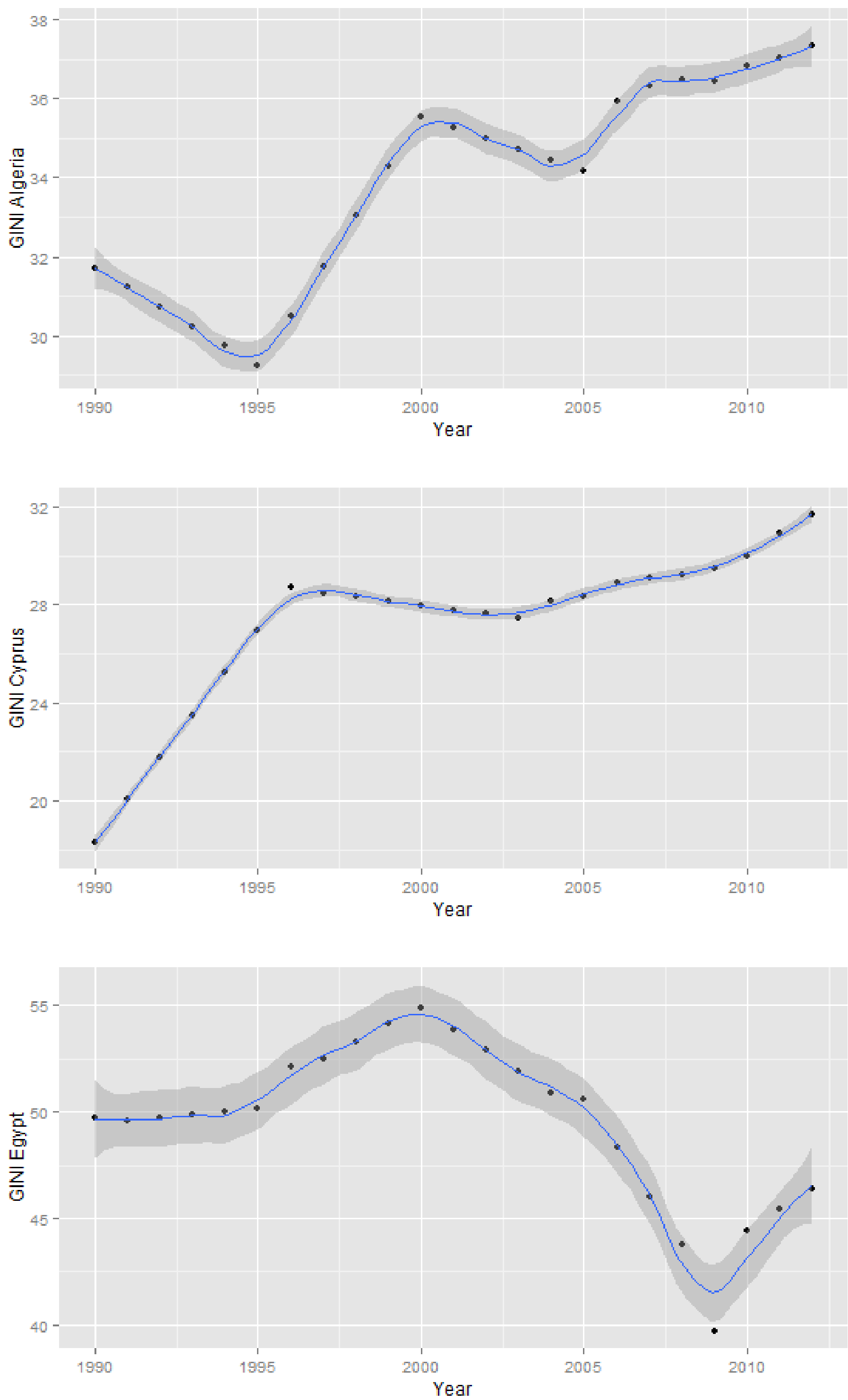
The variables used in the model include global CO_2 emissions per capita, income inequality (GINI index), GDP per capita and other control variables (urban population (UPOP), political rights (POL) and civil rights (CIVIL)). Data concerning CO_2, GDP and other control variables are extracted from the World Bank Development Indicators online database. Income inequality data are extracted from the latest version of the Standardized World Income Inequality Database (SWIID) (Solt, 2016). Figure 2 provides the distribution of income inequality in the selected countries. The rationale for using CO_2 emissions is because CO_2 emissions are the main contributor to climate change. In addition, data concerning CO_2 emissions is available for all countries.

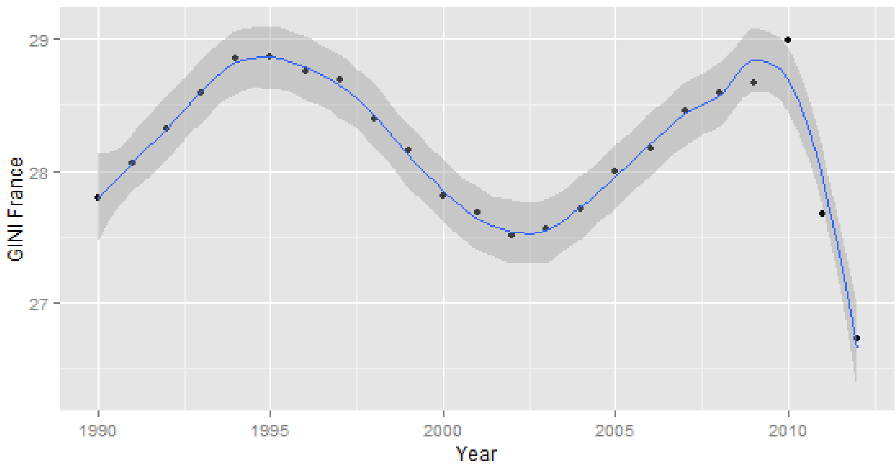
The model proposed in this research extends an EKC to allow for an income inequality effect. To approximate a possibly nonlinear function in GDP per capita and GINI index, we propose the following quadratic long–run function:

