Does globalization worsen environmental quality in developed economies?

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Abstract

We examine the causal relationship between globalization and CO_2 emissions for 25 developed economies in Asia, North America, Western Europe and Oceania using both time series and panel data techniques, spanning the annual data period of 1970–2014. Because of the presence of cross-sectional dependence in the panel, we employ Pesaran's (2007) cross-sectional augmented panel unit root (CIPS) test to ascertain unit root properties. The Westerlund (2007) cointegration test is also used to ascertain the presence of a long-run association between globalization and carbon emissions. The long-run heterogeneous panel elasticities are estimated using the Pesaran (2006) common correlated effects mean group (CCEMG) estimator and the Eberhardt and Teal (2010) augmented mean group (AMG) estimator. The causality between the variables is examined by employing the Dumitrescu and Hurlin (2012) and Emirmahmutoglu and Kose (2011) Granger causality tests. The empirical results reveal that globalization increases carbon emissions, and thus the globalization-driven carbon emissions hypothesis is valid. This empirical analysis suggests insightful policy guidelines for policy makers using 'globalization' as an economic tool for better long-run environmental policy.

Keywords: Carbon Emissions, Causality, Globalization

JEL Classification: F1, K32, C10

1. Introduction

Globalization, a worldwide phenomenon, has affected the socio-economic-political aspects of human life. Globalization connects world economies via trade, capital flows, innovative opportunities and cultural ties. It improves financial and trade openness and thus facilitates economic growth and development; however, it also impacts the environment through various channels. The emissions of pollutants have further adverse implications for global climate change and ecological imbalance. Moreover, the effects of these emissions may result in lower sustainable economic growth and development through welfare retarding channels (Shahbaz et al. 2015a).

Globalization has many dimensions, including economic, social and political, and each may play a vital role in increasing or decreasing carbon emissions. Since globalization interlinks economies through trade, investment and financial activities, the expansion of global economies and the increase in global financial activities result in higher energy consumption, and hence more carbon emissions. Social globalization connects people since it enhances information flows and cultural proximity. For instance, social globalization enables countries to access information, particularly prevailing best business practices. The knowledge and implementation of best practices help to reduce energy consumption in production processes, and thereby may help to improve environmental quality. Finally, countries engaged in international treaties and working groups are expected to be concerned with climate change, and they will try to comply with global environmental standards[1].

[1] It is argued that any efforts by policy makers and governments of developing and developed countries to improve the quality of the environment will not be effective enough in the long term unless and until they control for the role of globalization on the environment in the CO_2 emissions function.

The recent decades have witnessed an increasing trend in global warming and climate change, which will eventually lead to deforestation; rising sea levels; loss of biodiversity; unusually increased winds, rainfalls and/or droughts; and massive crop failures (Hawken et al. 2008)[2]. Moreover, the protocols of the 2015 Paris Climate Change Conference[3] urge taking steps to reduce global warming.[4] We posit that globalization can be a policy tool for the efforts towards a better environment. Previous studies have mainly used trade openness as a proxy for globalization with less attention paid to its other aspects, i.e., socio-economic and political globalization. This study uses a globalization index that encompasses different dimensions of globalization, and hence tries to enhance the understanding of the globalization–environment links in developed countries. The choice of developed countries in Asia, North America, Western Europe and Oceania is based on the fact that these economies produce a higher share of the global CO_2 emissions (Paris Climate Change Conference, 2015).[5] Furthermore, these developed economies are selected not only because of their greater degree of economic development and higher investment in clean energy projects[6] but also because international organizations do not compel developed economies to reduce their energy consumption-related CO_2 emissions (Kyoto Protocol Summit, 1997; UN Emissions Gap Report, 2012; Paramati et al. 2016).

This paper aims to empirically examine the relationship between globalization and CO_2 emissions for 25 developed economies in Asia, North America, Western Europe and Oceania, using both time series and panel data techniques and spanning the period 1970–2014. The present study

[2] Environmental loss or degradation comes in various forms, including loss of a country's landmass, the disappearance of small island nations, a widespread destruction of life and property, heavy population displacement and statelessness.
[3] http://unfccc.int/meetings/paris_nov_2015/meeting/8926.php
[4] http://blogs.worldbank.org/climatechange/reflections-paris-agreement-critical-juncture-cif
[5]Available at http://infographics.pbl.nl/website/globalco2-2015/
[6] Four developed countries, U.S., Japan, Germany and UK as well as China account for 68.7% of the global investments in clean energy projects (Paramati et al., 2016).

contributes to the energy economics literature in four ways: (i) The unit root properties of globalization and CO_2 emissions are examined through the Pesaran (2007) cross-sectionally augmented panel unit root test (CIPS test) because of the presence of cross-sectional dependence in the panel of 25 developed countries. (ii) The Westerlund (2007) cointegration test, which allows slope heterogeneity and dependence in the cross-sectional units[7], is used to ascertain the long-run association between globalization and carbon emissions. (iii) Long-run heterogeneous panel elasticities are estimated through the Pesaran (2006) common correlated effects mean group (CCEMG) estimator and the Eberhardt and Teal (2010) augmented mean group (AMG) estimators. (iv) The bivariate heterogeneous panel short-run causal links between globalization and CO_2 emissions are established using the Dumitrescu and Hurlin (2012) and Emirmahmutoglu and Kose (2011) Granger causality tests. The results show that globalization increases carbon emissions in developed countries. The implications of these results for environmental policy in developed economies are also discussed.

The rest of the paper is structured as follows. Section 2 summarizes the related literature. Section 3 briefly presents the estimation strategy. Section 4 discusses the results. Finally, the conclusion and policy suggestions are provided in Section 5.

2. Review of the related literature

The existing empirical literature provides visible insights into the dynamics of environmental quality; however, a concrete consensus has yet to be reached. Grossman and Krueger (1991, 1995)

[7] Imposing homogeneity restrictions on the parameters and cross-section independence across individual units can further mislead empirical results. To solve this issue, we apply the cross-sectional independence and slope homogeneity tests to decide the appropriate panel causality approaches proposed by Pesaran et al. (2008) and Pesaran & Yamagata (2008).

pioneered the Environmental Kuznets curve (EKC) that establishes the debatable relationship between environmental pollution and economic growth through an inverted U-shaped curve.[8] However, efforts to stimulate economic development have kept environmental quality preservation as a secondary goal in policy making. In response, many countries have started implementing environmental policies to minimize the consequences of air and water pollution and solid waste disposal (Jena and Ulrike, 2008).

Globalization leads to a greater integration of economies and societies (Agénor, 2004). Heckscher (1919) and Ohlin (1933) argue that '*trade is the main engine that provides an innovative opportunity to enhance the process of production as well as productivity of abundant natural resources*'. Higher economic integration and trade openness are primary sources of economic development. Grossman and Krueger (1991, 1995) and Copeland and Taylor (2004) postulate that trade openness can affect environmental quality in both positive and negative ways. Grossman and Krueger (1991) argue that the environmental effects of international trade depend on policies implemented in domestic economies, irrespective of their size and development levels. The proponents of trade openness suggest that trade openness results in production efficiency of the trade-participating countries by allocating scarce resources among them. Trade openness lowers CO_2 emissions by using standard and cleaner technologies in production and consumption activities (Runge, 1994; Helpman, 1998). Jayadeappa and Chhatre (2000) also observe that trade enhances economic development and that trade-derived income can fund improved environmental management and disseminate environmentally sound technology.

[8] The Environmental Kuznets Curve (EKC) theory suggests an inverted U-shaped relationship between environmental quality and economic growth in the course of economic development. Environmental degradation first increases and then decreases as economies grow (Kuznets, 1955). Their argument for such a finding is that after a certain level of income, concern for environmental degradation becomes more relevant, and hence institutional quality mechanisms are put in place to reduce the environmental consequences of economic development.

