Effects of Export Concentration on CO_2 Emissions in Developed Countries: An Empirical Analysis

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Abstract

This paper is the first to provide evidence on the short- and the long-run effects of the export product concentration on the level of CO_2 emissions in 19 developed (high-income) economies, spanning the period 1962−2010. To this end, the paper makes use of the nonlinear panel unit root and cointegration tests with multiple endogenous structural breaks. It also considers the mean group estimations, the autoregressive distributed lag model, and the panel quantile regression estimations. The findings illustrate that the environmental Kuznets curve (EKC) hypothesis is valid in the panel dataset of 19 developed economies. In addition, it documents that a higher level of the product concentration of exports leads to lower CO_2 emissions. The results from the panel quantile regressions also indicate that the effect of the export product concentration upon the per capita CO_2 emissions is relatively high at the higher quantiles.

Keywords: environmental Kuznets curve hypothesis; carbon emissions; export product concentration; panel cointegration; panel quantile regression

JEL Classification: Q53; Q56; O13; C33

1. Introduction

Nowadays, one of the most important issues the humanity must cope with is the phenomenon of "global warming", while countries attempt to establish agreements and a general consensus to overcome it. The global warming issue is mostly related to environmental degradation; as a result, global economies have attempted to provide certain solutions via environmental agreements, e.g. the Paris Agreement in 2015 United Nations Climate Change Conference. According to the Paris Agreement, global economies plan to meet at regular intervals, while sharing the evaluations of carbon emissions for restricting environmental degradation. In the light of this improvement, our paper focuses on the effects of the concentration of the export product basket on carbon emissions as a potential determinant of the environmental degradation using the panel dataset of 19 developed countries for the period from 1962 to 2010. To the best of our knowledge, this paper is the first to analyze the effect of export product concentration on environmental degradation.

Grossman and Krueger's studies (1991 and 1995) have had a huge impact on the rise of the revived interest in environmental issues. Following these studies, research has focused on the link between per capita income and environmental degradation (Apergis and Payne, 2009; Narayan and Narayan, 2010; among many others). These studies analyze the issue of environmental degradation in the context of the Environmental Kuznets Curve (EKC) hypothesis, proposed by Grossman and Krueger (1991 and 1995). According to the EKC hypothesis, environmental degradation increases at the early stage of economic development, and when the income per capita reaches a certain level (i.e. the upper-middle income level), environmental degradation begins to decrease (Onafowora and Owoye, 2014). This phenomenon occurs because global economies plan to basically generate business and employment opportunities, rather than to support the environmental quality at the first stages of development. However, environmental awareness increases as income also increase, which makes it the fundamental reason for the reduction of environmental degradation in later stages of economic development (Yang et al., 2015). Additionally, at these stages, manufacturers use cleaner technologies to get away from the factors that contributed to air pollution during the production process. Moreover, high-income countries tend to limit those manufacturing products that cause pollution (Can and Gozgor, 2017).

Scholars have attempted to test the validity of the EKC hypothesis in different country samples in the literature, but these studies have heavily focused on developing countries. By contrast, there are a limited number of papers that explores environmental degradation in the context of the EKC hypothesis in developed countries (Ajmi et al., 2015; Al-Mulali and Ozturk, 2016; Ang, 2007; Apergis et al., 2016; Bento and Moutinho, 2016; Bilgili et al., 2016; He and Richards, 2010; Iwata et al., 2010; Jebli et al., 2016; Wang et al., 2015). In the majority of these studies, research aims to control the effects of different indicators within the EKC hypothesis, while the variables of employment, financial development, foreign direct investment (FDI), gross fixed capital formation, health expenditures, population density, tourism arrivals, trade openness, and urbanization, are among the controls. At this point, within the EKC literature, the most popular control variable is the international trade, i.e. the trade openness (Gozgor, 2017). This is due to the evidence that while low carbon dioxide emissions are closely related to imports of industrial products, high carbon dioxide emissions are also correlated with exports of industrial products (Song et al., 2008). However, the literature on international trade has recently realized the importance of export basket product concentration (or diversification) instead of the volume of international trade (trade openness) (Aditya and Acharyya, 2013; Agosin et al., 2012; Gozgor and Can, 2016a and 2017a; Hausmann et al., 2007; Rodrik, 2006). However, our knowledge on the effect of these new variables on environmental degradation is very limited, and there is only a single study that analyzes the environmental degradation issue within export diversification as a new indicator of international trade (Gozgor and Can, 2016b). In their empirical study, Gozgor and Can (2016b) analyze the effects of export product diversification on carbon emissions within the EKC for the period from 1971 to 2010. However, Gozgor and Can (2016b) focus on a single (developing) country, i.e. Turkey. Their empirical model also controls for income and energy consumption and the findings illustrate that export basket diversification leads to higher levels of carbon emissions in the Turkish economy. Our paper develops the findings of Gozgor and Can (2016b) in two ways: First, our paper focuses on the panel dataset of 19 countries instead of a single country case using a comprehensive set of econometric methodology. Second, our paper examines the case of high-income countries instead of the developing country.

It is important to note that changes in the export product basket have two stages, with the first stage being the export basket diversification. More specifically, the export baskets of the least developed and developing countries consist of limited and traditional products (Gozgor and Can, 2017b), but the export baskets of these countries can be diversified only up to a turning point (Dennis and Shepherd, 2011). This turning point has been calculated to be $22,500 by Klinger and Lederman (2006), while it has been equal to $25,000 by Cadot et al. (2011). Beyond this turning point, countries proceed to the second stage, i.e. the "export concentration" stage. In other words, high-income countries do not manufacture every product, while they only focus on more complicated and knowledge-intensive products (Can and Gozgor, 2017). Therefore, it is suggested that there is an *inverted-U* relationship between the diversification of exports and the per capita income (Imbs and Wacziarg, 2003), implying that product diversification in the export basket increases by income growth, while diversification is replaced by concentration after a certain turning point. This issue also involves a process that possibly affects environmental degradation across countries (Apergis et al., 2013), since countries limit the manufacturing products that increase environmental pollutions within the concentration stage. Within this context, it should be expected a significant decrease in carbon emissions in countries within the concentration stage. Therefore, this paper focuses on the effects of the second stage in the case of the export product basket, i.e. the "export concentration" on environmental degradation (carbon emissions).

