The Technical Decomposition of Carbon Emissions and the Concerns about FDI and Trade Openness Effects in the United States

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Abstract

This paper decomposes the environmental Kuznets curve into the scale, technique and composition effects while incorporating the roles of energy consumption, trade openness and foreign direct investments (FDI) effects in a carbon emissions function for the United States (U.S.). We have incorporated information about unknown structural breaks into this function while investigating the cointegration between the related variables. The empirical results confirm the existence of cointegration between the variables in the presence of structural breaks. Moreover, the scale effect increases carbon dioxide emissions, but the technique effect reduces it as expected. Energy consumption also adds to carbon emissions, while the composition effect improves environmental quality by lowering carbon dioxide emissions. Further, trade openness decreases carbon dioxide emissions. However, increases in FDI hamper environmental quality by increasing carbon emissions. To reduce the level of carbon emissions, the technical processes of production should be improved by investing in technological innovations and capital stock and upgrading environmental regulations to channel in environment-friendly FDIs. There should also be a transformation of the energy consumption structure towards cleaner energy sources.

Keywords: carbon emissions; scale effect; composition effect; technique effect; international trade; foreign direct investment

JEL Codes: F18; Q56; C33

1. Introduction

In today's world, climate change is one of the most prominent problems of recent days, and the underlying cause of climate change is global warming. It is also well known that the leading cause of global warming is greenhouse gas emissions. These emissions are considered to be a leading indicator of environmental pollution, but previous studies have used many measures of gas emissions. At this point, carbon dioxide (CO2) emissions seem to be the leading indicator of environmental pollution (Tiba and Omri, 2017). In doing so, our paper focuses on the determinants of carbon dioxide emissions in the United States (U.S.). A unique role is given to foreign direct investment (FDI) and trade openness as they could be potential drivers of carbon dioxide emissions in this country.

According to the previous literature, per capita income is the primary driver of carbon dioxide emissions (Jaunky, 2011; Narayan and Narayan, 2010; Shahbaz et al., 2018). At this stage, the effects of income on carbon dioxide emissions can be explained by three effects (Tsurumi and Managi, 2010; Yin et al., 2015). The first effect is known as that *scale effect* which stipulates that as per capita income rises with higher inputs; this will systemically raise the level of carbon dioxide emissions. In other words, that *scale effect* implies that a higher level of per capita income leads to higher energy consumption, which results in increases in carbon emissions (i.e., environmental degradation).

The second effect is the *composition effect* which states that an increase in per capita income can exhibit a positive or a negative impact on carbon emissions. At this point, as per capita income increases, there could be a significant structural change in the economy and a change in economic activity, which can lead to a higher or a lower level of environmental degradation. Specifically, at the first stage of economic development which entails a structural change of the economy from agriculture to the industry, an expansion in this development is expected to increase environmental degradation. However, at the second stage of economic growth, that is the process of structural change from industry to services or from an energy-intensive industrial production process to a more technology-intensive production process, the level of environmental degradation is expected to decline (Kearsly and Riddel, 2010).

Similarly, the third effect is known as the *technique effect,* that is, a change in the production process (i.e., technology shocks) can introduce a negative or a positive impact on carbon emissions (Rezek and Rogers, 2008). In the developed countries, like the U.S., one should expect a negative technique effect of per capita income on the level of carbon emissions because the U.S. is one of the leading technology producers in the world.[1] In other words, the *technique effect* systematically decreases environmental degradation in developed countries due to a higher level of technology (Lau et al., 2014).[2]

At this stage, trade openness and FDI will create a technique effect on the relationship between per capita income and environmental degradation. Therefore, to motivate the decomposition analysis, our empirical models include trade openness and FDI as potential drivers of carbon emissions. International trade will help countries engage in cross border trade to share in technology diffusions and access clean energy technology. FDI also helps in transferring technology to host countries. It is suggested that FDI transmits technological knowledge, as well as contributing to the physical capital stock. Moreover, the technology transferred through FDI has the effect of stimulating competing firms in the domestic market to carry out technological upgrading.

[1] Indeed, according to the data from the World Intellectual Property indicators of the World Intellectual Property Organization, 24.3% of the world's total patent applications were made by the U.S. companies in 2016.

[2] For example, according to Can and Gozgor (2017), the economic complexity indicator is a robust indicator of the level of technology as well as it is a significant determinant of the carbon dioxide emissions in France.

Finally, following previous papers (e.g., Ang, 2007; Tiwari, 2014; Shahbaz et al., 2017), we consider the pivotal role of energy consumption, which contributes not only to the process of economic development but also to environmental degradation, and we mainly focus on consumption from fossil sources which are a fundamental input in the production process.

Indeed, a country can achieve a higher level of efficiency in the production process through technology transfer. The effect of technology transfer can be measured by international trade (measured by the nominal trade openness that is the ratio of the sum of exports and imports to GDP) and FDI inflows (as a % of GDP). Therefore, various studies have empirically tested the validity of the EKC hypothesis and have considered trade openness and FDI inflows as the benchmark indicators of technology transfer (Gozgor, 2017). As trade openness increases, there will be a structural transformation in the economy which promotes environmental quality due to the transfer of technology. Consequently, one should expect that trade openness will improve environmental quality in developed countries in particular.[3] However, the effect of FDI inflows on environmental degradation can be positive or negative, and it depends on whether the country will attract direct investments from the heavy industry and the energy-intensive industry to the technology-intensive sector and services. Therefore, there could be positive or negative effects of FDI on environmental quality in developing and developed countries (Lau et al., 2014; Shahbaz et al., 2015). In short, the effect of technology transfer via FDI on environmental degradation depends on the inputs used in the production process. To this end, our paper analyzes the effects of trade openness and FDI on carbon emissions hypothesis in the U.S. economy.