Similarly, researchers argue that a win–loss position is always present for developed countries because trade openness not only stimulates their economy but also brings detrimental changes to their environmental quality (Copeland and Taylor, 1994, 2003; Christmann and Taylor, 2001; Copeland, 2005; Shin 2004). For instance, the pollution haven hypothesis refers to the relocation of heavy industries from developed countries with stringent environmental policies to countries with lax environmental regulations. However, transnational environmental problems such as ozone depletion, global warming and global climate change, deforestation and acid rain have cross-border effects, and thus they have an impact on every country.

Influenced by this role of globalization, recent studies have explored the relationship between this phenomenon and various environmental indicators for a single country or for a panel framework. Most of the studies have placed their empirical efforts on understanding the impacts of traditional and modern globalization indicators on environmental quality (Machado, 2000; Antweiler et al., 2001; Christmann and Taylor, 2001; Shin, 2004; Managi, 2004, 2008; Chang, 2012; Shahbaz et al., 2012; Kanzilal and Ghosh, 2013; Shahbaz et al., 2013; Tiwari et al., 2013; Ling et al., 2015; Lee and Min, 2014; Shahbaz et al., 2015a, b). For instance, Antweiler et al. (2001) examine the effect of trade on environmental quality by introducing composition, scale and technological effects through decomposing a trade model. Their study concludes that trade openness is beneficial to the environment if the technological effect is greater than both the composition and scale effects. Copeland and Taylor (2003, 2004), through their pollution haven hypothesis, also support international trade as highly beneficial to environmental quality through the enforcement of strong environmental regulations. They document that free trade reduces CO_2 emissions because it shifts the production of pollution-intensive goods from developed countries to developing nations.

Using panel data over the period of 1960–1999 for 63 developed and developing countries, Managi (2004) explores the environmental consequences of trade liberalization and finds that trade openness increases CO_2 emissions. Using survey data, Shin (2004) reports that trade openness is not harmful to the domestic environment in Chinese cities. McCarney and Adamowicz (2006) assert that trade openness improves the quality of the environment, depending on government policies. Managi et al. (2008) also find that environmental quality is improved if the effect of environmental regulations is stronger than the capital-labour effect. Moreover, Jena and Ulrike (2008) report that though the impact of trade liberalization is not unique across pollutants, it improves environmental quality by lowering CO_2 and NO_2 emissions for industrial cities in the Indian economy.

Baek et al. (2009) examine the environmental consequences of trade liberalization on the quality of the environment for 50 developed and developing countries over the data period of 1960–2000. Despite validating the environmental Kuznets curve hypothesis and the pollution haven hypothesis for both developed and developing economies, they find that trade liberalization improves environmental quality by lowering SO_2 emissions in developed economies, whereas it has a detrimental effect on the quality of environment in most developing economies. These authors also show the presence of unidirectional causality running from trade openness to SO_2 emissions for developed economies. For most developing economies, unidirectional causality runs from SO_2 emissions to trade openness, indicating that any change in the quality of the environment causes a consequential change in trade openness.

In single country studies, Saboori et al. (2012) conclude that trade openness is not the major contributing factor to the environment in Malaysia, whereas Solarin (2014) finds that Malaysia's exports to Singapore have a positive correlation with CO_2 emissions. On the other hand, Ling et al. (2015) report that trade openness improves environmental quality in Malaysia by lowering CO_2 emissions. Chang (2012) finds that the impacts of trade openness and foreign direct investment on environmental quality are ambiguous in China, depending on the type of pollutants. This finding also supports the conclusion of Cole et al. (2011) that the environmental effect of openness depends on the pollutants concerned. Further, Machado (2000) indicates the presence of positive link between foreign trade and CO_2 emissions in Brazil. Shahbaz et al. (2012) reveal that trade openness reduces CO_2 emissions in Pakistan. Shahbaz et al. (2013) also report that trade openness reduces CO_2 emissions in Indonesia. Similarly, Kanzilal and Ghosh (2013) find that trade openness reduces CO_2 emissions in India. In contrast, Tiwari et al. (2013) reinvestigate the dynamic causal relationship between trade openness and CO_2 emissions for India and find that trade openness significantly increases CO_2 emissions.

It is pertinent to survey the existing literature on the impact of the newly developed globalization index on CO_2 emissions using time series and panel frameworks. Using survey data for China, Christmann and Taylor (2001) examine the linkage between globalization and the environment and confirm that globalization is not detrimental to environmental quality. They also claim that Chinese firms' international linkages largely contribute to environmental quality through the effective implementation of environmental regulations. They further argue that environmental quality is achieved because of the self-regulation of Chinese firms. Subsequently, Lee and Min (2014) examine the effect of globalization on CO_2 emissions for a larger annual panel data set of both developed and developing countries in a panel framework and find that globalization significantly reduces CO_2 emissions. Shahbaz et al. (2015a) investigate the impact of globalization on environmental quality for India and find a positive effect of globalization on CO_2 emissions, indicating that globalization weakens environmental quality in India. In contrast, Shahbaz et al.

(2015b) also investigate the impact of globalization on CO_2 emissions for the Australian economy and find a role for globalization in lowering CO_2 emissions, highlighting that environmental quality in Australia is achieved in the presence of globalization.

From a critical perspective, we notice that most of the studies that examine the linkage between globalization and CO_2 emissions use trade openness as a narrowly defined indicator of globalization. The use of trade openness as an indicator of globalization only covers trade intensity. This has led to mixed and inconclusive empirical findings. However, the emergence of mixed and inconclusive findings due to the use of trade openness will also misguide policy makers in the process of designing policies towards improving environmental quality. To address this issue, this study employs the overall globalization index developed by Dreher (2006), which has been constructed based on sub-indices such as economic globalization, political globalization and social globalization.[9] Globalization plays a vital role in stimulating economic growth and development but also influences environmental quality by affecting CO_2 emissions (Lee and Min, 2014; Shahbaz et al., 2015a, b).

3. Methodology and estimation strategy

This study investigates the relationship between globalization and CO_2 emissions by using a panel of 25 developed countries. The selected countries are highly integrated because of their strong international economic and financial ties, through which one country may be impacted by economic shocks occurring in other countries and vice versa. The empirical evidence may be biased or ambiguous if we ignore the economic, financial or cultural ties of countries during the

[9] More details of overall globalization index have been discussed in the subsequent section of results interpretation.

process of model specification. Imposing homogeneity restrictions on the parameters and cross-sectional independence across individual units can further mislead empirical results. To solve this issue, we apply the cross-sectional independence and slope homogeneity tests to determine the appropriate panel causality approach.

We apply the Langrage multiplier (LM) cross-sectional dependence test, introduced by Breusch and Pagan (1980), which is widely used in the existing applied economics literature to determine whether cross-sectional dependence is present in the panel of countries. The LM test is suitable for relatively small N with adequately large T. Furthermore, the LM test has asymptotic chi-square distributed with $(N(N-1)/2)$ degrees of freedom. The cross-sectional dependence test loses its explanatory power if the pair-wise correlation is close to zero (Pesaran et al. 2008). The cross-sectional dependence test may accept the null hypothesis if factor loadings contain zero-mean in the cross-sectional dimension. To overcome these issues, Pesaran et al. (2008) modified the LM test by adjusting for these biases.

With the presence of strong cross-sectional dependence, it is possible that every country may have similar dynamics for their economic development process. This leads us to control for the cross-sectional heterogeneity while investigating the empirical results. When the panel is heterogeneous, assuming slope homogeneity could result in misleading estimates (Breitung, 2005). The null hypothesis of the slope homogeneity test is $H_0 : \beta_i = \beta_j$ and is tested using an F-test against the alternative hypothesis $H_a : \beta_i \neq \beta_j$ for all i_s[10]. When the cross-sections are fixed with large time dimensions, the independent variables are strictly exogenous with homogenous error variance.

[10] The null hypothesis is that slope coefficients (no heterogeneity) are homogenous against no homogeneity (heterogeneity).