To the best of our knowledge, this paper is the first to analyze the effect of export product concentration on environmental degradation within the context of the EKC hypothesis. The analysis employs a sample of 19 developed countries, spanning the period 1962 to 2010; this particular period comprises the calculated income levels by Cadot et al. (2011) and Klinger and Lederman (2006) as a turning point to the concentration stage. The analysis in our paper illustrates that the EKC hypothesis is valid in the panel dataset of 19 developed economies, while a higher product concentration of exports leads to a lower carbon emission.

The remaining of the paper is organized as follows. Section 2 describes the data used, the empirical model, and methodological issues. Section 3 provides the empirical results and discusses the implications. Finally, Section 4 concludes.

2. Data, Empirical Model and Econometric Methodology

2.1. Data and Empirical Model

The analysis makes use of data from 19 high-income countries[1] for the period from 1962 to 2010. The data for the export product diversification index, used as a proxy for export product concentration, were obtained from the International Monetary Fund (IMF) database.

[1] Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom (UK), the United States (U.S.), and Uruguay.

The Theil index is the benchmark measure of a country's exports, with a higher value of the index implying higher export concentration. Thus, the negative association of the concentration of exports with carbon emissions implies that the relationship between them is negative.[2] Data on the real (constant $ price in 2005) GDP per capita, the squared real GDP per capita (constant $ price in 2005), and carbon emissions, measured in metric tons per capita over the same time span were obtained from the World Development Indicators (WDI) database, provided by the World Bank.[3] All data are transformed into natural logarithmic values, while the frequency of the data is annual. Finally, a summary of descriptive statistics is reported in Appendix I.

Our paper tests a hypothesis that export concentration may be a significant driver of the level of carbon emissions. Following the EKC approach, the empirical model can be constructed as follows:

$$C02_{it} = f(GDP_{it}^{\beta 1}, {GDP_{it}^{2}}^{\beta 2}, ECI_{it}^{\beta 3}) \tag{1}$$

The EKC approach in Equation (1) can be written in an empirical model in the natural logarithmic form as follows:

$$lnC02_{it} = \beta_0 + \beta_1 lnGDP_{it} + \beta_2 lnGDP_{it}^2 + \beta_3 lnECI_{it} + \mu_{it} \tag{2}$$

In Equations (1) and (2), $lnC02_{it}$ is the level of carbon emissions in the natural logarithmic form in country *i* at time *t*, $lnGDP_{it}$ and $lnGDP_{it}^2$ are the income level and the squared of the income level in the natural logarithmic form in country *i* at time *t*, $lnECI_{it}$ is the index of the export concentration in the natural logarithmic form in country *i* at time *t*. The error term is also represented by μ_{it}.

[2] See Papageorgiou and Spatafora (2012) for the technical details and the calculation methodology of the Theil index.
[3] Note that data on both variables are also expressed in per capita terms, by dividing the relevant variables with population; these data were also obtained from the WDI.

According to the EKC hypothesis, we should expect that β_1>0 and β_2<0, and their coefficients are needed to be statistically significant. Under these circumstances, there will be a valid EKC function in the countries, which means that there will be valid policy implications for the environmental degradation. The impact of the index of the export concentration (β_3) on carbon emissions should be negative. As we have discussed in the introduction and according to our empirical model, as a country's export basket develops, a lower level of carbon emissions will be produced in the advanced (high-income) economies.

2.2. Econometric Methodology

In the first step, the analysis checks out for the presence of stationary across all three variables, and chooses a nonlinear version of the unit root test as the literature indicated that the chosen variables may contain significant nonlinear components in the data generating process (DGP) (Apergis, 2016; Apergis et al., 2016).

2.2.1. Nonlinear Panel Unit Root Tests

This part makes use of the nonlinear panel unit root test, recommended by Cerrato et al. (2011 and 2013); in that sense, the DGP for the time series y_{it} could be modeled as an Exponential Smooth Transition Autoregressive (ESTAR) process:

$$y_{it} = \xi_i y_{i,t-1} + \xi_i^* y_{i,t-1} Z(\theta_i; y_{i,t-d}) + \mu_{it} \quad t = 1,...,T \quad i = 1,...,N , \tag{3}$$

where

$$Z(\theta_i; y_{i,t-d}) = 1 - \exp[-\theta_i (y_{i,t-d} - \chi^*)^2] \tag{4}$$

and θ_i is a positive n parameter, while χ^* is the equilibrium value of y_{it}. When the initial value of y_{it} exists, then the error term, μ_{it}, has a one-factor structure that yields:

$$\mu_{it} = \gamma_i f_t + \varepsilon_{it}, (\varepsilon_{it})_t \sim i.i.d.(0, \sigma_i^2) \tag{5}$$

in which, f_t is the unobserved common factor, and ε_{it} is the individual-specific (idiosyncratic) error. Following the literature, we set the delay parameter *d* to be unity and the Equation (5) in its first difference yields:

$$\Delta y_{i,t} = \alpha_i + \xi_i y_{i,t-1} + \sum_{h=1}^{h-1} \delta_{ijh} \Delta y_{ij,t-h} + (\alpha_i^* + \xi_i^* y_{i,t-1} + \sum_{h=1}^{h-1} \delta_{ih}^* \Delta y_{i,t-h}) * Z(\theta_i; y_{i,t-d}) + \gamma_i f_t + \varepsilon_{it} \quad (6)$$

