The Long-Run Effects of Trade and Income on Carbon Emissions: Evidence from Heterogeneous Dynamic Panel of Developing Countries

Muhammed Benli[1]

[1]Asst. Prof. Department of Economics, Bilecik Seyh Edebali University, muhammed.benli@bilecik.edu.tr

Abstract: This study examines the effect of trade growth and per capita income growth on long run carbon emissions per capita using data on a sample of 79 developing countries over the period 1960-2017. To do so, we employ three different specifications (standard panel ARDL, CS-ARDL and CS-DL) to eliminate the shortcomings and limitations of time series analyses and problems related to the panel data models. Specifically, we consider the dynamics, heterogeneity, cross-sectional dependence, and possible feedback effects from CO_2 emissions to free trade and per capita income. The empirical evidence extracted from the aforementioned frameworks suggests a positive and significant effect of both openness and income on long-run carbon emissions in developing countries.

Keywords: Trade; Carbon Emissions; Heterogeneous Panel Data Models; Cross-sectional dependence

JEL Classifications: F18, F64, F41, F43, F15, C33

1. Introduction

The last four decades have witnessed rising overall well-being around the globe thanks to the unprecedented technological progress, modernization, globalization and industrialization. However, the same period was marked by the increasing environmental concerns as pollution and pollution-related problems have skyrocketed. Recent decades have seen remarkable growth of trade, completely transforming the world economy. This growth has been possible mainly because of both technological developments and declines in trade barriers through a number of preferential trade agreements. Today, the value of exported goods around the globe is about one fourth of the total global output. This is mainly due to the virtues attributed to trade. Openness to trade is viewed as an important growth-enhancing factor through competition, economies of scale and learning and innovation. Open trade regime is considered to be a catalyzer for the integration process of less developed countries into the global economy, often called globalization, which in turn has enabled technology transfer among the countries and *led to a remarkable rise in trade volumes accompanied by the tremendous growth of the global economy over the last couple of decades.*

*There is a significant amount of evidence in theoretical and empirical literature that outward-*looking economies tend to grow faster than those of inward-oriented. However, as with many of the other aspects of globalization trend, the growth of global trade has raised an important debate regarding the environmental consequences of this trend. Although CO2 emissions stagnated over the period 2014-2016 thanks to the energy efficiency improvements even as the global economy continued to expand, the dynamics have changed in 2017 and 2018. According to the Global Energy and CO_2 Status Report of the International Energy Agency (2019), global total energy consumption increased by 2.3%, nearly double the average rate of growth of the last eight years, leading to a growth of CO_2 emissions by 1.7% (%70 higher than the average growth since 2010 and highest rate of growth since 2013) to a historic high of 33.1 Gt CO_2. Therefore, it is not surprising that the environmental consequences of global economic rise have become part of the national and international policies especially after the 2000s.

Encouraging trade liberalization for future economic growth and sustainable development, understanding how trade flows possibly affect the CO_2 emissions and the potential trade-offs is obvious importance as environmental sustainability is considered to be a precondition for higher living standards of future generations. The efforts to unveil the environmental consequences of trade are not new and dates back to Grossman and Krueger (1991) exploring the environmental effects of North American Free Trade Agreement (NAFTA) and presenting empirical evidence to assess the magnitudes of channels as they apply to further liberalization of trade in Mexico. Since then, considerable attention has been devoted to quantifying the environmental consequences of trade liberalization over the last decades. On the one hand, some studies find that free trade has a detrimental effect on the environment, supporting the PHH (Heil and Selden 2001, Ang 2009, Ramcke and Abdulai 2009, Managi et al. 2009, Sharma 2011, Shahbaz and Leita 2013, among others). On the other hand, some other studies report that trade openness is good for the environment (Antweiler et al. 2001, Dean 2002, Löschel et al. 2013, Aller et al. 2015, among others). There also studies, such as Mukhopadhyay and Chakraborty (2005) and Kander and Lindmark (2006), which do not identify any significant association between trade and environmental degradation, and studies, such as Njindan Iyke and Ho (2017), which estimate a nonlinear impact of trade openness on the environment.