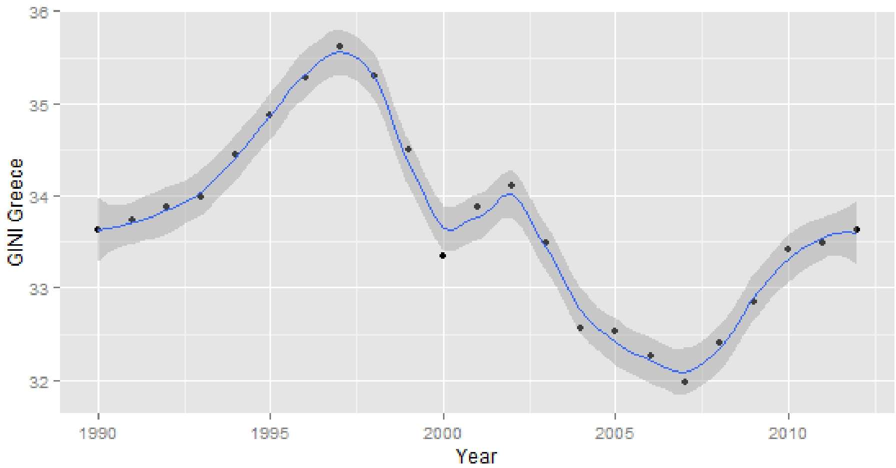
$$Log\ \mathrm{CO}_{2it} = \alpha_{it} + \beta_1 \log GDP_{it} + \beta_2 \log {GDP^2}_{it} + \beta_3 \log GINI_{it} + \beta_4\ log\ {GINI^2}_{it} + \beta_5\ log\ GDP_{it} * \log GINI_{it} + \beta_5 \log UPOP + \beta_6 \log CIVIL + \beta_7 \log POL + \varepsilon_{it} \quad (1)$$

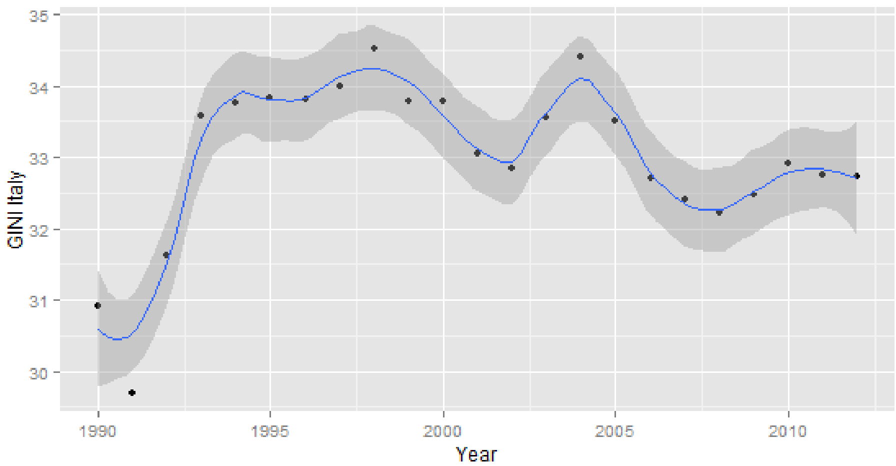
where CO_2, GDP, GDP^2, GINI, $GINI^2$, UPOP, CIVIL, POL denote CO_2 emissions per capita, GDP per capita, square of GDP per capita, income inequality index, square of income inequality index, urban population, civil and political rights, respectively. ε is the error term. The subscript i refers to countries and t denotes the year. The interaction effect between GDP and GINI index allows both the shape and the level of the relationship between CO_2 emissions per capita and income inequality to depend on the value of GDP per capita.

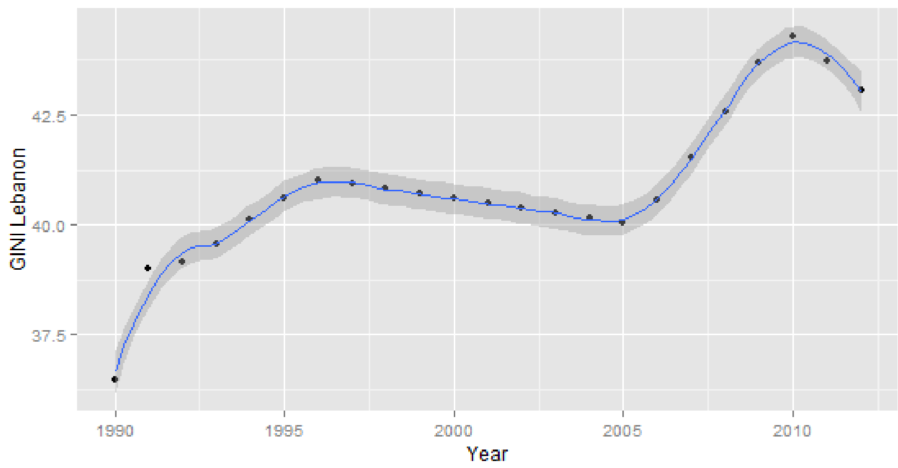
Figure 2. Income inequality distribution