Swamy (2007) introduced a new test for slope homogeneity, the 'relating homoscedasticity assumption', by applying a suitable pooled estimator to the dispersion of individual slope estimates. The standaard F-test and the Swamy test require that N should be fixed relative to T. Pesaran and Yamagata (2008) extended this test for examining slope homogeneity for large panels. Considering these significant improvements in the slope homogeneity and cross-sectional dependence testing literature, we employ different tests to first assess the presence of these characteristics in our panel and thereafter select the appropriate econometric framework.

3.1. Panel unit root test

Pesaran (2007) developed a new panel unit root test by augmenting the standard ADF regressions with the cross-sectional averages of the lagged level and of the first differences of the individual series. In the presence of N cross-sectional and T time series observations, Pesaran (2007) uses the following simple dynamic linear heterogeneous model:

$$\Delta x_{i,t} = \alpha_i + \rho_i x_{i,t-1} + c_i \bar{x}_{t-1} + d_i \Delta\bar{x} + \varepsilon_{i,t} \tag{1}$$

where $\bar{x}_{t-1} = (1/N)\sum_{i=1}^{N} x_{i,t-1}$ *and* $\Delta\bar{x}_t = (1/N)\sum_{i=1}^{N} \Delta x_{i,t}$

The cross-sectional averages of the lagged levels $\bar{x}_{t-1}$ and of the first differences $\Delta\bar{x}_t$ of individual series capture the cross-sectional dependence via a factor structure. Pesaran suggests modifying Equation (1) with appropriate lags in the presence of a serially correlated error term. Pesaran (2007) obtains the modified IPS statistics based on the average of individual CADFs, which is denoted as a cross-sectional augmented IPS (CIPS). This is estimated from the following:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{2}$$

where $CADF_i$ is the cross-sectional augmented Dickey-Fuller statistic for the ith cross-sectional unit given by the t-ratio of ρ_i in the CADF regression of Equation (1). The distribution of the CIPS statistic is found to be non-standard even for large *N*.

3.2. Panel cointegration test

The panel cointegration tests that have been proposed in the literature thus far can be divided into two groups: the first group is based on the null hypothesis of cointegration (McCoskey and Kao 1998; Westerlund, 2007), while the second group takes no cointegration as the null hypothesis (Pedroni 1999; Kao 1999; Larsson et al., 2001; Groen and Kleibergen, 2003).

Four error-correction-based panel cointegration tests are developed by Westerlund (2007) and employed in the present study. These tests are based on structural dynamics rather than residual dynamics so that they do not impose any common factor restrictions. The null hypothesis of no cointegration is tested by the error-correction term in a conditional error model of being equal to zero. If the null of no error correction is rejected, then the null hypothesis of no cointegration is rejected. The error-correction model based on the assumption that all the variables are integrated of order 1 is as follows:

$$\Delta z_{it} = \delta_i' d_i + \theta_i (z_{i(t-1)} - \beta_i' y_{i(t-1)}) + \sum_{j=1}^{m} \theta_{ij} \Delta z_{i(t-j)} + \sum_{j=0}^{m} \phi_{ij} \Delta y_{i(t-j)} + \omega_{it} \quad (3)$$

where $d_t = (1-t)'$ holds the deterministic components and $\delta_i' = (\delta_{1i}, \delta_{2i})'$ is the associated vector of parameters. To allow for the estimation of the error-correction parameter θ_i by the least square, Equation (3) can be rewritten as:

$$\Delta z_{it} = \delta_i' d_i + \theta_i (z_{i(t-1)} + \pi_i' y_{i(t-1)}) + \sum_{j=1}^{m} \theta_{ij} \Delta z_{i(t-j)} + \sum_{j=0}^{m} \phi_{ij} \Delta y_{i(t-j)} + \omega_{it} \quad (4)$$

Here, θ_i is the adjustment term that determines the speed by which the system adjusts back to the equilibrium relationship. The re-parameterization of the model ensures that parameter θ_i remains unaffected by imposing an arbitrary β_i. It is now possible to construct a valid test of the null hypothesis versus the alternative hypothesis that is asymptotically similar and whose distribution is free of nuisance parameters. Westerlund (2007) developed four tests that are based on the least squares estimates of θ_i and its t-ratio for each cross-sectional *i*. Two of them are called the group mean statistics and can be presented as:

$$G_\tau = \frac{1}{N} \sum_{i=1}^{N} \frac{\theta_i}{S.E(\hat{\theta}_i)} \quad (5)$$

and

$$G_\alpha = \frac{1}{N} \sum_{i=1}^{N} \frac{T\theta_i}{\theta_i'(1)} \quad (6)$$

G_τ and G_α test the null hypothesis of $H_0 : \theta_i = 0$ for all *i* versus the alternative hypothesis of $H_1^g : \theta_i < 0$ for some *i*. The rejection of the null hypothesis indicates the presence of cointegration for at least one cross-sectional unit in the panel. The other two tests are panel statistics and can be presented as:

$$P_\tau = \frac{\hat{\theta}_i}{S.E(\hat{\theta}_i)} \quad (7)$$

$$P_{\alpha} = T\hat{\theta} \tag{8}$$

P_{τ} and P_{α} test the null hypothesis of $H_0 : \theta_i = 0$ for all i versus the alternative hypothesis of $H_1^p : \theta_i = \theta < 0$ for all i. The rejection of the null hypothesis means the rejection of no cointegration for the panel as a whole.

Next, to examine the country-specific and panel impact of globalization on environmental quality, we use the estimators that allow heterogeneity in factor loadings by augmenting the regression equation(s) with proxies or estimates for the unobserved common factors. This augmentation avoids the identification problem and accounts for other cross-sectional dependence (e.g., spatial correlation) in the presence of nonstationary variables (Pesaran and Tosetti, 2010; Chudik et al., 2010; Kapetanios et al., 2011). The Pesaran (2006) CCE estimator, more specifically its heterogeneous version (CMG), accounts for the presence of unobserved common factors by averaging the individual country estimates, following the Pesaran and Smith (1995) MG approach. A related approach, the Augmented Mean Group (AMG) estimator, accounts for cross-sectional dependence by inclusion of a common dynamic process in the country regression. Both models, CMG and AMG, are used to obtain the country-specific and panel estimates.

3.3. Panel causality tests

3.3.1. Emirmahmutoglu and Kose (2011) panel causality test

To examine whether globalization causes CO_2 emissions or CO_2 emissions cause globalization, we apply the Emirmahmutoglu and Kose (E-K; 2011) panel causality test. This test is based on the Toda and Yamamoto (T-Y) causality procedure that can be applied without testing the integrating properties of the variables. The E-K causality test is applicable if the variables are stationary at

I(0) or I(1) or I(0)/I(1)[11]. The analysis of Fisher (1932) is the basis for the proposition of the E-K panel causality test. Emirmahmutoglu and Kose (2011) modified the lag augmented VAR (LA-VAR) approach developed by Toda and Yamamoto (1995). The E-K panel causality test employs the VAR model at levels using extra *dmax* lags to determine the Granger causality association between the series in heterogeneous fixed panels. The level VAR model containing k_i + *dmax* lags using heterogeneous mixed panels is as follows:

$$x_{i,t} = \mu_i^x + \sum_{j=1}^{k_i + d\max} \mathrm{A}_{11,ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max} \mathrm{A}_{12,ij} y_{i,t-j} + \mu_{i,t}^x \tag{9}$$

$$y_{i,t} = \mu_i^y + \sum_{j=1}^{k_i + d\max} \mathrm{A}_{11,ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max} \mathrm{A}_{12,ij} y_{i,t-j} + \mu_{i,t}^y \tag{10}$$

where k_i is the lag structure, $i(i = 1, \ldots, N)$ indicates individual cross-sections and $t(t = 1, \ldots, T)$ represents the time periods, while $\mu_{i,}^x$ and μ_i^y are the fixed effects vectors. Moreover, $A_{i1}, \ldots, A_{ik_i}$ are fixed (p×p) matrices of parameters that are allowed to vary across units. The column vectors of error terms are $\mu_{i,t}^x$ and $\mu_{i,t}^y$, which is assumed to be predetermined or different for different cross-sectional units, and *d*max indicates the optimal integrating order for each *i* in the VAR system. The bootstrap causality procedure developed by Emirmahmutoglu and Kose (2011) for causality running from *x* to *y* is summarized as follows:

i. The ADF unit root test is applied to determine the appropriate (*d*max) order of integration of the variables that will be used in the VAR system for each cross-sectional unit. The