2. Literature Review

The association between trade liberalization and environmental degradation is complex and hard to estimate. Grossman and Krueger (1991) argue that a reduction in trade barriers generally will affect the environment through scale, composition and technology effects. The scale effect refers to the increase in emissions associated with production rise due to increasing demand in international markets. The composition effect refers to the change in the share of dirty goods (composition) in output, which is determined by the degree of trade openness and the comparative advantage of the country. Trade openness would increase the comparative advantage of pollution-intensive production in countries with lenient environmental standards, and thus the emission of pollutants would rise in these countries, while reducing the comparative advantage of such production and emission of pollutants in countries with relatively strict environmental policies. In other words, the source of the comparative advantage and thus high emission is less stringent environmental regulations, which is often the case in developing and less developed countries. This phenomenon is also known as the pollution haven hypothesis (PHH). Finally, the technique effect refers to a change in the emission amount per unit of output and shows the effect of technology used in production activities, such as cleaner or environmentally-friendly production methods (Managi et al. 2008). The net effect of trade on the environment is determined according to the weights of these effects.

In sum, the theoretical arguments above indicate that the association between free trade and emissions can be either negative or positive. This theoretical ambiguity is also in conformity with empirical evidence varying across countries, methodologies and indicators of environmental degradation.

The early studies primarily relied on cross country analyses suffering from unobserved heterogeneity and endogeneity of explanatory variables (see Grossman and Krueger 1991, Lucas et al. 1992, Birdsall and Wheeler 1993, Mani and Wheeler 1998, among others). Therefore, the subsequent studies switched to panel data as well as individual country studies.

Antweiler et al. (2001) investigate how trade openness, GDP, and per capita income affect pollution using data on 44 countries over the period 1975-1994. The findings from panel data analysis indicate that international trade creates a small composition effect but technology and scale effects imply a net reduction in sulfur dioxide concentrations. They argue that combining the estimates of these effects reveal that free trade is actually good for the environment.

Taskin and Zaim (2001) employ data on 51 countries over the period 1970-1990 and provide evidence that the degree of openness has a significant effect on environmental efficiency. They also argue that the countries which mostly export services have relatively higher environmental efficiency compared to the countries which have other export orientation types.

Dean (2002), using pooled Chinese water pollution data pertaining to the provinces, develops a simultaneous equation system incorporating multiple impacts of free trade on the environment. They find that freer trade intensifies environmental degradation via the terms of trade while mitigating it via income growth. The evidence suggests that the net effect on China is beneficial.

Frankel & Rose (2005) investigate the impact of trade on the environment for a given level of GDP, using seven different measures of environmental quality. Taking the endogeneity of trade into account using instrument variables, they find that trade tends to reduce some measures of environmental quality (particularly some measures of air pollution, such as SO_2 and NO_2) though not all. Overall, their findings provide little evidence of the detrimental effect of trade on the environment.

Ramcke and Abdulai (2009) employ a set of panel data on developed and developing countries for the period 1980-2003. They analyze several environmental factors and one sustainability indicator for a different sample of countries. Their findings imply a modest evidence of PHH and they argue that free trade might benefit sustainable development in rich countries, but can harm the poor countries.

Managi et al. (2009) investigate the overall effect of trade openness on the environment by treating trade and income as endogeneous. The results form instrumental variables technique indicate that trade is good for the environment in OECD countries. However, openness increase SO_2 and CO_2 emissions in non-OECD countries, but lower biochemical oxygen demand emissions in these countries. They note that these effects are relatively larger in the long run work through the environmental regulation and capital labor effect with the former having a larger impact.

Löschel et al. (2013) investigate the effect of international trade and structural change on environmental pressure using the World Input Output Database (WIOD) for 40 countries. They construct instruments for both trade openness and income to overcome the problem of endogeneous regressors. Their endogeneous panel estimations indicate a harmful effect of trade on the environment, whereas taking nonlinearities and endogeneity into account shows that trade reduces sulfur oxide pollution with a similar magnitude as in Antweiler et al. (2001).

Aller et al. (2015) analyses the role of the world trade network on the environment using data on a sample of 96 countries over the period 1996-2010. 3SLS estimations show that free trade improves the environment in developing countries, but has a detrimental effect on the environment in developed economies.

Njindan Iyke and Ho (2017) investigate the effects of free trade on CO_2 emissions in 17 Central and Eastern European (CEE) countries over the period 1994 to 2014. Their findings imply that high trade openness is associated with a low level of CO_2 emissions in the long run up to a turning point beyond which openness may increase emissions. On the other hand, they argue that the measure of openness matter as the magnitudes in the long run and the results in the short run differ across different proxies for openness.