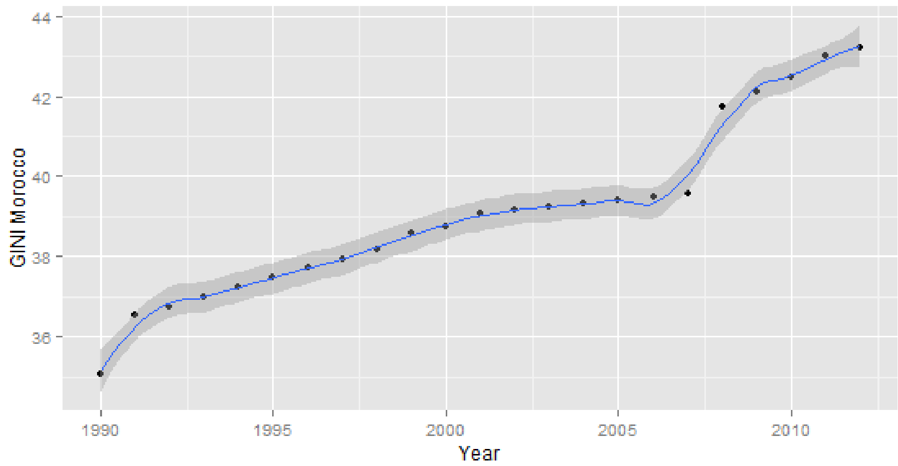


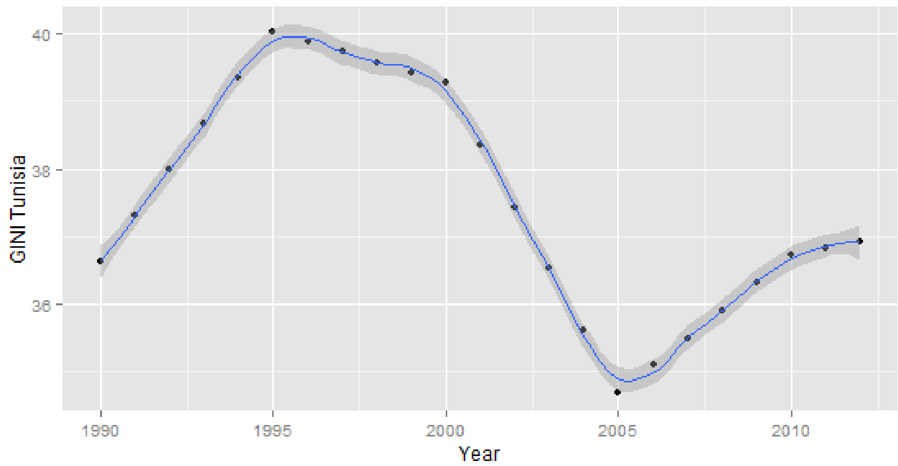

GINI France
29
28
27
1990
1995
2000
2005
2010
Year

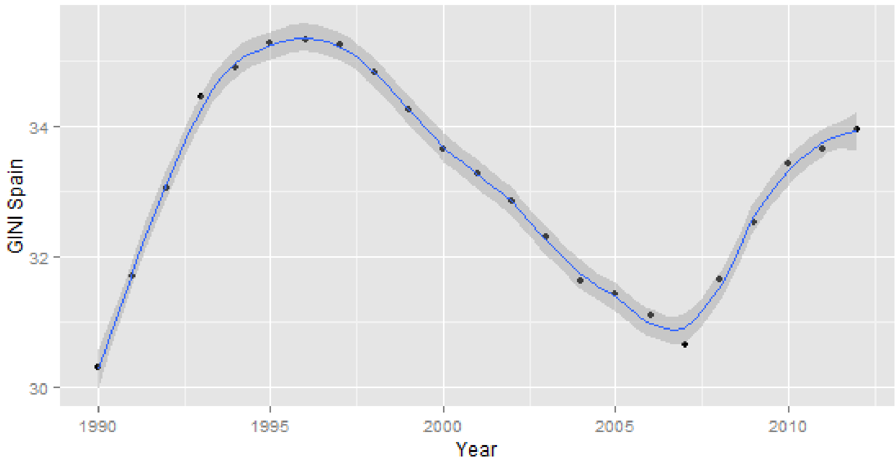

GINI Greece
36
35
34
33
32
1990
1995
2000
2005
2010
Year

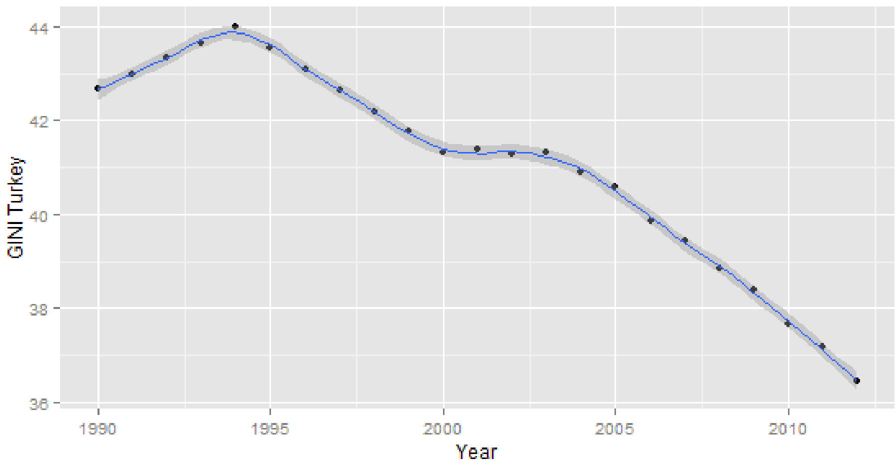

GINI Italy
35
34
33
32
31
30
1990
1995
2000
2005
2010
Year


GINI Lebanon
42.5
40.0
37.5
1990
1995
2000
2005
2010
Year


GINI Morocco
44
42
40
38
36
1990
1995
2000
2005
2010
Year


GINI Tunisia
40
38
36
1990
1995
2000
2005
2010
Year





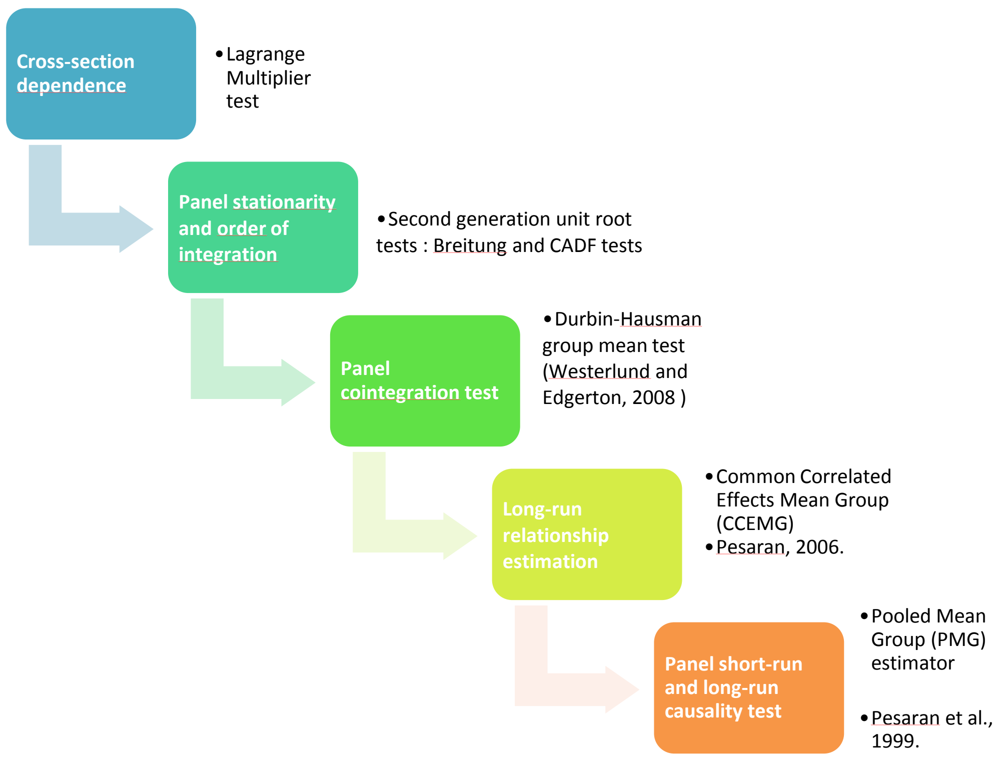
3.2. Empirical approach and model estimation strategies