Following the previous literature (Apergis, 2016; Apergis et al., 2016), once we assert that $y_{i,t}$ follows a unit root process in the middle regime, of $\xi_i = 0$, then Equation (6) can be rewritten as:

$$\Delta y_{i,t} = \xi_i^* y_{i,t-1} \left[1 - \exp(-\theta_i y_{i,t-1}^2)\right] + \gamma_i f_t + \varepsilon_{i,t} \quad (7)$$

We can form the null hypothesis of non-stationarity $H_0 : \theta_i = 0 \forall i$, against its alternative $H_1 : \theta_i > 0$ for i = 1,2,…, N_1 and $\theta_i = 0$ for i = N_1+ 1,…,N. The fact that ξ_i^* is not identified under the null hypothesis, the null hypothesis cannot be tested. Cerrato et al. (2011) use a first-order Taylor series approximation methodology to re-parameterize Equation (7) and the auxiliary regression yields:

$$\Delta y_{i,t} = a_i + \delta y_{i,t-1}^3 + \gamma_i f_t + \varepsilon_{i,t} \quad (8)$$

Equation (8) can be extended if errors are serially correlated, and it yields:

$$\Delta y_{i,t} = a_i + \delta y_{i,t-1}^3 + \sum_{h=1}^{h-1} \vartheta_{ih} \Delta y_{i,t-h} + \gamma_i f_t + \varepsilon_{i,t} \quad (9)$$

Cerrato et al. (2011) further show that the common factor f_t can be approximated by:

$$f_t \sim \frac{1}{\tilde{\gamma}} \Delta \tilde{y}_t - \frac{\bar{b}}{\bar{\gamma}} \tilde{y}_{t-1}^3 \quad (10)$$

where $\tilde{y}_t$ is the mean of y_{it} and $\bar{b} = \frac{1}{N} \sum_{i=1}^{N} b_i$.

Combining Equations (9) and (10), it can be written as the following nonlinear cross-sectionally augmented DF (NCADF) regression:

$$\Delta \overline{y}_{i,t} = a_i + b_i \overline{y}_{i,t-1}^3 + c_i \Delta \ddot{y}_t + d_i \Delta \ddot{y}_{t-1}^3 + \varepsilon_{i,t} \quad (11)$$

t-statistics can be derived from $\hat{b}_i$, which are denoted by:

$$t_{iNL}(N,T) = \frac{\hat{b}_i}{s.e.(\hat{b}_i)} \quad (12)$$

where $\hat{b}_i$ is the OLS estimator of b_i, and $s.e.(\hat{b}_i)$ is its associated standard error. The t-statistic value in Equation (12) is used to construct a panel unit root test by averaging the individual test statistics:

$$\bar{t}_{iNL}(N,T) = \frac{1}{N}\sum_{i=1}^{N} t_{iNL}(N,T) \quad (13)$$

2.2.2. Panel Cointegration Tests and Long-run Estimations

After confirming the presence of non-stationarity in the variables of interest, the analysis performs the cointegration tests by Westerlund (2007) and Westerlund and Edgerton (2008) to investigate the link between the export concentration and the carbon emissions, while including per capita income as an explicit control variable. Given the evidence of panel cointegration across variables, the analysis estimates a long-run relationship among the per capita carbon emissions, the income per capita, the squared income per capita, and the export concentration index in the natural logarithmic form (see Equation 2).

2.2.3. Autoregressive Distributed Lag (ARDL) Model

The analysis also uses the autoregressive distributed lag (ARDL) model, proposed by Pesaran et al. (2001) as a robustness check to incorporate the nonlinear relationship among the per capita carbon emissions, the income per capita, the squared income per capita, and the export concentration index. The model is specified as follows:

$$\Delta lnC02_{it} = \lambda_{0+} \sum_{i=1}^{m} \lambda_{1i}\ \Delta lnC02_{it-1} + \sum_{i=1}^{m} \lambda_{2i}\ \Delta lnGDP_{it-1} + \sum_{i=1}^{m} \lambda_{3i}\ \Delta lnGDP_{it-1}^{2} + \sum_{i=1}^{m} \lambda_{4i}\ \Delta lnECI_{it-1} + \lambda_5 lnC02_{it-1} + \lambda_6 GDP_{it-1} + \lambda_7 lnGDP_{it-1}^{2} + \lambda_8 lnECI_{it-1} + \upsilon_{it}$$

(14)

where m is the lag order and v_t is assumed to be an independent and identically distributed error term. Equation (14) can be transformed into an error correction model (ECM) yielding:

$$\Delta lnC02_{it} = \lambda_{0+} \sum_{i=1}^{m} \lambda_{1i} \ \Delta lnC02_{it-1} + \sum_{i=1}^{m} \lambda_{2i} \ \Delta lnGDP_{it-1} + \sum_{i=1}^{m} \lambda_{3i} \ \Delta lnGDP_{it-1}^{2} + \sum_{i=1}^{m} \lambda_{4i} \ \Delta lnECI_{it-1} + \xi(lnC02_{it-1} + \beta_1 GDP_{ti-1} + \beta_2 lnGDP_{it-1}^{2} + \beta_3 lnECI_{it-1}) + \mu_{it}$$

(15)

where ξ is the speed of adjustment parameter. β_1 , β_2 , and β_3 are the long-run coefficients for the real GDP per capita, the squared real GDP per capita, and the export concentration index respectively. The short-run parameters are represented by σ_{1i} , σ_{2i} , σ_{3i} , and σ_{4i} Therefore, the ARDL (p, q, k, g) model yields:

$$\Delta lnC02_{it} = \sigma_{0+} \sum_{i=1}^{p} \Delta\sigma_{1i} \ \Delta lnC02_{it-1} + \sum_{i=1}^{q} \Delta\sigma_{2i} \ \Delta lnGDP_{it-1} + \sum_{i=1}^{k} \Delta\sigma_{3i} \ \Delta lnGDP_{it-1}^{2} + \sum_{i=1}^{g} \Delta\sigma_{4i} \ \Delta lnECI_{it-1} + \xi(lnC02_{it-1} + \beta_1 lnGDP_{ti-1} + \beta_2 lnGDP_{it-1}^{2} + \beta_3 lnECI_{it-1}) + \mu_{it} \quad ,$$