[11] There is no need to test for the presence or absence of cointegration between the variables, while investigating co-integration between the variables by applying the T-Y causality test.

optimal lag order $k_i s$ is chosen following the Akaike Information Criterion (AIC) by applying the ordinary least square (OLS) to estimate the regression in Equation (9).

ii. The non-causality hypothesis is empirically tested by re-estimating Equation (10) using $d$max and k_i. This process is conducted to calculate for each individual as follows:

$$\hat{\mu}^{y}_{i,t} = y_{i,t} - \hat{\mu}^{y}_{i} + \sum_{j=1}^{k_i + d\max} \hat{A}_{21,\,ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max} \hat{A}_{22,\,ij} y_{i,t-j} \tag{11}$$

iii. We follow the suggestion by Stine (1987) to centre residuals as follows:

$$\tilde{\mu} = \hat{\mu}_i - (T - k - l - 2)^{-1} + \sum_{t=k+l+2}^{T} \hat{\mu}_t \tag{12}$$

where $\hat{\mu} = (\hat{\mu}_{1t}, \hat{\mu}_{2t}, \hat{\mu}_{3t}, ...\hat{\mu}_{Nt})'$, $k = \max(k_i)$ and $l = \max(d\max_i)$. Further, these residuals are developed by using $[\tilde{\mu}_{i,t}]_{N\times T}$. The full column with the replacement matrix is chosen at a time to preserve the cross covariance of the errors' structure. The bootstrap residuals are indicated by $\tilde{\mu}^{*}_{t}$ and $(t = 1,......,T)$.

iv. A bootstrap sample of $\boldsymbol{y_i}$'s is generated as:

$$y^{*}_{i,\,t} = \hat{\mu}^{y}_{i} + \sum_{j=1}^{k_i + d\max} \hat{A}_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max} \hat{A}_{22,ij} y^{*}_{i,t-j} + \mu^{*}_{i,t} \tag{13}$$

The $\hat{\mu}^{y}_{i}$, $\hat{A}_{21,ij}$ and $\hat{A}_{22,ij}$ are obtained by using Step iii.

v. Further, the Wald test is applied to test the non-causality hypothesis for each individual by replacing $y_{i,t}$ with $y^{*}_{i,t}$. In this situation, we estimate Equations (9–10) in the absence of parameter restrictions. The individual *p-values* are used to correspond to the Wald statistics for the *ith* cross-section. The Fisher test statistic is calculated as follows:

$$\lambda = -2\sum_{i=1}^{N} \ln(p_i) \qquad i = 1,\ldots\ldots, N \tag{14}$$

Steps iii–v are repeated 1000 times to generate the empirical bootstrap distribution of the Fisher test statistics. An appropriate percentile sampling distribution is selected to generate the bootstrap critical values. Lastly, Emirmahmutoglu and Kose (2011) argue that the LA-VAR approach performs well under cross-sectional independence and cross-sectional dependence. This seems to be acceptable for the entire time period (*T*) and all observations (*N*).

3.3.2. Dumitrescu and Hurlin (2012) panel causality test

The problem with the Emirmahmutoglu and Kose (2011) bootstrap panel causality test is that it is based on the bivariate Toda-Yamamoto approach. Furthermore, the E-K panel causality test is applicable only if the time series length (*T*) is greater than the number of cross-sections (*N*). In response to these shortcomings, Dumitrescu and Hurlin (2012) developed new panel causality methods. Their approach is suitable in the absence of the restriction *T*>*N*. Moreover, this approach of panel causality is applicable if all the variables in the panel are stationary at a common level, i.e., I(1).

Dumitrescu and Hurlin (2012) modified the Granger (1969) non-causality test for heterogeneous panels assuming fixed estimates. This causality test considers the two heterogeneity dimensions: (i) the heterogeneous regression model to be employed for testing causality in a Granger sense and (ii) the heterogeneous causal associations. We consider the following linear model, and the linear specification of the empirical equation is modelled as follows:

$$z_{it} = \alpha_i + \sum_{m=1}^{M} \gamma_i^{(m)} z_{i,t-m} + \sum_{m=1}^{M} \beta_i^{(m)} y_{i,t-k} + \varepsilon_{it} \tag{15}$$

Equation (15) indicates that y and z are the series found to be stationary for N individuals in T periods. The intercept and coefficients such as α_i and $\beta_i = (\beta_i^{(1)}, \ldots\ldots, \beta_i^{(m)})'$ are fixed in the given time dimension. The autoregressive parameters $\gamma_i^{(m)}$ and the regression coefficient estimates $\beta_i^{(m)}$ are assumed to vary across cross-sections. The null hypothesis is 'no causal relationship exists between the variables' in the panel for any of the cross-sections and is termed as the homogenous non-causality (*HNC*) hypothesis, which can be described as follows:

$$H_0 : \beta_i = 0 \qquad \forall_i = 1, 2, \ldots\ldots, N$$

$$H_0 \neq \beta_i \neq 0 \qquad \forall_i = 1, 2, \ldots\ldots\ldots, N$$

The alternative hypothesis is termed as the heterogeneous non-causality (*HENC*) hypothesis, as we specify two sub-groups of cross-sectional units. The unidirectional causality runs from y to z in the first sub-group but not in the second sub-group. If there is no causal association from y to z for the second sub-group, then we use a heterogeneous panel data model by assuming fixed estimates of the group for empirical analysis. The alternate hypothesis can be described as follows:

$H_a : \beta_i = 0 \qquad \forall_i = 1, 2, ..., N_1$

$\beta_i \neq 0 \qquad \forall_i = N_1 + 1, ..., N$

It is assumed that β_i may be sensitive across cross-sections with $N_1 < N$ individual processes providing a neutral effect from *y* to *z*. The unknown N_1 determines the condition $0 \leq N_1 / N < 1$. This leads us to propose the average statistics $W_{N,T}^{HNC}$ following Dumitrescu and Hurlin (2012). The average statistic $W_{N,T}^{HNC}$ is directly linked to the homogenous non-causality (*HNC*) hypothesis as given below:

$$W_{N.T}^{HNC} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T} \tag{16}$$

where $W_{i,T}$ ($W_{i,T} = \hat{\theta}_i^{'} R^{'} \left[\hat{\sigma}_i^2 R (Z_i^{'} Z_i)^{-1} R^{'} \right] R \hat{\theta}_i$) are individual Wald statistics for each cross-sectional unit. The null hypothesis of non-causality reveals that each individual Wald statistic congregates to a Chi-squared distribution in the presence of *M* degrees of freedom for $T \rightarrow \infty$. This harmonized test statistic $Z_{N,T}^{HNC}$ for $T, N \rightarrow \infty$ is written as follows:

$$Z_{N,T}^{HNC} = \sqrt{\frac{N}{2M}} (W_{N,T}^{HNC} - M) \rightarrow N(0,1) \tag{17}$$

The harmonized test statistic $Z_{N,T}^{HNC}$ for fixed *T* samples is given as follows:

$$Z_{N,T}^{HNC} = \sqrt{\frac{N}{2 \times K} \times \frac{(T-2K-5)}{(T-K-3)}} \times \left[\frac{(T-2K-3)}{(T-2K-1)} W_{N,T}^{HNC} - K \right] \rightarrow N(0, 1) \tag{18}$$

where $W_{N,T}^{HNC} = (1/N)\sum_{1=1}^{N} W_{i,T}$. Dumitrescu and Hurlin (2012) have provided detailed information for these statistics.