The objective of this paper is to show that there is a nonlinear relationship between the Gini index and CO_2 emissions, and that the impact of income inequalities on CO_2 emissions largely depends on the level of development of the country. In addition, we explore the short and long-term relationship between income inequalities and CO_2 emissions.

The analysis is based on panel data between 1990 and 2012. By definition, panel data take into account the observable heterogeneities through the various explanatory variables, but above all, allow us to take into account the unobservable heterogeneities.

As for the empirical strategy, we firstly test the cross-section dependence using Pesaran's (2004) cross-sectional dependence test to decide which unit root test would be appropriate. Secondly, we use second generation unit root tests to check whether each variable of interest is stationary. Thirdly, we use the recently developed Durbin Hausman group mean cointegration test (Westerlund and Edgerton, 2008) to study the long-run equilibrium process. Fourthly, we employ the Common Correlated Effects Mean Group (CCEMG) estimator, proposed by Pesaran (2007), to estimate the long-run estimators that account for cross-sectional dependence. Finally, we apply the Pooled Mean Group (PMG) estimator proposed by Pesaran et al. (1999) to identify the sources of causality and distinguish between short-run and long-run relationships. To explore the dynamics of the relationships between both CO_2 emissions, GINI index, and GDP the following steps are performed. The steps of the model are summarized in Figure 3.

Figure 3. Modeling approach steps.



3.2.1. Testing cross section dependence

One important issue in a panel causality analysis is to take into account possible cross-section dependence across countries. First, the cross-section dependence is tested to decide which unit root test would be appropriate. We use the Lagrange Multiplier test

(LM) developed by Breusch and Pagan (1980). This test is favorable for large time dimension, i.e. if T (time period) is larger than N (number of sections) (Demetrescu and Homm, 2016). Pesaran's (2004) cross-sectional dependence (CD) test is more consistent when T is lower than N and can be used with balanced and unbalanced panels. A growing body of the panel-data literature concludes that panel-data models are likely to exhibit substantial cross-sectional dependence in the errors (De Hoyos and Sarafidis, 2006; Bélaïd and Youssef, 2017).Cross-correlations of errors could be due to omitted common effects, spatial effects, or could arise due to the presence of common shocks and unobserved components that ultimately become part of the error term (Pesaran, 2004).

The presence of some form of cross-sectional correlation of errors in panel data is likely to be the rule rather than the exception. According to De Hoyos and Sarafidis (2006), one reason for this result may be that during the last few decades we have experienced an ever-increasing economic and financial integration of countries and financial entities, which implies strong interdependencies between cross-sectional units. This is because high degree of economic and financial integrations makes one country more sensitive to the economic shocks in other countries.

However, ignoring cross-sectional dependence of errors can have serious consequences as it may affect the first-order properties (unbiasedness and consistency) of standard panel estimators and leads to incorrect statistical inferences. The decrease in estimation efficiency can be so large to the point that pooled (panel) least-squares estimators provide little gain over the single-equation ordinary least squares (Phillips and Sul, 2003).

3.2.2. Panel unit root tests

As a first step, it is necessary to check the stationarity of variables of interest. Since the seminal works of Levin and Lin (1992) and Quah (1994), the investigation of integrated series in panel data has known a great development and panel unit root tests have been applied to various fields of research. It is common practice in the literature to perform several panel unit root tests, given the shortcomings of any single test with regard to sample size and power properties. A number of panel unit root tests have been developed in the literature (e.g., Levin and Lin, 1992; Im, Pesaran and Shin, 1997; Harris and Tzavalis, 1999; Maddala and Wu, 1999; Pesaran, 2007).

Two generations of tests can be distinguished. The first is based on the cross-sectional independency hypothesis and includes the contributions of Maddala and Wu (1999), Choi (2001), and Hadri (2000). Various tests have been proposed in response to the need for panel unit root tests that relax the cross-sectional independence assumption and allows for cross-sectional dependence. The second generation includes the contributions of Bai and Ng (2004), Moon and Perron (2004), Smith et al. (2004) and Pesaran (2007). This last category of tests is still under development, given the diversity of the potential cross-sectional correlations.

In the presence of cross-section dependence, "first generation" panel unit root tests tend to reject the null hypothesis of a unit root excessively. Hence we propose two different panel unit root tests, namely, the Breitung test (Breitung, 2001; Breitung and Das, 2005) that assumes homogeneity among each cross-section, and a more recent CADF (Covariate Augmented Dickey-Fuller) test suggested by Pesaran (2007).

3.2.3. Panel cointegration tests

The next step consists in applying the cointegration test. When series are integrated of the same order, we can proceed to test for the presence of cointegration, i.e., whether there is a long-run relationship between the variables. Consequently, panel cointegration test can be used to study the long-run equilibrium process. For this purpose we use the Durbin Hausman group mean cointegration test developed by Westerlund and Edgerton (2008). This test allows for cross-sectional dependence and it does not rely heavily on a priori knowledge regarding the integration orders of the variables which allows the stability ranks of the independent variables to be different. Thus, it can be applied under very general conditions.

3.2.4. Short-run and long-run dynamic estimates

Given the existence of a cointegration relationship, the next step is to estimate the short-run and long-run dynamics. Therefore, we implement the PMG estimator proposed by Pesaran et al. (1997) that deals with the cross-sectional dependence of the error processes. The PMG estimator (see, Pesaran et al., 1997) relies on a combination of pooling and averaging of coefficients. This particular estimator allows us to deal with an important problem in empirical panel studies, parameter heterogeneity.