(16)

2.2.4 Panel Quantile Regression (PQR)

In this subsection, the analysis uses the panel quantile regression (PQR) methodology to account for the likelihood of heterogeneity and to estimate the parameters at different points of the (conditional) per capita carbon emission distribution. The added advantage of using the PQR is relating to address the issues of outlier observations. The PQR estimator is proved to be more efficient than OLS estimators if error terms are not normally distributed. Apart from econometric advantage, the main qualitative advantage of the PQR estimator is to give an opportunity to a detailed analysis in evaluating the carbon emission at the different per capita and export concentration levels in terms of the EKC hypothesis. We specify the τ^{th}

quantile (0< τ <1) of the conditional distribution of the dependent variable (i.e. the log of per capita CO_2), given a set of independent variables X_{it} , as follows:

$$Q_\tau\left(\frac{LnCO2_{it}}{X_{it}}\right) = \alpha_\tau + \beta_\tau X_{it} + \alpha_\tau \mu_{it} \quad (17)$$

In Equation (17), $LnCO_{2it}$ is the log of per capita carbon emissions of county *i* at time *t* and X_{it} represents a vector of three independent variables, i.e. the per capita GDP ($LnGDP_{it}$), the squared per capita GDP ($lnGDP_{it}^2$), and the export concentration index ($lnECI_{it}$) all in logs. u_{it} denotes the unobservable factors, such as cultural habits in using energy (Apergis et al., 2016). The parameters in Equation (17) are estimated by minimizing the absolute value of the residuals, using the following objective function:

$$Q_\tau(\beta_\tau) = \min_\beta \sum_{i=1}^{n}[|LnH_{it} - \beta_\tau X_{it}|] = \min_\beta \left[\sum_{i:LnH_{it}\geq\beta X_i}^{n} \tau|LnH_{it} - \beta_\tau X_{it}| + \sum_{i:LnH_{it}<\beta X_{it}}^{n}(1-\tau)|LnH_{it} - \beta_\tau X_{it}|\right] \quad (18)$$

Koenker (2004) suggests a class of penalizing QR estimators (i.e. the shrinkage methodology) to estimate a vector of individual effects, while Canay (2011) finds that Koenker's methodological approach is computationally intensive; and therefore, he introduces a two-step methodology of estimating panel quantile regression models with the fixed-effects. In the first stage, the conditional mean of u_{it} is needed to be found and then estimated parameters will be calculated to obtain the individual fixed-effects $\hat{\alpha}_i = \frac{\sum_{t=1}^{T}(LnCO2_{it} - X'_{it}\hat{\beta}_\mu)}{T}$, where $\hat{\beta}_\mu$ denotes the estimated parameters of the conditional mean regression. In the second stage, the estimated individual effect was excluded from the dependent variable, $\widehat{LnCO2}_{it} = LnHCO2_{it} - \hat{\alpha}_i$ and next stage, the standard quantile regression is applied.

3. Empirical Results and Discussion

3.1. Empirical Results

At the preliminary stage, the results of the nonlinear panel unit root (NCIPS) tests are reported in Table 1.

[Insert Table 1 about here]

According to the results in Table 1, the individual statistics indicating that most of the countries have non-stationary variables, with an exception of the United Kingdom (UK). The nonlinear panel unit root test statistics in Table 1 also indicate the presence of a unit root across the related variables.

After confirming the presence of non-stationarity in the variables of interest, the analysis performs cointegration tests to investigate the (long-run) relationship between the export concentration and carbon emissions, while including per capita income as an additional control variable. The analysis makes use of the error-correction-based panel cointegration tests under cross-sectional dependence, recommended by Westerlund (2007) and Westerlund and Edgerton (2008) for a robustness check and Table 2 reports the test statistics of Ga, G_t, P_a, and P_t.

[Insert Table 2 about here]

The first two statistics are the mean-group tests assuming unit-specific error correction parameters, while the null hypothesis is of no cointegration across all cross-sectional units. The rejection of the latter two statistics indicates the presence of cointegration for the panel as a whole. The break date is observed at 1993. The break year of 1993 is in line with previous studies, which have found 1993 as the structural break in per-capita carbon dioxide emission (e.g. Lanne and Liski, 2004). The break in the mid-1990s is mainly explained by begging of the rapid growth rates in Asian economies. Therefore, the analysis provides the results for the entire period (1962–2010), as well as in two sub-periods (1962–1993 and 1994–2010). As we can see from Table 2, there is evidence of cointegration across the variables over the entire period under study.

The results of the mean group estimations and residual tests are reported in Table 3. The analysis makes use of a conventional estimation methodology to estimate the long-run relationship.[4] Particularly, this analysis employs the CCE-MG estimation approach because it allows cross-sectional dependence and cross-section specific slope coefficients across panel members (Kapetanios et al., 2011; Pesaran, 2006). The CCE-MG estimator indicates that all estimated coefficients are significant at the 5% level.

[Insert Table 3 about here]

Table 4 presents the results for Equation (16); they highlight that the error-correction coefficient is negative and statistically significant at the 1% level. It also reports the long-run coefficients of the cointegrating equation; in particular, a 1% increase in per capita GDP results in a long-run increase of 5.55% in per capita CO_2 emissions; while a 1% increase in the export concentration index results in a long-run decrease of 0.295% in per capita CO_2 emissions. The ECM coefficient is −0.171, indicating implies that the adjustment speed is about 17%.