Understanding the association between openness and emissions has important ramifications for policy implications and it is certainly worthwhile to determine the true long run effect of openness on emissions. Therefore, it is the intent of this paper to re-examine and quantify the long run effects of trade openness and income on environment by eliminating the drawbacks of time series analyses and problems related to the panel data models.

3. Materials and Methods

This study investigates the quantitative impact of trade and income on CO_2 emissions using data on a sample of 79 developing countries over the period 1960-2017. The methods we employ in this study require a sufficient number of time periods to have consistent estimates of country-specific coefficients, so that only countries for which we have at least 30 consecutive annual observations on the variables are included into our analysis. The countries we include in our sample are presented in Table 1. For our purpose, we collect data on *per capita carbon dioxide emissions*, *trade* (exports + imports as % of GDP) and *GDP per capita* (constant at 2010 US$). The data for *trade* and *per capita income* are extracted from World Development Indicators provided by World Bank whereas the data for *per capita CO_2 emissions* are provided by Our World in Data which is based on estimates of Carbon Dioxide Information Analysis Centre (CDIAC), Global Carbon Project, Gapminder and United Nations (UN).

Table 1. Selected Countries

Algeria	Argentina	Bahrain	Bangladesh	Barbados
Benin	Bolivia	Botswana	Brazil	Burkina Faso
Burundi	Cameroon	Central Africa	Chad	Chile
China	Colombia	Comoros	Congo, Rep.	Costa Rica
Cote d'Ivoire	Cuba	Dominican Rep.	Ecuador	Egypt
El Salvador	Gabon	Gambia	Ghana	Guatemala
Guinea	Guinea-Bissau	Guyana	Honduras	Hong Kong
India	Indonesia	Iran	Iraq	Israel
Jamaica	Jordan	Kenya	Madagascar	Malawi
Malaysia	Mali	Mauritania	Mauritius	Mexico
Morocco	Mozambique	Nepal	Nicaragua	Niger
Nigeria	Oman	Pakistan	Panama	Papua New Guinea
Paraguay	Peru	Philippines	Rwanda	Saudi Arabia
Senegal	Sierra Leone	Singapore	South Africa	Sri Lanka
Sudan	Thailand	Togo	Tunisia	Turkey
Uganda	Uruguay	Venezuela	Zimbabwe	

The developing countries are highly integrated as they are vulnerable to economic and financial shocks coming from the others and vice versa. Therefore, the model specification requires taking account of the financial and economic ties of these countries. Furthermore, the assumption of parameter homogeneity and ignoring cross sectional dependence across units in such models may lead to misleading empirical results. To estimate the long run coefficients in dynamic heterogeneous panels with cross sectionally dependent errors, Chudik and Pesaran (2015) and Chudik et al. (2013 and 2016) propose a cross section augmented autoregressive distributed lag (CS-ARDL) and cross section augmented distributed lag (CS-DL) frameworks.

We first use the standard panel ARDL approach to assess the impacts of growth in trade and income per capita growth on per capita carbon emissions in the long run. ARDL model can be estimated consistently irrespective of the order of integration , whether I(0) or I(1) or a mixture of the two, and whether they are exogeneous or endogeneous (Pesaran and Smith 1995, Pesaran 1997, Pesaran and Shin 1999, Chudik et al. 2013). Therefore it enables one to account reverse causality among the variables which is highly likely, as indicated by the trade literature.

The basic panel ARDL (p, q) specification can be represented as in the following equation:

$$y_{i,t} = \sum_{l=1}^{p} \varphi_{i,l} y_{i,t-l} + \sum_{l=0}^{q} \beta_{i,l}' x_{i,t-l} + u_{i,t} \quad (1)$$

$$u_{i,t} = \gamma_i' f_t + \varepsilon_{i,t} \quad (2)$$

for i = 1, 2, …, N (units) and t = 1, 2, …, T (time periods), where f_t is an mx1 vector of unobserved common factors and γ_i' is the corresponding factor loading. p and q are the lag orders of the dependent variable and independent variables, respectively and chosen to be sufficiently long so that the error term ($u_{i,t}$) is serially uncorrelated across all units. $y_{i,t}$ is the dependent variable of the i^{th} cross section and $x_{i,t}$ is the kx1 vector of regressors. Therefore, the long run coefficients vector is given by

$$\theta_i = \frac{\sum_{l=0}^{p} \beta_{i,l}}{1-\sum_{l=1}^{q} \varphi_{i,l}} \quad (3)$$