The main advantage of PMG is that it allows short-run coefficients, including the intercepts, the speed of adjustment to the long-run equilibrium values, and error variances to be heterogeneous country by country, while the long-run slope coefficients are restricted to be homogeneous across countries. In addition, the PMG estimation technique is robust to outliers and the choice of lag orders.

The basic PMG estimator involves estimating an autoregressive dynamic distributive lag (ARDL) model of order (p_i, q_i). In this case, the ARDL dynamic panel specified as follows:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}^{*} X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{2}$$

where $X_{it}(k * 1)$ is the vector of explanatory variables; μ_i represents the fixed effects (group specific-effect); λ_{ij} are scalars; and δ_{ij}^{*} are $(k * 1)$ coefficient vectors. It is convenient to work with this following re-parameterization (see, Pesaran et al., 1997) of Equation (2):

$$\Delta y_{it} = \varphi_i\left(y_{i,t-1} + \theta_i' X_{it}\right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta y_{i,t-1} + \sum_{j=0}^{p-1} \delta_{ij}'^{*} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{3}$$

where

$$\varphi_i = -\left(-\sum_{j=1}^{p} \lambda_{ij}\right)$$

$$\theta_i = \sum_{j=0}^{q} \delta_{ij} \Big/ \left(1 - \sum_k \lambda_{ik}\right)$$

$$\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{i,m} \; ; j = 1, 2, \ldots, p-1$$

$$\delta_{ij}'^{*} = \sum_{m=j+1}^{q} \delta_{i,m} \; ; j = 1, 2, \ldots, q-1$$

φ_i represents the error-correction speed adjustment term. The long run equilibrium relationship can be tested statistically using the significance of φ_i. If the null hypothesis $\varphi_i = 0$ then there would be evidence of long-run equilibrium, i.e. the variables are cointegrated and there is evidence of long run causality running from independent variables to the dependent variable. The direction of short-run causality can be determined by testing the significance of the coefficients of each explanatory variable, that is, $\delta_{ij}^{\prime *} = 0$ in Equation (3).

In our case, we can specify Equation (4) in terms of variables in Equation (1) as follows

$$\Delta \mathrm{LnCO}_{2it_{it}} = \varphi_i\left(y_{i,t-1} + \theta_i^{\prime} X_{it}\right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*}\, \Delta\mathrm{LnCO}_{2i,t-1} + \sum_{j=0}^{p-1} \delta_{ij}^{\prime *} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (4)$$

where X is the vector of explanatory variables. It contains GDP, GDP^2, GINI, $GINI^2$, UPOP, CIVIL and POP. In the same way we can specify equation for other variables.

4. Results

4.1. Cross dependence tests

To test for cross-sectional dependency, we use the LM test of Breusch and Pagan (1980). The Breusch and Pagan test statistic is asymptotically distributed as Chi-squared with $N\ (N-1)/2$ degree of freedom, under the null hypothesis of cross-sectional independence. The results provided in Table 2 reject the null hypothesis of no cross-sectional dependency across the countries at the 1% significance level. This finding implies that a shock occurred in one of these Mediterranean countries seems to be transmitted to other countries. Therefore, a unit root test that allows for cross-sectional dependence is required.

Table 2. Correlation matrix of residual and LM test result

	__e1	__e2	__e3	__e4	__e5	__e6	__e7	__e8	__e9	__e10	__e11
__e1	1.000										
__e2	0.205	1.000									
__e3	-0.162	-0.212	1.000								
__e4	0.207	0.372	-0.679	1.000							
__e5	0.291	0.444	-0.673	0.775	1.000						
__e6	-0.072	0.333	-0.399	0.831	0.702	1.000					
__e7	0.202	0.377	-0.019	0.076	0.378	0.053	1.000				
__e8	-0.195	-0.380	0.760	-0.884	-0.782	-0.682	-0.114	1.000			
__e9	-0.298	0.357	-0.127	0.558	0.454	0.852	0.062	-0.340	1.000		
__e10	0.288	0.394	-0.747	0.715	0.783	0.490	0.038	-0.797	0.140	1.000	
__e11	-0.313	-0.401	0.657	-0.744	-0.944	-0.664	-0.288	0.695	-0.434	-0.779	1.000

Breusch-Pagan LM test of independence: chi2(55) = 341.795, Pr = 0.0000
Based on 23 complete observations over panel units

4.2. Stochastic properties of the series: Unit-root tests

To examine the stochastic properties of the six series (unit roots and stationarity), we apply the Pesaran CADF and Breitung tests (see, Table 3).

Table 3. Panel unit root test

Method	PCO_2	GDP	GINI	CIVIL	URPOP	POL
Breitung						
Level	1.2039 (0.8857)	2.6454 (0.9999)	1.5185 (0.9555)	-1.8816 (0.1235)	6.4866 (1.0000)	-1.3844 (0.1109)
First difference	-7.4028 (0.0000)***	-1.4813 (0.0421)**	-3.3221 (0.0004)***	-3.6758 (0.0001)***	-4.4574 (0.0000)***	-5.8963 (0.0000)***
Pesaran						
Level	2.402 (0.992)	-0.428 (0.334)	2.260 (0.999)	-2.636 (0.098)	-0.650 (0.258)	3.295 (1.0000)
First difference	-4.512 (0.0000)***	-3.307 (0.0000)***	-3.307 (0.0000)***	-4.640 (0.0000)***	-1.903 (0.0229)**	1.518 (0.0710)*

*Notes: The lambda-statistics and the standardized Zt-bars are reported for the Breitung (2001) and Pesaran (2007) unit root tests, respectively; p-values in parentheses; the null hypothesis for all tests is "Panels contain unit roots". ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

Once we have found the presence of dependence in the variables, we study their order of integration using different tests that account for dependence. All are from the "second generation" panel unit root tests. These tests relax the restrictive assumption of cross-sectional independence. First, we apply Pesaran's CADF test (Cross Augmented Dickey Fuller). To eliminate the cross-dependence, the standard DF regressions are augmented with cross-sectional averages of lagged levels and first differences of the individual series. The proposed test has the advantage of being relatively robust with respect to cross-sectional dependence, even if the autoregressive parameter is high. In addition, the approach is intuitive and simple to implement. It is also valid for panels where N and T are of the same orders of magnitude. Second, we also apply Breitung test, a suitable approach when cross-correlation is pervasive, as in this case. The Breitung test assumes that the error term ε_{it} is uncorrelated across both i and t. Breitung test adjusts the data before fitting a regression model so that bias adjustments are not needed. In addition, the Breitung procedure allows for a prewhitening of the series before computing the test. The null hypothesis of these unit root tests is that all series contain a unit root.