It is also interesting to note that France derived 76.9% of electricity from nuclear energy in 2014, while this figure turned out to be 29.2% in Japan in 2010 (World Nuclear Association, 2015). We also observe that there is an insignificant relationship between export concentration and carbon dioxide emission in the short-run. Similarly, we find the positive short-term relationship in the Netherlands, New Zealand, and the UK between the export concentration and carbon emissions. This finding is in line with Gozgor and Can (2016b) since providing a higher-level export concentration takes time (usually 3 to 5 years at least). The Netherlands and New Zealand are also important commodity exporter in the world. In addition, we find the positive long-run relationship in Uruguay. This finding can be explained

[4] They are the Mean Group (MG) estimator (Pesaran and Smith, 1995), The CD test of Pesaran (2004) indicated the existence of "cross-sectional dependence" in the residuals of mean group methodologies (the MG, the GM-FMOLS, and the GM-DOLS), which questions the assumption of cross-section independence.

by the fact the income level of Uruguay is below the concentration process. To this end, environmental policy implications due to providing the significant effect of the export concentration upon carbon emissions are only valid in the long-run.

[Insert Table 4 about here]

The results of the country level analysis are reported in Table 5; this analysis enables us to examine the presence of heterogeneity across countries. The empirical findings are conducive to the presence of an error-correction term for each country, while the coefficient is negative (except in the case of Japan) and statistically significant at the 1% level (except in the case of Japan, where evidence is found at the 5% significance level). The largest ECM coefficient occurs in the case of Denmark, −0.482, which implies that the adjustment speed is about 48%, while the smallest coefficient is in relevance to the case of the U.S. and the coefficient is found as −0.075 (see Panel A, Table 5). More importantly, most countries exhibit a significant negative long-run impact of the export concentration upon the per capita carbon emissions: a 1% increase in export concentration results in a long-run decrease of 1.531% in the case of France and 1.479 in Japan, while in the UK is 0.303% (Panel B, Table 5).

[Insert Table 5 about here]

The empirical findings from the PQR approach of Canay (2011) are reported in Table 6; they illustrate that the estimated EKC follows an inverted U-shaped relationship, while it has a maximum turning point of per capita income; the panel quantile estimations suggest the presence of correctly signed and statistically significant coefficients across countries. The marginal effects of the per capita GDP on the per capita carbon emissions are relatively high at the higher quantiles. More importantly, we observe that the marginal effect of the export concentration upon the per capita carbon emissions is relatively high at the higher quantiles.

[Insert Table 6 about here]

3.2. Discussion and Implications

The empirical findings indicate that both the income per capita and the export product concentration are the main drivers in explaining carbon emissions in 19 developed economies; therefore, the EKC hypothesis is valid. This finding indicates that carbon emissions increase with income at the first stage of economic development till they reach the stabilization plateau; next, they are reduced in the long run. These empirical results on the validity of the EKC hypothesis are in line with previous empirical findings on several developed countries (Al-Mulali and Ozturk, 2016; Ang, 2007; Bento and Moutinho, 2016; He and Richards, 2010; Iwata et al., 2010; Jebli et al., 2016; Wang et al., 2015). In addition, it is also found that the product concentration in the export basket leads to lower carbon emissions in the developed economies. To the best of our knowledge, these are the first empirical results on the effect of export basket concentration on carbon emissions in developed countries.

We also find that the marginal effect of export concentration on per capita carbon emissions is relatively high at higher quantiles. This finding implies that when countries at a higher level of export diversification the gains from reducing carbon emissions are higher. The main policy implication is that developed countries should proceed to specialize in their export products to reduce the level of carbon emissions. Probably, this would be easier than providing a higher level of income.

The empirical findings also show that there could be some environmental policy implications that would reduce carbon emissions. First, it was found that economic growth leads to higher environmental pollutants. Indeed, sustainable economic growth is crucial for any economy for generating new job opportunities. In other words, the effects of income on carbon emissions are systematic and the policy implications can focus on reducing the initial costs of environmentally friendly investments (Bento and Moutinho, 2016). In addition, the findings also illustrate that export product concentration significantly reduces carbon emissions in the high-income economies. In other words, the product concentration of export baskets can be beneficial for environmental pollutant management. For instance, firms in developed economies must avoid producing goods that cause severe carbon emissions, while products with high carbon emissions can be imported from developing economies. There could be some incentives to avoid producing carbon-intensive goods or a carbon emission tax can be implemented for such goods. Nevertheless, these policy implications require a detailed knowledge of the scale of environmental pollutants for each sector across these 19 developed economies (Bilgili et al., 2016).

Although export concentration itself is an outcome of the development process, it depends on economic conditions and parameters and this can provide some specific policy implications. Firstly, the endogenous growth models illustrate that the export basket can be developed by learning-by-doing and learning-by-exporting activities. To achieve this promoting the development of the financial sector and increasing FDI inflows through the incentives and the implications (e.g. decreasing the level of corruption and the power of state-owned business) can be considered. Secondly, previous literature observes that trade liberalization is the main source of the development of the export basket; and therefore, providing a fair degree of trade liberalization and reducing barriers and bureaucracy in international trade can help to enhance the export basket (Gozgor and Can, 2017a). Thirdly, using fiscal and financial incentives, investments can be made in R&D activities that enhance the level of technology, which can also develop the countries' ability to upgrade the export basket. Finally, regulations in the business world (e.g. hidden barriers to doing business as well as weak and unclear legal regulations) can affect the export basket. For example, efficient regulations in the business world can provide the higher level of efficiency in exporting firms and thus promote the export basket. Similarly, regulations in the credit market (e.g. expensive capital due to high-interest rates) and regulations in labour market (e.g. regulations in firing and hiring workers) could also be the determinant factor of the export concentration. It is important to note that those factors are quite heterogeneous even among the developed countries in our dataset.