One way to estimate to long run coefficients is to estimate the short run coefficients ($\varphi_{i,l}$ and $\beta_{i,l}$) and substitute these estimations in equation (3). Alternatively, Chudik et al. (2013) propose another approach ('DL approach') estimating the long run coefficients directly without estimating the short run coefficients first. They show that this can be done by rewriting the ARDL model in equation (1) as follows:

$$y_{i,t} = \theta_i x_{i,t} + \alpha_i' L \Delta x_{i,t} + \tilde{u}_{i,t}, \quad (4)$$

where $\tilde{u}_{i,t} = \varphi(L)^{-1} u_{i,t}$, $\varphi_i(L) = 1 - \sum_{l=1}^{p} \varphi_{i,l} L^l$, $\theta_i = \delta_i(1)$, $\delta_i(L) = \varphi_i^{-1}(L)\beta_i(L) = \sum_{l=0}^{\infty} \delta_{i,l} L^l$, $\beta_i(L) = \sum_{l=0}^{q} \beta_{i,l} L^l$, and $\alpha_i(L) = \sum_{l=0}^{\infty} \sum_{s=l+1}^{\infty} \delta_s L^l$.

Chudik et al. (2016) argues that, based on the least square regression of $y_{i,t}$ on $x_{i,t}$ and $\{x_{i,t-l}\}_{l=0}^{p}$, a consistent estimate of θ_i can be obtained. The truncation lag order, p, is chosen as an increasing function of the sample size (specifically, it is chosen as the integer part of $T^{1/3}$). However, there are a number of conditions to hold to have consistent estimate of θ_i. First, the coefficients of $\alpha_i(L)$ should be exponentially decaying, which requires the usual assumption on the roots of $\varphi_i(L)$ falling strictly outside the unit circle. In addition, there should not be feedback effects from lagged values of $y_{i,t}$ onto $x_{i,t}$. Chudik et al. (2015), on the other hand, note that strict exogeneity is not necessarily required for the consistency of DL framework. Once the individual estimates $\hat{\theta}_i$ are obtained using either ARDL or DL framework, they can be averaged across units to obtain a consistent estimate of the average long run effects ($\bar{\hat{\theta}} = N^{-1} \sum_i^N \hat{\theta}_i$).

However, ARDL methodology assumes that the errors are cross sectionally independent. This assumption, on the other hand, may not hold as there are a number of unobserved or omitted global factors which are likely correlated with the regressors, which in turn lead to biased estimates. To capture the cross sectional correlation in the error term, we employ the CS-ARDL approach which augments the ARDL model given in Equation (1) with a linear combination of the cross sectional averages of all the variables including the dependent variable and the sufficient number of lagged variables.

Nevertheless, Chudik et al. (2013) note that the sampling uncertainty could be large when the time is not very large and choosing the correct specification of the lag orders is too crucial for the performance of estimators. To overcome these issues, we also employ the CS-DL approach which exhibits better small sample performance. However, they note that CS-DL estimator is not consistent when the feedback effects are present.

Given that all the techniques discussed above have their own merits and limitations, it should be noted that they are not substitutes, but complementary models (Chudik et al. 2016).

4. Results and Discussions

We first consider using the standard panel ARDL approach which is given by

$$\Delta y_{i,t} = c_i + \sum_{l=1}^{p} \varphi_{i,l} \Delta y_{i,t-l} + \sum_{l=0}^{p} \beta_{i,l}' x_{i,t-l} + u_{i,t} \quad (5)$$

where $y_{i,t}$ is the log of per capita CO_2 emissions, $x_{i,t} = (\Delta lntrade_{i,t}, \Delta lngdppc_{i,t})'$ where $\Delta lntrade_{i,t}$ and $\Delta lngdppc_{i,t}$ are the growth of *trade* and *per capita income* which we defined above . We use the same lag order, p (ranging from 1 to 3), for all variables/countries.

For each lag order, we provide estimates of fixed effects (FE) in Panel A of Table 2 (assuming slope homogeneity) and Table 2 Panel B presents Mean Group (MG) estimates (allowing for regression slopes to vary across units. Pesaran and Smith (1995) note that the FE estimates would be inconsistent when slope coefficients are heterogeneous even if T is sufficiently large. On the other hand, under fairly general conditions, the MG estimates are consistent provided that the errors are cross-sectionally independent. The tables report the average estimates of the long-run effects of trade ($\theta_{\Delta lntrade}$) and per capita income ($\theta_{\Delta lngdppc}$) on per capita carbon emissions, and the mean estimate of the coefficients of the error term (λ).