4. Interpretation of Results

Over the period of 1970–2014, we use annual data of CO_2 emissions (in metric tons), which are converted into per capita units using total population (Lean and Smyth, 2010). The data are sourced from the *World Development Indicators* (CD-ROM, 2014). The globalization index is obtained from Dreher (2006) and is constructed as an overall globalization index from three sub-indices: economic globalization, social globalization and political globalization. Economic globalization involves two aspects: (i) actual economic flows (trade, foreign direct investment and portfolio investment) and (ii) restrictions on trade and capital flows (which include restrictions on trade and capital using hidden import barriers such as the mean tariff rates, taxes on international trade as a share of current revenue and an index of capital controls). Dreher (2006) defines social globalization as cultural ties among countries. Potential inputs used for political globalization are the number of embassies in a country, membership in international organizations and participation in the UN Security Council and international treaties. The globalization index is generated with the weights of 36%, 38% and 26% for economic, social and political indices, respectively (http://globalization.kof.ethz.ch/). This index is appropriate for empirical analysis between globalization and CO_2 emissions covering all aspects of globalization (economic, social and political) rather covering trade openness (trade liberalization) as used in previous studies in existing energy literature.

Table 1 reveals that CO_2 emissions are less volatile in Austria compared to Iceland, Italy, Japan, Netherlands and Switzerland as defined by standard deviations. High volatility is also observed for CO_2 emissions in Luxembourg, compared to Singapore and Korea. The volatility in CO_2 emissions is mixed in the remaining countries. Volatility in globalization is high in Portugal compared to Spain, Greece, Korea, Finland, Italy, Iceland and Israel, but in the remaining countries, globalization volatility is mixed.

Table 1: Descriptive statistics

	CO_2 emissions per capita				Globalization index			
Country	Mean	S.D	Min.	Max.	Mean	S.D	Min.	Max.
Australia	15.421	1.696	11.803	17.704	74.163	7.860	54.380	83.160
Austria	7.706	0.562	6.789	9.028	79.411	11.615	56.630	91.980
Belgium	11.245	1.502	8.556	14.255	82.935	8.905	68.270	92.370
Canada	16.249	1.328	11.809	18.209	81.593	5.298	69.510	88.790
Denmark	10.384	1.624	6.460	13.715	79.646	8.168	66.090	89.570
Finland	10.662	1.082	8.562	13.261	72.381	12.771	53.250	87.450
France	6.903	1.414	4.690	9.667	72.898	9.986	56.460	84.150
Greece	6.644	1.695	2.748	8.895	62.594	14.165	44.470	82.420
Iceland	7.297	0.796	5.118	8.805	62.258	11.039	45.610	78.090
Ireland	8.589	1.398	6.518	11.387	78.934	8.803	63.290	92.290
Israel	7.544	1.641	5.294	9.877	60.330	10.065	49.900	78.080
Italy	7.002	0.719	5.513	8.216	66.752	12.453	50.470	81.340
Japan	8.661	0.792	7.368	9.857	51.177	10.337	33.890	66.010
Korea	6.759	3.510	1.668	13.498	47.672	13.874	26.870	65.050
Luxembourg	25.853	6.417	17.320	40.590	76.888	5.304	69.880	85.410
Netherlands	10.840	0.821	9.385	13.379	83.152	8.380	64.350	91.980
New Zealand	6.993	1.075	5.050	8.893	69.372	8.720	53.860	79.970
Norway	8.482	1.119	6.918	11.616	76.465	7.320	61.990	84.430
Portugal	4.097	1.445	1.758	6.413	67.112	15.301	47.300	87.310
Singapore	10.763	4.331	2.395	19.119	77.953	9.866	58.270	88.820
Spain	5.840	1.141	3.458	8.097	69.010	14.921	45.950	85.410
Sweden	7.171	1.904	4.704	11.486	80.260	8.315	62.680	89.360
Switzerland	5.866	0.694	3.983	7.335	81.072	8.164	62.810	91.380
UK	9.501	1.347	6.025	11.823	76.549	7.795	59.590	85.390
USA	19.507	1.508	15.695	22.511	69.604	6.432	58.450	77.390
Panel	9.839	5.184	1.668	40.590	72.007	13.751	26.870	92.370

Note: S.D, Min., and Max., stand for standard deviation, minimum and maximum, respectively.

The presence of cross-sectional dependence and slope heterogeneity affects the causal estimates between globalization and CO_2 emissions, and consequently it is important to test the data for these properties. The results are reported in Table 2. The tests include the Lagrange multiplier (LM) test (Breusch and Pagan, 1980), the cross-sectional dependence test (Pesaran et al., 2008) and its LMadj version with the null hypothesis that there is no cross-sectional dependence. Pesaran and Yamagata (2008) recommend a standardized version of Swamy's test for examining the slope homogeneity in large panels as well as the biased-adjusted version. The results indicate the presence of cross-sectional dependence and slope heterogeneity in the panel of the 25 developed countries.

Table 2: Cross-sectional Dependence and Slope Homogeneity Tests

Test	Statistics
CD_{BP}	4895.376***
CD_{LM}	186.5848***
CD	20.84644***
LM_{adj}	186.3007***
$\tilde{\Delta}$	2356.20***
$\tilde{\Delta}_{adj}$	7.1321***

Note: *** represents significance at the 1% level. CD_{BP}, CD_{LM}, CD and LM_{adj} are the cross-sectional dependence (CD) tests by Breusch-Pagan LM (1980), Pesaran (2004) scaled LM and CD, and the Baltagi, Feng and Kao (2012) bias-corrected scaled LM tests, respectively. Further, $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ are the slope homogeneity tests proposed by Pesaran and Yamagata (2008) and a bias-adjusted version LM test of error cross-sectional independence also proposed by Pesaran et al. (2008), respectively.

To examine the stationarity properties of globalization and CO_2 emissions variables, we apply the panel unit root test of Pesaran (2007), and the results are reported in Table 3. We find that globalization and CO_2 emissions contain a unit root, while using both the constant and the constant and trend specifications. CO_2 emissions and globalization are found to be stationary in first differences, i.e., they are integrated of order I(1). To test the robustness of unit root analysis, we also apply the LM panel unit root test developed by Im et al. (2005), which accommodates a single unknown structural break in the series. The results are reported in Table 4, and they show that globalization and CO_2 emissions are stationary in the levels.

Table 3: Pesaran (2007) Panel Unit Root Test Analysis

	Constant	**Constant and trend**
a). Level series		
lnE_t	-2.235	-2.486
LnG_t	-2.019	-2.323
b). First difference series		
ΔlnC	-5.848***	-6.060***
ΔLnG	-5.521***	-5.783***

Note: *** indicates a rejection of the null hypothesis at the 1% level. LnC refers to the natural log of CO_2 emissions (metric tons per capita), while LnG denotes the natural logarithm of the overall globalization index covering social, political and economic globalization indices.