4. Conclusion

In recent years, countries have put serious efforts to tackle the global warming problem; therefore, the number of studies that have analyzed the economic growth–environmental quality nexus has dramatically increased. In this paper, the analysis provided the first empirical results of the short- and long-run effects of the export product concentration upon the carbon emissions in 19 developed (high-income) economies, spanning the period 1962−2010. To this end, it employed the nonlinear panel unit root test by Cerrato et al. (2011, 2013), as well as the panel cointegration tests by Westelund (2007) and Westerlund and Edgerton (2008) with multiple endogenous structural breaks. It also considered the mean group estimations of Pesaran (2006), the ARDL model, and the panel quantile regression estimations by Canay (2011). It illustrated that the EKC hypothesis was valid in the panel dataset. In addition, it observed that a greater product concentration of exports led to lower carbon emissions in the majority of countries under investigation. The results of the panel quantile regression also indicated that the effect of the export concentration upon the per capita carbon emissions was relatively high at the higher quantiles.

Future research venues could explore the effects of the export product concentration upon the carbon emissions in developing economies or other advanced countries. In addition, the effects of sub-indexes of the Theil index (e.g. the extensive margin and the intensive margin of products) on carbon emissions could also be analyzed by different econometric tools.

References

Aditya, A, Acharyya, R., 2013. Export diversification, composition, and economic growth: Evidence from cross–country analysis. Journal of International Trade and Economic Development 22(7): 959-92.

Agosin, M.R., Alvarez, R., Bravo–Ortega, C., 2012. Determinants of export diversification around the world: 1962–2000. The World Economy 35(3): 295-315.

Ajmi, A.N., Hammoudeh, S., Nguyen, D.K., Sato, J.R., 2015. On the relationships between CO_2 emissions, energy consumption and income: The importance of time variation. Energy Economics 49: 629-38.

Al-Mulali, U., Ozturk, I., 2016. The investigation of environmental Kuznets curve hypothesis in the advanced economies: The role of energy prices. Renewable and Sustainable Energy Reviews 54: 1622-31.

Ang, J.B., 2007. CO_2 emissions, energy consumption, and output in France. Energy Policy 35(10): 4772-8.

Apergis, N., 2016. Environmental Kuznets curves: New evidence on both panel and country-level CO_2 emissions. Energy Economics 54: 263-71.

Apergis, N., Eleftheriou, S., Payne, J.E., 2013. The relationship between international financial reporting standards, carbon emissions, and R&D expenditures: Evidence from European manufacturing firms. Ecological Economics 88: 57-66.

Apergis, N., Gupta, R., Lau, C.K.M., Mukherjee, Z., 2016. An analysis of the relationship between U.S. state level carbon dioxide emissions and health care expenditure. University of Pretoria, Department of Economics Working Paper, No. 18, Pretoria: University of Pretoria.

Apergis, N., Payne, J.E., 2009. CO_2 emissions, energy usage, and output in Central America. Energy Policy 37(8): 3282-6.

Bento, J.P.C., Moutinho, V., 2016. CO_2 emissions, non-renewable and renewable electricity production, economic growth and international trade in Italy. Renewable and Sustainable Energy Reviews 55: 142-55.

Bilgili, F., Kocak, E., Bulut, U., 2016. The dynamic impact of renewable energy consumption on CO_2 emissions: A revisited environmental Kuznets curve approach. Renewable and Sustainable Energy Reviews 54: 838-45.

Cadot, O., Carrere, C., Strauss–Kahn, V., 2011. Export diversification: What's behind the hump? Review of Economics and Statistics 93(2): 590-605.

Can, M., Gozgor, G., 2017. The impact of economic complexity on carbon emissions: evidence from France. Environmental Science and Pollution Research 24(19): 16364-70.

Canay, I.A., 2011. A simple approach to quantile regression for panel data. Econometrics Journal 14(3): 368-86.

Cerrato, M., De Peretti, C., Larsson, R., Sarantis, N., 2011. A nonlinear panel unit root test. University of Glasgow, Department of Economics Working Paper, Glasgow: University of Glasgow.

Cerrato, M., De Peretti, C., Stewart, C., 2013. Is the consumption-income ratio stationary? Evidence from linear and non-linear panel unit root tests for OECD and non-OECD countries. Manchester School 81(1): 102-20.

Dennis, A., Shepherd, B., 2011. Trade facilitation and export diversification. The World Economy 34(1): 101-22.

Gozgor, G., 2017. Does trade matter for carbon emissions in OECD countries? Evidence from a new trade openness measure. Environmental Science and Pollution Research, 24(36): 27813-21.

Gozgor, G., Can, M., 2016a. Effects of the product diversification of exports on income at different stages of economic development. Eurasian Business Review 6(2): 215-35.

Gozgor, G., Can, M., 2016b. Export product diversification and the environmental Kuznets curve: Evidence from Turkey. Environmental Science and Pollution Research 23(21): 21594-603.

Gozgor, G., Can, M., 2017a. Causal linkages among the product diversification of exports, economic globalization, and economic growth. Review of Development Economics 21(3): 888-908.

Gozgor, G., Can, M., 2017b. Does export product quality matter for CO_2 emissions? Evidence from China. Environmental Science and Pollution Research 24(3): 2866-75.

Grossmann, G.M., Krueger, A.B., 1991. Environmental impact of a North American Free Trade Agreement. National Bureau of Economic Research Working Paper, No. 3914, Cambridge, MA: National Bureau of Economic Research.

Grossmann, G.M., Krueger, A.B., 1995. Economic growth and the environment. Quarterly Journal of Economics 110(2): 353-77.

Hausmann, R., Hwang, J., Rodrik, D., 2007. What you export matters. Journal of Economic Growth 12(1): 1-25.

He, J., Richards, P., 2010. Environmental Kuznets curve for CO_2 in Canada. Ecological Economics 69(5): 1083-93.

Imbs, J., Wacziarg, R., 2003. Stages of diversification. American Economic Review 93(1): 63-86.

Iwata, H., Okada, K., Samreth, S., 2010. Empirical study on the environmental Kuznets curve for CO_2 in France: The role of nuclear energy. Energy Policy 38(8): 4057-63.