4.3. Cointegration tests

Given that each of the variables presents a panel unit root, we employ the error correction based cointegration test for (unbalanced) panels developed by Westerlund (2007) to examine the long-run equilibrium relationships among the variables. The existence of negative error correction term is taken as proof for cointegration. To accommodate cross-sectional dependence, critical values are obtained through bootstrapping.

The test is meaningful in our case for the following reasons; First, it is general enough to allow for a large degree of heterogeneity, both in the long-run cointegration relation and in the short-run dynamics (Persyn and Westerlund, 2008). Second, it is developed to cope with cross-sectionally dependent data. Third, the test comes along with an optional bootstrap procedure that allows for multiple repetitions of the cointegration tests which is meaningful since we have indications for cointegration in the panel. While, the group-mean tests (Gt and Ga) examine the alternative hypothesis that at least one unit is cointegrated, the panel tests (Pt and Pa) examine the alternative hypothesis that the panel is cointegrated as a whole (Persyn and Westerlund, 2008).

Table 4. Westerlund cointegration test

Statistic	Value	Z-value	P-value	Robust P-value
Group-t	-3.529	-4.558	0.000	0.000***
Group-a	-8.622	1.105	0.866	0.200
Panel-t	-11.050	-4.428	0.000	0.000***
Panel-a	-10.121	-1.346	0.089	0.010***

*Notes: ***and ** indicate the test statistics are significant at 1% and 5% levels, respectively. Following Westerlund (2007), the maximum lag length is selected according to $4(T/100)^{2/9}$. See Persyn and Westerlund (2008) for the details.*

The results in Table 4 of Wasterland's test shows that Groupe-t and Panel-a test statistics are significant and reject the null hypothesis of no cointegration.

4.4. Short-run and long-run dynamic estimates

We employ the PMG methodology introduced by Pesaran et al. (1999) to examine the long-run and short-run dynamic relationships. The Hausman test allows discriminating among different levels of heterogeneity (Baltagi et al., 2000). Under the null hypothesis of the Hausman test, the PMG estimator is efficient and preferred over MG model. We report estimates of our panel error correction model with heterogeneous slopes in Table 5. The PMG results presented as two-equation model: the normalized long-run cointegrating vector and the short-run dynamic estimates.

As for the long-run vector, error correction term coefficient is negative and statistically significant. The ECT term is equal to —0.411, meaning that the deviation from the long-term path of per capita CO_2 emissions is corrected by 41% in each period. Thus, following shock to the system it takes about two years for per capita CO_2 emissions in Mediterranean countries to get back to the level predicted by its cointegration relationship.

Table 5. Panel error correction model with heterogeneous slopes: normalized long-run cointegrating vector and the short-run dynamic coefficients

Independent variable: CO_2	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Long-run						
LGDPP	1.956	0.387	5.05	0.000***	1.197	2.714
Y2	-0.176	0.030	-5.85	0.000***	-0.236	-0.117
LGINI	-1.837	0.332	-5.53	0.000***	-2.488	-1.187
LGINI2	0.447	0.243	1.84	0.066*	-0.029	0.923
GINI*GDP	0.097	0.184	0.52	0.600	-0.264	0.458
LUPOP	-0.475	0.096	-4.95	0.000***	-0.663	-0.287
CIVIL	0.029	0.006	4.86	0.000***	0.017	0.040
POL	-0.011	0.002	-6.39	0.000***	-0.014	-0.007
Short-run error Correction Model						
ECT	-0.411	0.161	-2.56	0.010***	-0.725	-0.096
Δ LGDPP	-0.374	0.422	-0.89	0.375	-1.201	0.453
Δ LGDPP^2	0.144	0.068	2.12	0.034**	0.011	0.278
Δ LGINI	0.685	0.313	2.19	0.029**	0.071	1.298
Δ LGINI^2	-0.140	0.255	-0.55	0.584	-0.640	0.361
Δ LGINI* Δ GDP	-0.266	0.298	-0.89	0.371	-0.850	0.317
Δ LUPOP	0.371	0.442	0.84	0.402	-0.496	1.238
Δ CIVIL	-0.019	0.008	-2.41	0.016**	-0.035	-0.004
V POL	0.012	0.006	1.90	0.050**	0.000	0.024
Constant	0.024	0.028	0.86	0.391	-0.030	0.078

*Note. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. ECT corresponds to the error correction term*

According to Table 5, the coefficient of the Gini index shows a negative sign on the long-run, meaning that an increase in income inequalities leads to a decrease in CO_2 emissions. This result is consistent with the findings of Scruggs (1998), Ravallion et al. (2000) and Heerink et al. (2001). However, on the short run, an increase in income inequality leads to an increase in CO_2 emissions. This finding is consistent with that of Boyce (1994) and Magnani (2000).

The non-linearity hypothesis is valid on the long-run. The second derivative is negative, meaning that the non-linearity takes the shape of an inverted U-shaped curve. In other words, we have two extreme situations, with a maximum. CO_2 emissions increase with income inequalities and then decrease after a certain threshold of income inequalities.

We can say that by reducing income inequality in countries with a relatively high Gini index, CO_2 emissions would follow an upward trend. This finding is consistent with the results of Scruggs (1998), Ravallion et al. (2000) and Heerink et al. (2001), who argue that income inequality has a negative effect on environmental degradation. In other words, an increase in the level of income inequality results in an improvement in the quality of the environment. Indeed, the increase in inequalities translates into a concentration of wealth among the rich, whose economic behavior generates less environmental pressure.

On the other hand, in countries with a relatively low Gini index, the reduction of income inequality is associated with a reduction in CO_2 emissions, and vice versa. An increase in income inequality would harm environmental quality. This is in line with Boyce's analysis (1994). According to this author, when income inequalities are low, the relative power of the rich (who have no interest in preserving the environment) decreases, leaving more room for the median voters who care about the environment. Magnani (2000) also comes to the same conclusion by saying that in countries with low levels of income inequalities, the government is more interested in environmental policies than in policies to reduce inequalities.