We present the results in three different specifications (a: only trade variable is included in the model, b: only per capita income variable is included in the model, and c: both variables are included). When considering FE estimates, across different lag orders and pooling strategies, the coefficients of trade are always positive but insignificant whereas the coefficients of per capita income are always positive and significant at 1% significance level. MG estimates, on the other hand, always produce positive (with larger magnitude) and highly significant estimates of coefficients of both variables. Specifically, MG estimates based on ARDL approach imply that trade openness will increase carbon emissions in the long run, with the coefficient ranging from 0.109 to 0.313 and per capita income positively affect CO_2 emissions in the long run, with the coefficients ranging from 0.758 to 0.962.

As mentioned earlier, the possible cross sectional error dependencies due to unobserved global factors which might affect both the dependent variable and explanatory variables simultaneously and might be correlated with the regressors may lead to biased estimates. The results for the Cross-section Dependence (CD) test of Pesaran (2004, 2013) reported in Tables 2 and 3 indicate the presence of the cross-sectional dependence, which in turn might lead to misleading estimates. Therefore, we employ the CS-ARDL approach with a sufficient number of lags, which is set to 3 regardless of p in our case. The CS-ARDL regressions are given by

$$\Delta y_{i,t} = c_i + \sum_{l=1}^{p} \varphi_{i,l} \Delta y_{i,t-l} + \sum_{l=0}^{p} \beta_{i,l}' x_{i,t-l} + \sum_{l=0}^{3} \psi_i' \bar{z}_{t-m} + e_{i,t} \quad (6)$$

where $\bar{z}_t = (\bar{y}_t, \bar{x}_t')'$, and all the other variables are as defined in equation (5).

Panel C of Table 2 summarizes the estimation results. For all specifications, the long run estimates of trade and per capita income are always positive and highly significant with similar magnitudes to the case in ARDL ranging from 0.132 to 0.268 for trade and from 0.722 to 0.876 for per capita income. Furthermore, the CD test statics are substantially lower compared to the ones in Panels A and B, and confirm a gradual decline when considering the CS-ARDL model. Finally, the speed of convergence to equilibrium is moderate, which is similar to the case of ARDL model. However, Chudik et al. (2016) note that these values should be viewed as indicative because of the small sample bias in the short run estimates.

As noted earlier, there are certain drawbacks of ARDL and CS-ARDL approaches. Therefore, we estimate the CS-DL versions of our previous specifications. More specifically, we run the following regressions

$$\Delta y_{i,t} = c_i + \theta_i' x_{i,t} + \sum_{l=1}^{p-1} \delta_{i,l}' \Delta x_{i,t-l} + \omega_{i,y} \overline{\Delta y}_t + \sum_{l=0}^{3} \omega_{i,xl}' \bar{x}_{t-l} + e_{i,t} \quad (7)$$

where the variables are defined as in equation (5). We present the MG estimates in Panel D of Table 2. The results are somewhat similar to those based on ARDL and CS-ARDL in terms of the sign and magnitude range of the coefficients. Specifically, the long run effects of openness and per capita income on carbon emissions are always highly significantly positive across all specifications. The long run coefficients of trade range from 0.137 to 0.272, whereas the ones of per capita income range from 0.712 to 817. Finally, we observe that the CD test statics are substantially lower compared to the ones of ARDL and similar to those of CS-ARDL.

Overall, except for the FE estimates based on the ARDL, all the estimation techniques agree on the significant positive long run effects of trade and income per capita on per capita CO_2 emissions in our set of developing countries. It can be expected that the true magnitude of the effects to be somewhere in between the two estimates based on CS-ARDL and CS-DL, ranging from 0.132 to 0.272 for trade and from 0.712 to 0.876 for per capita income (Chudik et al. 2013).