Jebli, M.B., Youssef, S.B., Ozturk, I., 2016. Testing environmental Kuznets curve hypothesis: The role of renewable and non-renewable energy consumption and trade in OECD countries. Ecological Indicators 60: 824-31.

Kapetanios, G., Pesaran, M.H., Yagamata, T., 2011. Panels with non-stationary multifactor error structures. Journal of Econometrics 160: 326-48.

Klinger, B., Lederman, D., 2006. Diversification, innovation, and imitation inside the global technology frontier. World Bank Policy Research Working Paper, No. 3872, Washington, D.C.: World Bank.

Koenker, R., 2004. Quantile regression for longitudinal data. Journal of Multivariate Analysis 91(1): 74-89.

Lanne, M., Liski, M., 2004. Trends and breaks in per-capita carbon dioxide emissions, 1870–2028. Energy Journal 25(4): 41-65.

Narayan, P.K., Narayan, S., 2010. Carbon dioxide emission and economic growth: Panel data evidence from developing countries. Energy Policy 38(1): 661-6.

Onafowora, O.A., Owoye, O., 2014. Bound testing approach to analysis of the environment Kuznets curve hypothesis. Energy Economics 44: 47-62.

Papageorgiou, C., Spatafora, N., 2012. Economic diversification in LICs: Stylized facts and macroeconomic implication. IMF Staff Discussion Notes 12/13, Washington, D.C.: International Monetary Fund.

Pesaran, M.H., 2004 General diagnostic tests for cross section dependence in panels. Center for Economic Studies and the IFO Institute (CESifo) Working Paper Series, No. 1229, Munich: CESifo.

Pesaran, M.H., 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica 74(4): 967-1012.

Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics 16(3): 289-326.

Pesaran, M.H., Smith, R., 1995. Estimating long-run relationships from dynamic heterogeneous panels. Journal of Econometrics 68(1): 79-113.

Rodrik, D., 2006. What's so special about China's export? China and World Economy 14(5): 1-19.

Song, T., Zheng, T., Tong, L., 2008. An empirical test of the environmental Kuznets curve in China: A panel cointegration approach. China Economic Review 19(3): 381-92.

Wang, Y., Zhang, X., Kubota, J., Zhu, X., Lu, G., 2015. A semi-parametric panel data analysis on the urbanization-carbon emissions nexus for OECD countries. Renewable and Sustainable Energy Reviews 48: 704-9.

Westerlund, J., 2007. Testing for error correction in panel data. Oxford Bulletin of Economics and Statistics 69(6): 709-48.

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.

World Nuclear Association, 2015. Nuclear shares of electricity generation, 2015. London: World Nuclear Association.

Yang, G., Sun, T., Wang, J., Li, X., 2015. Modeling the nexus between carbon dioxide emissions and economic growth. Energy Policy 86: 104-17.

Table 1. Results of the Nonlinear Panel Unit Root (NCIPS) Tests

Countries	Export Concentration in Log	Per Capita CO_2 Emissions in Log	Per Capita GDP in Log
Austria	0.271	–1.5962	–2.6618
Belgium	0.182	–0.4980	–2.8323*
Canada	–0.524	–0.9381	–1.8481
Denmark	–0.605	–1.3300	0.2360
Finland	–0.598	–0.5602	–1.2144
France	–0.349	–0.9675	–1.5227
Germany	–0.115	–1.3351	–1.3273
Italy	0.324	–1.5071	–3.8788***
Japan	–1.411	–1.0662	–1.0680
The Netherlands	–0.828	–0.0257	–2.3653
New Zealand	–2.532	–2.5911	0.4418
Norway	–0.335	–0.7021	–2.2038
Portugal	–0.333	1.4578	–1.3303
Spain	–2.888*	0.2072	–2.1307
Sweden	–1.338	–0.9118	–2.3661
Switzerland	–1.771	–3.2853***	0.3286
The United Kingdom	–3.761***	–4.4765***	–2.9998*
The United States	–1.246	–0.3573	–1.8992
Uruguay	–2.223	–1.3837	–1.2089
NCADF	–1.057		
Critical Values of Panel NCADF Distribution (N = 19, T = 49):			
1%	–3.70		
5%	–3.04		
10%	–2.73		
Critical Values of Individual NCADF Distribution (N = 19, T = 49):			
1%	–2.18		
5%	–2.05		
10%	–1.98		

Notes: The critical values are taken from Tables 13 and 14 of Cerrato et al. (2011). ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2. Results of the Panel Cointegration Tests

Test	(1962–2010)	(1962–1993)	(1994–2010)
Westerlund (2007) and Westerlund and Edgerton (2008)–Gt	–2.687*	–2.844	–2.391
Westerlund (2007) and Westerlund and Edgerton (2008)–Ga	–6.064**	–5.351	–7.405**
Westerlund (2007) and Westerlund and Edgerton (2008)–Pt	–13.304***	–14.696	–8.421
Westerlund (2007) and Westerlund and Edgerton (2008)–Pa	–5.834**	–5.363**	–7.597**

Note: ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Results of the Mean Group Estimations and Residual Tests

	CD Test	α	β	γ	θ
1) MG	47.96***	–20.74**	4.515***	–0.163*	0.139***
	[0.000]	[0.010]	[0.007]	[0.055]	[0.00]
2) CCE–MG	–2.49**	3.08	31.164***	–1.557***	–1.737*
	[0.013]	[0.666]	[0.000]	[0.000]	[0.062]

Notes: Figures in square brackets denote the p-values. Eq. (13) was estimated. MG stands for standard Mean Group (Pesaran and Smith, 1995). MG. CCE-MG refers to the Common Correlated Effects Mean Group estimation and the inference method (Pesaran, 2006), and allows for cross-sectional dependence. The CD-test refers to the Pesaran's (2004) test of cross-sectional dependence. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Results of the ARDL Model Estimations of the Panel Data