To find if this non-linearity is due to the level of GDP in the country, we add an interaction term between GDP and the Gini index coefficient. This interaction term is not statistically significant, suggesting that this non-linearity is not caused by the level of GDP. It could be to other characteristics of the economy.

In the short-run, the non-linearity hypothesis is not valid. Similarly, the interaction term is not statistically significant. However, the Gini index coefficient is positive, suggesting an increase of income inequalities in the short-run leads to an increase in CO_2 emissions.

5. Conclusions and policy implications

Based on recent advances on non-stationary heterogeneous panel literature — the Common Correlated Effects Mean Group and the pooled mean group estimator— this study examine the dynamic relationships between income inequalities, GDP and carbon emissions. PMG estimator allows for the short-run coefficients, intercept, and error variances to differ across the groups while they constrain the long-run coefficients to be equal across the groups.

This study uses the Westerlund's cointegration analysis technique to explore the long-run relationship between the variables. The empirical results broadly confirm the existence of the long-run equilibrium relationships among the variables. Therefore, inter-country income inequality has a significant impact on the mean emissions.

The results indicate a negative and significant association between income inequality and per capita carbon emissions in the long-run, which means that greater inequality could decrease environmental degradation. However, in the short-run, results reveal a positive and significant relationship between income inequality and CO_2 emissions.

In addition, we show that there is a concave relation between the Gini index and CO_2 emissions. Therefore, in both extreme cases of high or low income inequality, CO_2 emissions are low. In the first part of the curve, as income inequality increases, CO_2 emissions increase. This finding is consistent with that of Boyce (1994) and Magnani (2000). In the second part of the curve, an increase of the Gini index leads to a decrease in CO_2 emissions. This observation is consistent with that of Scruggs (1998), Ravallion et al. (2000) and Heerink et al. (2001).

Our results are consistent with the conclusions of Ravallion et al. (2000) and Heerink et al. (2001) in countries with high levels of inequalities. This might be explained by the fact that the majority of the population in countries with high income inequalities is considered out of the carbon economy. It has a limited access to electricity or other forms of modern energy. Therefore, the lower the average income levels of the country, the lower the aggregate CO_2 emissions.

In countries with low levels of income inequality, more equality results in less power inequality. In other words, the relative power of the rich decreases and it is the median voter who decides on public policy. Moreover, given that there is more equality, it is easier to reach a consensus on environmental public policies. We can therefore conclude that in countries with high levels of income inequalities, there is a trade-off between environmental policies and policies aiming to reduce inequalities. This finding is consistent with that of Magnani (2000) and Ravallion (2001). The trade-off could only be resolved when policies to reduce inequalities do not translate into an increase in CO_2 emissions. As a result, inequalities could be reduced without increasing CO_2 emissions and degrading the environment. In countries with low levels of income inequalities, this trade-off is absent.

The main contribution of the paper is to empirically investigate the inter-temporal links between income inequality, economic growth, and the environment quality, for 11 Mediterranean Countries based on recent advances on non-stationary heterogeneous panel literature. The findings of this analysis are unique to the Mediterranean countries due to the specific institutional and economic characteristics of the region. The results, however, must be interpreted with caution although the adopted methodology mainly provides consistent findings; the empirical results are highly dependent on the empirical approach and data quality.

References

Agras J., Chapman D. (1999), 'A dynamic approach to the Environmental Kuznets Curve hypothesis', *Ecological Economics*, 28(2), 267-277.

Baek J., Gweisah G. (2013), 'Does income inequality harm the environment? Empirical evidence from the United States', *Energy Policy*, 62, 1434–1437.

Bai J., Ng S. (2004), 'A PANIC attack on unit roots and cointegration', *Econometrica*, 72(4), 1127-1177.

Baldwin R. (1995), 'Does sustainability require growth?', in Goldin, I. and Winters, L.A. (eds.) *The economics of sustainable development*, Cambridge, Cambridge University Press, 19–46.

Baltagi B. H., Griffin J. M., Xiong W. (2000), 'To pool or not to pool: Homogeneous versus heterogeneous estimators applied to cigarette demand', *Review of Economics and Statistics*, 82(1), 117-126.

Bélaïd F., Youssef M. (2017), 'Environmental degradation, renewable and non-renewable electricity consumption, and economic growth: Assessing the evidence from Algeria', *Energy Policy*, 102, 277-287.

Berthe A., Elie L. (2015), 'Mechanisms explaining the impact of economic inequality on environmental deterioration', *Ecological Economics*, 116, 191-200.

Bimonte S. (2002), 'Information access, income distribution, and the environmental Kuznets curve', *Ecological Economics*, 41(1), 145-156.

Borghesi S. (2006), 'Income Inequality and the Environmental Kuznets Curve', in *Environment, Inequality and Collective Action*. Routledge.

Boyce J.K. (1994), 'Inequality as a cause of environmental degradation', *Ecological Economics*, 11(3), 169–178.

Breitung J. (2001), 'The local power of some unit root tests for panel data', in *Nonstationary panels, panel cointegration, and dynamic panels,* Emerald Group Publishing Limited, 161-177

Breitung J., Das S. (2005), 'Panel unit root tests under cross-sectional dependence', *Statistica Neerlandica*, 59(4), 414-433.

Breusch T. S., Pagan A. R. (1980), 'The Lagrange multiplier test and its applications to model specification in econometrics', *The Review of Economic Studies*, 47(1), 239-253.

Cho G., Li J. (2014), 'Environmental Kuznets Curve: Conclusive econometric evidence for CO2', *Pacific Economic Review*, 19(1), 1-7.

Choi I. (2001), 'Unit root tests for panel data', *Journal of international money and Finance*, 20(2), 249-272.

Clément M., Meunié A. (2010), 'Inégalités, développement et qualité de l'environnement: mécanismes et application empirique', *Mondes en développement*, 151(3), 67–82.

Cropper M., Griffiths C. (1994), 'The Interaction of Population Growth and Environmental Quality', *American Economic Review*, 84(2), 250-54.

De Hoyos R. E., Sarafidis V. (2006), 'Testing for cross-sectional dependence in panel-data models', *Stata Journal*, 6(4), 482.

Demetrescu M., Homm U. (2016), 'Directed Tests of No Cross-Sectional Correlation in Large-N Panel Data Models', *Journal of Applied Econometrics*, 31(1), 4-31.