Table 2. Estimation results (ARDL, CS-ARDL, CS-DL)

	1 lag			2 lag			3 lag		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
Panel A. Fixed Effects (FE) Estimates (ARDL)									
$\theta_{\Delta lntrade}$	0.035		0.039	0.039		0.038	0.066		0.053
	(0.023)		(0.041)	(0.029)		(0.051)	(0.047)		(0.061)
$\theta_{\Delta lngdppc}$		0.488***	0.472***		0.550***	0.554***		0.641***	0.656***
		(0.157)	(0.143)		(0.166)	(0.162)		(0.192)	(0.197)
λ	-1.06***	-1.08***	-1.08***	-1.11***	-1.16***	-1.16***	-1.09***	-1.17***	-1.17***
	(0.029)	(0.028)	(0.029)	(0.059)	(0.060)	(0.061)	(0.082)	(0.084)	(0.086)
CD test stats	11.258	8.543	8.164	12.376	9.572	8.971	11.076	8.142	7.959
NxT	4143	4170	4108	4061	4089	4026	3980	4009	3945
Panel B. Mean Group (MG) Estimates (ARDL)									
$\theta_{\Delta lntrade}$	0.141***		0.109***	0.207***		0.130***	0.313***		0.211***
	(0.036)		(0.038)	(0.044)		(0.043)	(0.066)		(0.063)
$\theta_{\Delta lngdppc}$		0.758***	0.770***		0.870***	0.897***		0.962***	0.938***
		(0.069)	(0.069)		(0.085)	(0.088)		(0.092)	(0.0983)
λ	-1.04***	-1.11***	-1.11***	-1.07***	-1.18***	-1.17***	-1.06***	-1.20***	-1.20***
	(0.022)	(0.021)	(0.022)	(0.034)	(0.034)	(0.035)	(0.044)	(0.044)	(0.047)
CD test stats	9.35	6.11	5.36	9.51	6.12	5.56	8.87	5.70	5.36
NxT	4143	4170	4108	4061	4089	4026	3980	4009	3945
Panel C. Mean Group (MG) Estimates (CS-ARDL)									
$\theta_{\Delta lntrade}$	0.132***		0.139***	0.174***		0.132***	0.268***		0.211***
	(0.042)		(0.044)	(0.054)		(0.051)	(0.048)		(0.067)
$\theta_{\Delta lngdppc}$		0.723***	0.722***		0.830***	0.850***		0.876***	0.810***
		(0.076)	(0.085)		(0.093)	(0.096)		(0.100)	(0.123)
λ	-1.09***	-1.14***	-1.16***	-1.16***	-1.29***	-1.27***	-1.16***	-1.33***	-1.32***
	(0.022)	(0.021)	(0.023)	(0.036)	(0.036)	(0.039)	(0.044)	(0.047)	(0 .052)
CD test stats	-2.50	-2.4	-2.05	-2.43	-2.51	-2.43	-2.39	-1.74	-1.93
NxT	3980	4009	3945	3980	4009	3945	3980	4009	3945
Panel D. Mean Group (MG) Estimates (CS-DL)									
$\theta_{\Delta lntrade}$	0.145***		0.148***	0.188**		0.137**	0.272***		0.210***
	(0.043)		(0.050)	(0.053)		(0.058)	(0.053)		(0.070)
$\theta_{\Delta lngdppc}$		0.731***	0.712***		0.789***	0.808***		0.791***	0.817***
		(0.083)	(0.087)		(0.095)	(0.103)		(0.101)	(0.116)
CD test stats	-2.51	-2.75	-2.55	-2.31	-2.90	-2.49	-2.31	-2.49	-1.65
NxT	4036	4057	4008	4013	4038	3982	3988	4017	3953

Notes: The specifications are given by equations 15-17. Standard errors are reported in parenthesis and they are robust to cross-sectional heterogeneity and serial correlation in residuals. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Conclusion

The contribution of this study to the literature is that we empirically reinvestigate the long-run effects of growth in trade and per capita income on carbon emissions in a sample of 79 developing countries over the period 1960-2017. For the purpose of taking account of error cross-country dependence, cross-country heterogeneity, and feedback effects from CO_2 emissions to trade and income, we employ both the CS-ARDL and CS-DL approaches. The empirical evidence suggests a positive and significant effect of both trade and income on long-run carbon emissions in developing countries.