Table 4: Unit Root Analysis with Structural Breaks

Variable	Globalization			CO_2 Emissions		
Countries	T-statistic	Lag	Break Year	T-statistic	Lag	Break Year
Japan	-2.52	0	2005	-2.52	0	1986
Korea	-4.07	1	1992	-2.36	2	1997
Israel	-1.69	2	1994	-2.39	0	1989
Singapore	-2.08	0	1978	-1.47	1	1994
USA	-2.55	1	1995	-2.02	0	1978
Canada	-1.23	0	1990	-2.72	0	2002
Austria	-1.93	0	1991	-2.45	0	1987
Belgium	-2.36	0	1997	-3.08	0	1982
Denmark	-3.17	1	1988	-4.02	0	1990
Finland	-2.62	0	1995	-3.96	0	1987
France	-2.37	0	1978	-1.54	2	1996
Greece	-1.57	0	1990	-0.28	2	1998
Iceland	-2.04	2	1991	-5.64	0	1982
Ireland	-1.45	0	1988	-1.54	0	1985
Italy	-1.61	0	1988	-3.42	0	2005
Luxembourg	-1.92	0	2001	-1.83	1	1999
Netherlands	-1.22	0	1992	-1.79	0	1979
Norway	-1.41	0	1991	-2.77	0	1989
Portugal	-2.04	1	2003	-1.79	0	1988
Spain	-2.19	0	1988	-1.88	0	2005
Sweden	-1.74	0	1991	-1.45	0	1979

Switzerland	-1.87	0	1991	-4.15	0	2004
UK	-1.72	0	1991	-2.01	0	2002
Australia	-1.32	0	1990	-2.54	0	1989
New Zealand	-2.83	1	1984	-2.84	0	1984
Panel LM Test	-0.709			-1.350		

Note: *** and ** show significance at the 1% and 5% levels, respectively.

The unique order of integration of both variables allows us to apply the error-correction based panel cointegration tests developed by Westerlund (2007) to examine whether a long-run relationship between globalization and CO_2 emissions is present. Table 5 reports the results of these panel cointegration tests. We find that the null hypothesis of no cointegration can be rejected, as indicated by group (G_t and G_α at the 10% and 1% levels, respectively)[12] and panel statistics (P_t and P_α at the 10% and 1% levels, respectively). This supports the hypothesis that globalization and CO_2 emissions are cointegrated in our sample of developed countries over the period 1970–2014.

Table 5: Westerlund (2007) Cointegration Tests Analysis

	Value	**z-value**	**Robust p-value**
G_t	-3.042*	-2.120	[0.063]
G_α	-12.335***	-4.134	[0.000]
P_t	-7.253***	-3.014	[0.001]
P_α	-5.086***	-1.951	[0.002]

Note: *** and * indicate a rejection of the null hypothesis of no cointegration at the 1% and 5% levels, respectively. The optimal lag/lead length is determined by the Akaike Information Criterion (AIC) with a maximum lag/lead length of 2. The width of the Bartlett kernel window is set to 3. The number of bootstraps to obtain the bootstrapped p-values, which are robust against cross-sectional dependencies, is set to 400.

[12] We are thankful to the anonymous referee for highlighting that the test statistics for G_t are significant at 10%, and hence should be interpreted with caution. We have only reported the bootstrapped, 400 bootstraps, p-values. The asymptotic p-values, not reported, are however significant at 5% for both group tests. Although asymptotically not an issue, the normalization of G_α by T may cause the test to reject the null too frequently. Based on the bootstrapped p-values, we end up with one rejection, for G_t, at the 10% level. However, as this rejection is marginal, we choose to interpret these results as evidence in favor of cointegration between the selected variables.

The existence of a panel cointegration relationship between globalization and CO_2 emissions in the 25 developed countries enables us to examine the time series and panel effects of globalization on CO_2 emissions. Table 6 reports the country-specific and heterogeneous panel elasticities using the common correlated effects mean groups (CCEMG) and augmented mean group (AMG) models. Concerning the country-specific time series evidence from the CCEMG model shown in Table 6, we find that globalization has a positive impact on CO_2 emissions in 14 developed countries, including Japan (at 1%), Korea (at 5%), Singapore (at 1%), Canada (at 5%), Belgium (at 1%), Denmark (at 1%), Finland (at 5%), France (at 1%), Greece (at 1%), Iceland (at 10%), Ireland (at 1%), Luxembourg (1%), Sweden (at 1%) and Australia (at 1%). This implies that globalization deteriorates environmental quality by increasing CO_2 emissions. The increasing pollution levels may be caused by rising economic growth and more use of energy-intensive technology in the production process of firms in those 14 developed economies.

In contrast, globalization decreases CO_2 emissions in the United States (at 5%), Austria (at 5%), the Netherlands (at 1%), Spain (at 5%) and the UK (at 1%), which demonstrates that those five developed economies are capable of improving environmental quality by lowering CO_2 emissions via globalization. Although the rest of the developed countries, such as Israel, Italy, Norway, Portugal, Switzerland and New Zealand, lower CO_2 emissions via globalization, the effect is statistically insignificant. Finally, this result demonstrates that globalization and CO_2 emissions are positively (negatively) and statistically significant for 14 (56%) and 5 (20%) of the 25 sampled developed countries, while in the remaining 6 countries (24%), globalization is negatively but insignificantly linked with CO_2 emissions.

The panel estimates also show a positive link between globalization and CO_2 emissions at the 1% and 5% levels of significance. Following the country-specific time series analysis based on the CCEMG estimate, we conclude that globalization is not beneficial for the sustainable environmental health of most developed countries (56%), as it discharges increasing CO_2 emissions into the natural environment. As a result, the absorption capacity of the natural environment decreases, and therefore the quality of environmental health deteriorates. This finding is also consistent with the panel results. Overall, the findings of this study are robust and can effectively guide policy makers of developed countries to design a single environmental policy for improving their long-run environmental health. From a policy perspective, we further suggest that policy makers and governments in most of the developed countries consider globalization as a key economic tool in their long-term environmental policy frameworks.

Notably, the CCEMG estimates accommodate cross-sectional dependence and time-variant un-observable factors, but unobservable common factors may cause overestimates in the empirical analysis (Eberhardt and Teal, 2010). The CCEMG is simply an average of the individual common country effects. The CCEMG estimator is unable to distinguish between temporal and general dynamics, which are confined by the common and exogenous individual-specific time series. Finally, CCEMG is unable to model spatial patterns occurring in the globalization–CO_2 emissions nexus; it provides slope estimates without considering spatial error. These issues are resolved using the AMG developed by Eberhardt and Teal (2010).

The results of the AMG estimation again show that globalization is positively and significantly linked with CO_2 emissions in the following 12 developed countries: Japan, Korea, Singapore, Canada, Belgium, Denmark, Finland, France, Greece, Luxemburg, Sweden and Australia. However, globalization is inversely and significantly linked with CO_2 emissions for four developed countries: United States (at the 1% level), Austria (at 1%), the Netherlands (at 1%) and the UK (at 1%). Globalization has a positive (negative) but insignificant impact on CO_2 emissions in Iceland, Ireland and Portugal (Israel, Italy, New Zealand, Norway, Spain and Switzerland). This concludes that globalization increases CO_2 emissions in 12 developed countries (48%) out of 25 total sampled countries, although it reduces CO_2 emissions in 4 (16%) sampled countries; 36% (9 developed economies) of the sampled countries show a statistically insignificant effect of globalization on CO_2 emissions either positively or negatively.

The panel analysis also shows that globalization degrades environmental quality by increasing CO_2 emissions. In view of the AMG evidence based on the country-specific time series analysis, we also conclude that globalization weakens environmental quality in half of the developed countries (48% countries) by increasing CO_2 emissions. This finding is also consistent with the result of panel analysis. The environmental consequences of globalization for most developed countries are larger because globalization adds carbon emissions. Increasing carbon emissions is not only harmful for degrading the environmental health of developed countries but also results in unwarranted climate change and global warming in the long run. Given the environmental consequences of globalization, we further suggest that the role of globalization in the dynamics of carbon emissions in most of the developed countries should not be underestimated by policy makers when designing their comprehensive and long-term environmental policy framework. In addition, the p-values of the Pesaran (2007) CIPS test, with 2 lags, reject the null hypothesis and model residuals are stationary. Further, the root mean square error (RMSE) suggests that AMG has a better model fit.