Friedl B., Getzner M. (2003), 'Determinants of CO2 emissions in a small open economy', *Ecological economics*, 45(1), 133-148.

Galeotti M., Manera M., Lanza A. (2009), 'On the robustness of robustness checks of the environmental Kuznets curve hypothesis', *Environmental and Resource Economics*, 42(4), 551.

Grossman G., Krueger A. (1995), 'Economic growth and the environment', *The Quarterly Journal of Economics*, 110(2), 353–377.

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.

Hadri K. (2000), 'Testing for stationarity in heterogeneous panel data', *The Econometrics Journal*, 3(2), 148-161.

Harris R. D., Tzavalis E. (1999), 'Inference for unit roots in dynamic panels where the time dimension is fixed', *Journal of eEconometrics*, 91(2), 201-226.

Heerink N., Mulatu A., Bulte E. (2001), 'Income inequality and the environment: Aggregation bias in environmental Kuznets curves', *Ecological Economics*, 38(3), 359–367.

Heil M.T., Selden T. (2001), 'Carbon emissions and economic development: Future trajectories based on historical experience', *Environment and Development Economics*, 6(01), 63–83.

Holtz-Eakin D., Selden T.M. (1995), 'Stoking the fires? CO emissions and economic growth', *Journal of Public Economics*, 57(1), 85–101.

Im K. S., Pesaran M. H., Shin Y. (1997), 'Testing for Unit Roots in Heterogeneous Panels', *Working Paper*, 9526, University of Cambridge.

Inglehart R. (1981), 'Post-materialism in an environment of insecurity', *The American Political Science Review*, 75(4), 880–900.

Kaufmann R. K., Davidsdottir B., Garnham S., Pauly P. (1998), 'The determinants of atmospheric SO2 concentrations: Reconsidering the environmental Kuznets curve', *Ecological Economics*, 25(2), 209–220.

Levin A., Lin C. F. (1992), 'Unit root tests in panel data: asymptotic and finite-sample properties', *San Diego, mimeographed*, University of California.

Li Q., Reuveny R. (2006), 'Democracy and environmental degradation', *International Studies Quarterly*, 50(4), 935–956.

Maddala G. S., Wu S. (1999), '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.

Magnani E. (2000), 'The environmental Kuznets curve, environmental protection policy and income distribution', *Ecological Economics*, 32(3), 431–443.

Malanima P. (2013), 'When did England overtake Italy? Medieval and early modern divergence in prices and wages', *European Review of Economic History*, 17(1), 45-70.

Mikkelson G. M., Gonzalez A., Peterson G. D. (2007), 'Economic inequality predicts biodiversity loss', *PloS one*, 2(5), e444.

Milbrath L.W. (1984), *Environmentalists: Vanguard for a new society*, edited by Barbara V. Fisher, United States, SUNY Press.

Moon H. R., Perron, B. (2004), 'Testing for a unit root in panels with dynamic factors', *Journal of Econometrics*, 122(1), 81-126.

Panayotou, T. (1993), 'Empirical tests and policy analysis of environmental degradation at different stages of economic development', *ILO Working Papers*, 992927783402676, International Labour Organization.

Persyn D., Westerlund J. (2008), 'Error-correction-based cointegration tests for panel data', *Stata Journal*, 8(2), 232-241.

Pesaran M. H. (2004), *General diagnostic tests for cross section dependence in panels*.

Pesaran M. H. (2007), 'A simple panel unit root test in the presence of cross-section dependence', *Journal of Applied Econometrics*, 22(2), 265-312.

Pesaran M. H., Shin Y., Smith R. P. (1999), 'Pooled mean group estimation of dynamic heterogeneous panels', *Journal of the American Statistical Association*, 94(446), 621-634.

Phillips P. C., Sul D. (2003), 'Dynamic panel estimation and homogeneity testing under cross section dependence', *The Econometrics Journal*, 6(1), 217-259.

Quah D. (1994), 'Exploiting cross-section variation for unit root inference in dynamic data', *Economics letters*, 44(1-2), 9-19.

Ravallion M. (2001), 'Growth, inequality and poverty: looking beyond averages', *World Development*, 29(11), 1803-1815.

Ravallion M., Heil M., Jalan J. (2000), 'Carbon emissions and income inequality', *Oxford Economic Papers*, 52(4), 651–669.

Richmond A. K., Kaufmann R. K. (2006), 'Is there a turning point in the relationship between income and energy use and/or carbon emissions?', *Ecological Economics*, 56(2), 176-189.

Scruggs L. A. (1998), 'Political and economic inequality and the environment', *Ecological Economics*, 26(3), 259–275.

Selden T., Song D. (1994), 'Environmental quality and development: Is there a Kuznets curve for air pollution emissions?', *Journal of Environmental Economics and Management*, 27(2), 147–162.

Shafik N. (1994), 'Economic development and environmental quality: An econometric analysis', *Oxford Economic Papers*, 46, 757–773.

Smith L. V., Leybourne S., Kim T. H., Newbold P. (2004), 'More powerful panel data unit root tests with an application to mean reversion in real exchange rates', *Journal of Applied Econometrics*, 19(2), 147-170.

Solt F. (2016), 'The standardized world income inequality database', *Social science quarterly*, 97(5), 1267-1281.

Suri V., Chapman D. (1998), 'Economic growth, trade and energy: implications for the environmental Kuznets curve', *Ecological Economics*, 25(2), 195–208.

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

Torras M., Moskalev S. A., Hazy J. K., Ashley A. S. (2011), 'An econometric analysis of ecological footprint determinants: implications for sustainability', *International Journal of Sustainable Society*, 3(3), 258-275.

Unruh G. C., Moomaw W. R. (1998), 'An alternative analysis of apparent EKC-type transitions', *Ecological Economics*, 25(2), 221–229.

Vona F., Patriarca F. (2011), 'Income inequality and the development of environmental technologies', *Ecological Economics*, 70(11), 2201-2213.

Westerlund J. (2007), 'Testing for error correction in panel data', *Oxford Bulletin of Economics and statistics*, 69(6), 709-748.

Westerlund J., Edgerton D. L. (2008), 'A simple test for cointegration in dependent panels with structural breaks', *Oxford Bulletin of Economics and Statistics*, 70(5), 665-704.