These results have strong policy implications for developing countries. The undesirable environmental consequences of trade openness and output rises are not only local and today's problems but also threaten global society and future generations. Country level precautions or preventive measures taken by a group of countries might only benefit a small part of the global society and seem to be continually deferring solutions. Instead of exclusive and temporary efforts to reduce pollution, adopting radical and global environmental policies such as smoothing the way of cross-country environmental technology transfer through trade and foreign investment, debureaucratizing of environmental regulations, and before anything else, prioritizing the social costs of the global economic system. By all means, rise in global production and encouraging trade liberalization for future economic growth and global economic well-being has important economic gains for the global society and environmental consequences of globalization and economic development have been in the agenda of governments for a while. However, these efforts have obviously not been sufficient to reduce pollution down to the tolerable levels. World economies should carefully take potential trade-offs into account and put sufficient efforts to understand the working mechanisms behind production and trade. Since the individual efforts create comparative disadvantages especially for less developed countries, acting globally towards environmental problems is of great and obvious importance. Therefore, first of all, by putting all the differences and historic ties aside, mitigating the negative environmental effects of the economic actions should be the main common target for the global economy.

References

Aller C., Ductor L., Herrerias M.J. (2015). The world trade network and the environment. *Energy Economics*, 52: 55-68.

Ang J.B. (2009). CO2 emissions, research and technology transfer in China. *Ecological Economics*, 68(10): 2658-2665.

Antweiler W., Copeland B.R., Taylor M.S. (2001). Is free trade good for the environment?. *American economic review*, 91(4): 877-908.

Birdsall N., Wheeler D. (1993). Trade policy and industrial pollution in Latin America: where are the pollution havens?. *The Journal of Environment & Development*, 2(1): 137-149.

Chudik A., Mohaddes K., Pesaran M.H., Raissi M. (2013). Debt, inflation and growth: robust estimation of long-run effects in dynamic panel data models. *Cafe research paper*, (13.23).

Chudik A., Pesaran M.H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2): 393-420.

Chudik A., Mohaddes K., Pesaran M.H., Raissi M. (2016). Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors. In *Essays in Honor of man Ullah* (pp. 85-135). Emerald Group Publishing Limited.

Dean J.M. (2002). Does trade liberalization harm the environment? A new test. *Canadian Journal of Economics/Revue canadienne d'économique*, 35(4): 819-842.

Frankel J.A., Rose A.K. (2005). Is trade good or bad for the environment? Sorting out the causality. *Review of economics and statistics*, 87(1), 85-91.

Grossman G.M., Krueger A.B. (1991). *Environmental impacts of a North American free trade agreement* (No. w3914). National Bureau of Economic Research.

Heil M.T., Selden T.M. (2001). International trade intensity and carbon emissions: a cross-country econometric analysis. *The Journal of Environment & Development*, 10(1): 35-49.

Kander A., Lindmark M. (2006). Foreign trade and declining pollution in Sweden: a decomposition analysis of long-term structural and technological effects. *Energy policy*, 34(13): 1590-1599.

Löschel A., Rexhäuser S., Schymura, M. (2013). Trade and the environment: An application of the WIOD database. *Chinese Journal of Population Resources and Environment*, 11(1): 51-61.

Lucas R.E., Wheeler D., Hettige H. (1992). *Economic development, environmental regulation, and the international migration of toxic industrial pollution, 1960-88* (Vol. 1062). World Bank Publications.

Managi S., Hibiki A., Tsurumi T. (2008). Does trade liberalization reduce pollution emissions. *Discussion papers*, *8013*.

Managi S., Hibiki A., Tsurumi T. (2009). Does trade openness improve environmental quality?. *Journal of environmental economics and management*, 58(3): 346-363.

Mani M., Wheeler D. (1998). In search of pollution havens? Dirty industry in the world economy, 1960 to 1995. *The Journal of Environment & Development*, 7(3): 215-247.

Mukhopadhyay K., Chakraborty D. (2005). Is liberalization of trade good for the environment? Evidence from India. *Asia Pacific Development Journal*, 12(1): 109.

Njindan Iyke B., Ho, S.Y. (2017). Trade openness and carbon emissions: Evidence from Central and Eastern Europe.

Pesaran M.H. (1997). The role of economic theory in modelling the long run. *The Economic Journal*, 107(440): 178-191.

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

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

Ramcke L., Abdulai A. (2009). The Impact of Trade and Economic Growth on the Environment: Revisiting the Cross-Country Evidence.

Shahbaz M., LeitÃ N.C. (2013). Portuguese carbon dioxide emissions and economic growth: a time series analysis. *Bulletin of Energy Economics*, 1(1): 1-7.

Sharma, S.S. (2011). Determinants of carbon dioxide emissions: empirical evidence from 69 countries. *Applied Energy*, 88(1): 376-382.

Taskin F., Zaim, O. (2001). The role of international trade on environmental efficiency: a DEA approach. *Economic Modelling*, 18(1): 1-17.