Table 6: Long-Run Heterogeneous Elasticities

Country	CCEMG		AMG	
	Coeff.	Z-stats	Coeff.	Z-stats
Australia	0.425^{*}	(1.750)	0.697^{***}	(2.650)
Austria	-0.476^{**}	(-2.080)	-0.638^{***}	(-4.030)
Belgium	1.676^{***}	(4.370)	1.147^{***}	(4.130)
Canada	0.414^{**}	(1.060)	0.301^{*}	(0.940)
Denmark	1.165^{**}	(1.350)	0.619^{**}	(1.530)
Finland	0.662^{**}	(1.200)	0.602^{*}	(1.920)
France	1.276^{***}	(3.810)	1.170^{***}	(5.090)
Greece	0.438^{***}	(3.210)	0.208^{*}	(1.590)
Iceland	0.390^{*}	(0.310)	0.116	(1.340)
Ireland	1.108^{***}	(3.140)	0.120	(0.320)
Israel	-0.092	(-0.570)	-0.095	(-0.530)
Italy	-0.075	(-0.760)	-0.001	(-0.010)
Japan	0.637^{***}	(4.150)	0.491^{***}	(2.660)
Korea	0.974^{**}	(2.230)	0.696^{*}	(1.910)
Luxembourg	2.649^{***}	(3.920)	1.015^{**}	(1.240)
Netherlands	-1.128^{***}	(-3.740)	-1.241^{***}	(-5.770)
New Zealand	-0.858	(-1.570)	-0.340	(-0.770)
Norway	-0.184	(-0.270)	-0.397	(-0.780)
Portugal	-0.268	(-1.140)	0.359	(1.410)
Singapore	3.573^{***}	(2.990)	4.449^{***}	(5.470)
Spain	-0.739^{**}	(-2.290)	-0.115	(-0.500)
Sweden	2.811^{***}	(4.410)	2.877^{***}	(6.340)
Switzerland	-0.268	(-0.970)	-0.198	(-0.980)
UK	-1.098^{***}	(-4.700)	-0.762^{***}	(-3.820)
USA	-0.462^{**}	(-2.410)	-0.591^{***}	(-3.440)
Panel statistics	0.970^{**}	(0.370)	0.802^{**}	(0.320)
Diagnostic				
I(1)	[0.001]		[0.000]	
RMSE	0.0819		0.0723	

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Z-statistics are in parenthesis. Coeff. = coefficient; CCEMG = Common Correlated Effects Mean Group estimator by Pesaran (2006); AMG = Augmented Mean Group estimator by Eberhardt and Teal (2010). 'I(1)' reports p-values for a Pesaran (2007) CIPS test with 2 lags, null of nonstationarity. RMSE is the root mean square error.

To examine the causal relationship shown in the panel between globalization and CO_2 emissions, we apply the panel Granger causality test proposed by Emirmahmutoglu and Kose (2011). The empirical results are reported in Table 7. We find unidirectional causality running from globalization to CO_2 emissions in six developed countries: Japan (at 5%), Belgium (at 5%), Greece (at 10%), Portugal (at 1%), Switzerland (at 5%) and the UK (at 10%), but CO_2 emissions Granger cause globalization in four countries: Canada (at 10%), Sweden (at 10%), Australia (at 10%) and New Zealand (at 10%). The feedback effect exists between globalization and CO_2 emissions for the Netherlands at the 5% level of significance, indicating that both globalization and CO_2 emissions are influencing each other. This further implies that a change in globalization can cause a change in carbon emissions and vice-versa for the Netherlands economy.[13] Moreover, a neutral effect is also found for Korea, Israel, Singapore, USA, Austria, Denmark, Finland, France, Iceland, Ireland, Luxemburg, Norway and Spain. The panel estimates reveal a unidirectional causality running from globalization to CO_2 emissions at the 1% level of significance, indicating that a change in globalization causes a consequential change in CO_2 emissions for developed countries. Moreover, we find mixed and inconclusive time series evidence that is not largely consistent with the result of panel analysis. Following the panel Granger causal evidence of the E-K (2011) model, we further suggest that policy makers in developed countries add globalization as a key variable when assessing their long-run environmental health condition.

Table 7: Emirmahmutoglu and Kose (E-K, 2011) Panel Granger Causality Analysis

Null Hypothesis	G_t does not Granger cause E_t			E_t does not Granger cause G_t		
	$G_t \neq> E_t$			$E_t \neq G_t$		
Individual statistics						
Country	k_i	W_i	p_i	k_i	W_i	p_i
Australia	2	0.9160	[0.6330]	2	5.3140*	[0.0700]
Austria	1	1.9420	[0.1630]	1	0.1090	[0.7420]
Belgium	1	4.6890**	[0.0300]	1	0.0610	[0.8040]
Canada	1	0.0430	[0.8360]	1	2.8210*	[0.0930]
Denmark	1	0.7490	[0.3870]	1	0.0390	[0.8430]
Finland	1	1.1440	[0.2850]	1	1.3490	[0.2450]

[13] The potential reason for the emergence of the feedback causal effect between the series is also explained in the result explanation of the D-H (2012) panel Granger causality model.

France	1	0.0130	[0.9090]	1	0.2490	[0.6180]
Greece	1	3.7400*	[0.0530]	1	0.1860	[0.6660]
Iceland	1	0.0060	[0.9370]	1	0.3830	[0.5360]
Ireland	2	1.2080	[0.5470]	2	1.2390	[0.5380]
Israel	2	0.9140	[0.6330]	2	1.4120	[0.4940]
Italy	1	1.2000	[0.2730]	1	0.2810	[0.5960]
Japan	2	7.3720**	[0.0250]	2	0.5900	[0.7450]
Korea	1	1.6540	[0.1980]	1	0.3480	[0.5550]
Luxembourg	3	0.4130	[0.9370]	3	4.9920	[0.1720]
Netherlands	3	8.3420**	[0.0390]	3	6.4700*	[0.0910]
New Zealand	2	1.4610	[0.4820]	2	4.6430*	[0.0980]
Norway	1	2.3780	[0.1230]	1	1.1430	[0.2850]
Portugal	3	13.8160***	[0.0030]	3	3.3040	[0.3470]
Singapore	3	0.7880	[0.8520]	3	6.1980	[0.1020]
Spain	1	0.4430	[0.5060]	1	0.0520	[0.8200]
Sweden	1	1.6250	[0.2020]	1	3.6520*	[0.0560]
Switzerland	3	5.4740**	[0.0400]	3	0.8010	[0.8490]
UK	2	4.2140**	[0.0600]	2	0.1250	[0.9390]
USA	1	1.8560	[0.1730]	1	0.2920	[0.5890]
Panel test statistics						
Fisher test value				Fisher test value		
77.094**				52.537		
Bootstrap critical values:				Bootstrap critical values:		
*** 1%: 83.588				*** 1%: 84.791		
** 5%: 75.087				** 5%: 76.716		
* 10%: 69.444				* 10%: 71.115		

Note: ***, ** and * show significance at the 1%, 5% and 10% levels, respectively. P values are in [ ].

As a robustness test, we also apply the D-H panel causality test developed by Dumitrescu and Hurlin (2012), and the results are reported in Table 8. We note a feedback effect (i.e., globalization causes CO_2 emissions and CO_2 emissions cause globalization) in Israel, Belgium, Italy, the Netherlands and Portugal, but a neutral effect is also present for the United States, Canada, Austria, Denmark, Norway, the UK and Australia. Broadly speaking, the feedback or bidirectional causality between globalization and CO_2 emissions is found for five developed countries within the time series framework, indicating that both globalization and carbon emissions are influencing each other. The emergence of a feedback causal effect between globalization and carbon emissions can be strengthened by the fact that these countries are often exposed to the package of social, political and economic globalization in the 21st century. Hence, any temporary or permanent shocks arising from the overall globalization can cause a change in carbon emissions in these countries and vice versa. For instance, if these countries are growing at the cost of environmental health by increasing energy consumption, then globalization will be beneficial for them in improving environmental quality by lowering energy consumption via the use of imported advanced energy-saving technology in the production process.