Dependent Variable: D(Per Capita CO_2 Emissions in Log) Selected Model: ARDL (1,1,1,1)				
Variables	Coefficients	Standard Errors	t-Statistics	Probability
	Long Run Equation			
Per Capita GDP in Log	5.546725***	1.811869	3.061327	0.0023
Squared Per Capita GDP in Log	–0.28919***	0.093386	–3.09671	0.0020
Export Concentration in Log	–0.29458***	0.096738	–3.04516	0.0024
	Short Run Equation			
COINTEQ01	–0.17094***	0.026959	–6.34093	0.0000
D(Per Capita GDP in Log)	–0.79733	3.429405	–0.2325	0.8162
D(Squared Per Capita GDP in Log)	0.085577	0.180149	0.475035	0.6349
D(Export Concentration in Log)	–0.13305	0.08491	–1.56696	0.1175
Constant Term	–3.20348***	0.499259	–6.41647	0.0000

Note: *** denotes the statistical significance at the 1% level.

Table 5. Results of the ARDL Model Estimations for Individual Countries

Panel A: Short Run Dynamics

Country/Variable	COINTEQ01	D(Per capita GDP in log)	D(Squared per capita GDP in log)	D(Export concentration in log)
Austria	–0.1686***	–10.0244	0.5720	–0.3296***
Belgium	–0.2055***	4.4316	–0.1650	–0.0886
Canada	–0.1492***	2.9778	–0.1423	–0.0477*
Denmark	–0.4828***	3.5188	–0.1304	–0.1230
Finland	–0.2731***	–13.6636	0.7525**	–0.8210***
France	–0.1118***	13.3024	–0.6296*	0.0196
Germany	–0.0802***	–33.3192	1.7943*	–1.033*
Italy	–0.1082***	–6.4290	0.3932**	0.0334
Japan	0.0047**	3.5081	–0.1202**	–0.0747
The Netherlands	–0.1985***	–3.6031	0.2258	0.3416***
New Zealand	–0.13195***	2.9202	–0.1358	0.4291**
Norway	–0.1406***	–15.4006	0.7274	0.0279
Portugal	–0.0883***	–13.1267	0.7771***	–0.4582***
Spain	–0.2139***	–22.6304	1.2967***	-0.0283
Sweden	–0.0758***	16.4436	–0.7768*	–0.5396***
Switzerland	–0.3086***	14.8909	–0.7346	0.1755
The United Kingdom	–0.3592***	28.1739	–1.4488***	0.0248**
The United States	–0.0754***	1.2700	–0.0224	–0.2224***
Uruguay	–0.0804***	11.6105	–0.6070	0.1865

Panel B: Long Run Equilibrium

Country/Variable	Per capita GDP in log	Squared per capita GDP in log	Export concentration index in log
Austria	1.2241***	–0.0435***	–0.4332*
Belgium	1.6361***	–0.0802***	–0.7485
Canada	1.5771***	–0.0716***	–0.2658
Denmark	1.8673***	–0.1034***	–0.8699***
Finland	1.4594***	–0.0575***	–1.0027***
France	1.1420***	–0.0334	–1.5314***
Germany	1.2987***	–0.0605*	–2.0940***

Italy	0.9191***	−0.0102	−1.1198
Japan	0.7229***	0.01834**	−1.4795***
The Netherlands	1.4658***	−0.0661***	−0.0965
New Zealand	1.2169***	−0.0398**	−0.5081***
Norway	0.8122***	0.0045	−0.68812***
Portugal	0.0747***	0.06679***	−0.8193***
Spain	0.9013***	−0.0075*	−0.9035***
Sweden	2.3787***	−0.1559***	−1.4605***
Switzerland	1.4171***	−0.0628***	−0.8537***
The United Kingdom	1.8567***	−0.1062***	−0.3038***
The United States	1.8238***	−0.0983***	0.4842
Uruguay	0.3981	0.0204	1.0831***

Note: ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Results of the Panel Quantile Estimates for the EKC (The Fixed-effects Quantile Regression)

Variables	10%	20%	30%	40%	50%	60%	70%	80%	90%
Per Capita GDP in Log	8.524***	6.8982***	6.56***	6.6305***	6.6107***	7.1312***	7.1417***	6.9358***	8.0221***
	(0.1499)	(0.9173)	(0.704)	(0.4852)	(0.4096)	(0.4405)	(0.0063)	(0.8755)	(0.6744)
Squared Per Capita GDP in Log	–0.3867***	–0.3017***	–0.2857***	–0.2900***	–0.2889***	–0.3171***	–0.3187***	–0.3104***	–0.3692***
	(0.0788)	(0.0481)	(0.0370)	(0.0257)	(0.0217)	(0.0233)	(0.0331)	(0.0453)	(0.0356)
Export Concentration in Log	–0.3370***	–0.3618***	–0.3448***	–0.3254***	–0.2806***	–0.2542***	–0.2423***	–0.2207***	–0.1812***
	(0.0270)	(0.0211)	(0.0275)	(0.0325)	(0.0298)	(0.0297)	(0.0297)	(0.0322)	(0.0289)

Notes: The standard errors are in parentheses with 2,000 replications. *** indicates the significance at the 1% level. The robust OLS standard errors are used.

Appendix I. Descriptive Statistics and the Description of the Variables in the Panel Data of 19 Countries: 1962–2010

Variable	Unit	Data Source	Mean	Standard Deviation	Skewness	Kurtosis	Observations
Real per Capita GDP (constant $ price in 2005)	Logarithmic Form	World Bank, WDI	9.559	0.417	–0.750	3.292	931
Squared Real per Capita GDP (constant $ price in 2005)	Logarithmic Form	World Bank, WDI	19.11	0.835	–0.750	3.292	931
CO_2 Emissions (metric tons per capita)	Logarithmic Form	World Bank, WDI	7.626	0.584	–1.076	4.515	902
Export Concentration (Theil index)	Logarithmic Form	International Monetary Fund	0.551	0.282	0.640	3.241	919