Similarly, a change in carbon emissions in these countries can also make a change in globalization. For instance, if these countries desire to intensify the pace for growth and prosperity, then they need to consume more energy and eventually will increase carbon emissions. Thus, environmental quality is likely to be deteriorated because of rising carbon emissions, and therefore these countries are forced to be widely integrated globally in the search of an alternative imported energy-saving technology from the rest of the world. As a result, these countries will improve their environmental quality by using imported energy-saving technology in the production process. However, we confirm the existence of a neutral effect for seven developed countries, which shows that there exists no unidirectional or bidirectional causal relationship between globalization and carbon emissions. This implies that a change in globalization will not cause any change in their carbon emissions and vice versa for these seven developed countries.

Furthermore, globalization Granger causes CO_2 emissions in the cases of Japan, Singapore, Finland, France, Ireland, Luxembourg, Spain, Sweden and Switzerland. This indicates that a change in globalization causes a change in carbon emissions for nine developed countries. It also shows that globalization is a key to the dynamic evolution of carbon emissions in the cases of nine developed countries. In contrast, a unidirectional causality running from CO_2 emissions to globalization is found for Korea, Greece, Iceland and New Zealand, indicating that a change in CO_2 emissions causes a consequent change in globalization. This similarly shows the importance of carbon emissions in changing the perspective of overall globalization for four developed countries. Additionally, the panel analysis shows that the feedback effect between globalization and CO_2 emissions is significant, indicating that no divergence between globalization and CO_2 emissions can be found, as each is causing the other. As concluded by the D-H (2012) Granger panel causal evidence, the feedback panel causal effect between globalization and CO_2 emissions is becoming stronger because five developed countries out of the 25 sampled economies confirm similar results within the country-specific time series framework. On the policy front, this finding suggests that the causal role of globalization and CO_2 emissions should not be underestimated by the policy makers of developed countries when formulating their environmental policy framework.

Table 8: Dumitrescu and Hurlin (D-H, 2012) Granger Causality Analysis

Null Hypothesis	G_t does not Granger cause E_t			E_t does not Granger cause G_t		
	$G_t \neq > E_t$			$E_t \neq G_t$		
Individual statistics						
Country	k_i	W_i	p_i	k_i	W_i	p_i
Australia	3	1.4682	[0.1909]	1	0.6437	[0.4224]
Austria	1	2.3173	[0.1279]	1	0.8506	[0.3564]
Belgium	1	3.3829*	[0.0798]	2	5.0220*	[0.0812]
Canada	1	1.4092	[0.2352]	1	0.0860	[0.7693]
Denmark	1	1.7935	[0.1805]	1	2.6922	[0.1008]
Finland	2	5.0846*	[0.0787]	1	1.6153	[0.2038]
France	1	7.7845***	[0.0053]	1	0.7978	[0.3717]
Greece	1	0.4600	[0.4976]	1	5.6694**	[0.0173]
Iceland	1	2.1497	[0.1426]	1	7.9515***	[0.0048]
Ireland	1	5.3903**	[0.0202]	1	0.2000	[0.6547]
Israel	2	5.8112*	[0.0547]	1	14.850***	[0.0001]
Italy	1	3.9623**	[0.0465]	1	2.7449*	[0.0976]
Japan	1	6.3797**	[0.0378]	2	0.5014	[0.2387]
Korea	1	0.0497	[0.8236]	1	6.9242***	[0.0085]
Luxembourg	3	6.4348*	[0.0923]	1	2.4484	[0.1176]
Netherlands	1	5.7355**	[0.0166]	3	12.970***	[0.0047]

New Zealand	1	0.3416	[0.5589]	2	7.7085**	[0.0212]
Norway	1	2.6197	[0.1055]	1	1.9638	[0.1611]
Portugal	1	4.2365**	[0.0396]	1	18.047***	[0.0000]
Singapore	1	3.8171*	[0.0507]	1	1.2495	[0.2636]
Spain	1	3.6603*	[0.0557]	1	0.9974	[0.3180]
Sweden	1	4.4854**	[0.0342]	1	2.5354	[0.1113]
Switzerland	1	6.1048*	[0.0932]	1	1.2408	[0.2653]
UK	1	0.1858	[0.6664]	1	0.3116	[0.5767]
USA	1	0.3116	[0.5767]	1	0.4162	[0.5188]
Panel test statistics						
W^{Hnc}	3.1350***			4.2575***		
W_{NT}^{Hnc}	6.0644***			7.8577***		
W_{N}^{Hnc}	5.4635***			7.0425***		

Note: ***, ** and * show significance at the 1%, 5% and 10% levels, respectively. The p-values are in brackets [ ].

5. Conclusion and Policy Suggestions

To our knowledge, no published research in the field of environmental modelling and assessment has studied the role of globalization in the dynamic evolution of CO_2 emissions focusing on the case of developed countries, using fairly modern techniques. This study empirically addressed this research gap by examining the relationship between globalization and CO_2 emissions across 25 developed countries within country-specific time series and panel frameworks covering the data period of 1970–2014.

In doing so, we use a comprehensive globalization index proposed by Dreher (2006) that covers different dimensions of socio-economic and political globalization. A long-run association between the variables in the presence of cross-sectional dependence and slope heterogeneity is confirmed through the Westerlund (2007) cointegration tests, and country-specific and heterogeneous panel elasticities are estimated using Pesaran (2006)'s common correlated effects mean group (CCEMG) estimator and Eberhardt and Teal (2010)'s augmented mean group (AMG) estimator. Finally, bivariate heterogeneous panel casual links are examined through the Dumitrescu and Hurlin (2012) and Emirmahmutoglu and Kose (2011) Granger causality tests.

In terms of key empirical findings, we conclude that globalization increases carbon emissions for most of the developed countries. This finding is also consistent with the result of panel analysis.

More intuitively, we establish that globalization is not beneficial for the long-term environmental health of all developed countries, as it increases carbon emissions in many countries. In such circumstances, we also believe that the environmental consequences of globalization for most developed countries are negative because they engender unwarranted climate change and global warming in the future. The E-K (2011) Granger causality panel estimates reveal a unidirectional causality running from globalization to CO_2 emissions in developed countries. This implies that a change in globalization will also bring a change in carbon emissions in developed countries. Hence, globalization is a key to the dynamic evolution of carbon emissions in the case of developed countries.

Our findings are consistent with the seminal theoretical argument of Shafik and Bandyopadhyay (1992) in which they have argued that industrialized or developed economies (e.g., in terms of trade openness as a percent of GDP) tend to use traditional capital-driven production techniques, and consequently increase pollution levels. In light of this, this causal finding suggests that policy makers in developed countries should recognize the potential role of globalization in CO_2 emissions while formulating policy for environmental quality.

In terms of key policy implications, we suggest that governments of these economies may use proper and effective policy coordination to minimize the environmental cost caused by globalization. Given the harmful environmental consequences of globalization, we suggest that policy makers should not underestimate the role of globalization in the dynamics of carbon emissions in developed countries when designing their comprehensive and long-term environmental policy framework. We further suggest that policy makers in developed economies should consider ‘‘globalization’’ as a *key economic tool* in their environmental policy framework to improve the quality of environmental health in the long run. In addition, developed countries need to enhance their energy-related research and consider the wider role of globalization in energy demand and emissions functions. The use of cleaner and alternative technologies through innovation, investment and international collaborations can also play a vital role in achieving low carbon-driven sustainable environment-friendly economic growth in the long run.

Finally, the empirical findings of this study will reverse the established debate raised in the introduction that international organizations do not compel developed countries to reduce their energy consumption-related CO_2 emissions (Kyoto Protocol Summit, 1997; UN Emissions Gap Report, 2012; Paramati et al. 2016). Developing countries must pressure international organizations to compel developed countries to reduce the long-run impact of globalization in the long-run. Thus, it is the further need of hour among developing countries to strengthen their effective mode of collaboration in order to reduce the contagious effect of climate change and global warming mainly arising due to the environmental consequences of globalization in developed countries.

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