[3] The impact of the trade openness on environmental degradation can be negative or positive in developing economies. The sign of the related effect depends on the production structure of exporting and importing goods and services (Can and Gozgor, 2017).

It is also noteworthy to state that the validity of the EKC hypothesis has empirically been tested in developing countries, rather than developed countries (Stern, 2017). At this point, one of the prominent case for analyzing the effects of FDI and trade openness on carbon emissions is the U.S. Indeed, according to the data from the British Petroleum (BP)'s Statistical Review of World Energy 2017, the U.S. is solely responsible for 23.4% of carbon emissions in the globe for the period 1965-2016 (BP, 2017). Besides, according to the data from the World Development Indicators, the share of gross domestic product (GDP) (measured by the current price in USD) of the U.S. in global GDP is 26.9% for the period 1965-2016 (World Bank, 2018).

Our paper contributes to the existing energy literature by four-fold. (i) It is a novel contribution that decomposes the environmental Kuznets curve into scale, technique and composition effects for the U.S. economy while controlling for energy consumption among other variables. However, the special roles in this contribution are given to trade openness and FDI inflows as potential drivers of carbon emissions. Our current paper also contributes to the previous evidence on the effects of trade openness and FDI on the environment by using a relatively new dataset. We consider a long-term empirical analysis for the period from 1965 to 2016 in the U.S. (ii) Traditional, and structural breaks unit root tests are also applied to examine the stationary properties of the variables. (iii) The ARDL bounds testing approach to cointegration is employed to determine whether cointegration exists between carbon emissions and their determinants in the presence of structural breaks in the series. (iv) The direction of a causal relationship between carbon emissions and their determinants is investigated by applying the VECM Granger causality while accommodating structural breaks. Our empirical results confirm the presence of cointegration between the variables. Furthermore, they also show that the scale effect increases carbon emissions, but the composition and technique effects reduce CO_2 emissions. Trade openness has a negative effect on carbon emissions, while FDI hampers environmental quality by increasing carbon emissions in the U.S.

The remainder of the paper is organized as follows. Section 2 briefly reviews the previous literature. Section 3 explains the empirical model and the data. Section 4 details the empirical strategy. Section 5 provides the empirical results. Finally, Section 6 concludes and discusses policy implications.

2. Literature Review

It is important to note that the net effect of the composition, scale, and technique effects can be analyzed via the environmental Kuznets curve (EKC) hypothesis proposed by Grossman and Krueger (1995) (Esty and Porter, 2005).[4] The EKC hypothesis proposes that there will be an "inverted-U shaped" relationship between per capita income and environmental degradation since an increase in per capita income will lead to a rise in carbon emissions during the first stage of economic development. This issue is due to the evidence that the main aim of the related countries is to promote economic development, while the negative consequences of environmental degradation are not the priority of the policymakers in the related countries. However, as a country develops and the accompanying per capita comes around $4,000 per capita income level according to Gozgor (2017), carbon emissions should then start to decline. In particular, when a country reaches a high-income level, eliminating the adverse effects of environmental pollution becomes a priority of policymakers (Dinda, 2004).

The previous papers on the determinants of carbon emissions can be grouped into three different categories (Al-Mulali and Ozturk, 2016; Gozgor, 2017; Shahbaz et al., 2017). The first

[4] Note that specialization in relative abundance can be processed as a natural resource-comparative advantage effect which is one of the decomposed components like the scale effect and the other effects.

group of the studies investigates the direct link between per capita income and carbon emissions (Narayan and Narayan, 2010; Shahiduzzaman and Layton, 2015; Narayan et al., 2016). The second group analyzes not only the impact of per capita GDP but also the impact of energy consumption on CO_2 emissions (Ang, 2007; Acaravci and Ozturk, 2010; Pao and Tsai, 2010; Arouri et al., 2012). Following these papers, we include per capita income and energy consumption in our empirical analysis.

The third group investigates not only the effects of per capita income and energy consumption but also controls for additional control variable(s) such as FDI and trade openness. At this point, the effects of FDI and trade openness on carbon emissions are also included in the empirical studies on developing economies and developed countries. However, most of these studies have focused on the cases of emerging economies, such as Brazil, China, Egypt, India, Indonesia, Malaysia, Mexico, Nigeria, Turkey, and Tunisia (see e.g. Halicioglu, 2009; Jayanthakumaran et al., 2012; Lau et al., 2014; Onafowora and Owoye, 2014; Shahbaz et al., 2013 and 2014).[5]

There are also several studies that analyzed the determinants of CO_2 emissions in the U.S.[6] For instance, using the EKC hypothesis and the K-L growth model (Augmented Factor model) (including the capital and labor as control variables) for the U.S., Soytas et al. (2007) examine the effects of per capita income and energy consumption on carbon emissions for the period 1960 to 2004. Their empirical results imply that per capita income does not cause carbon emissions, and the main driver of CO_2 emissions is energy consumption in the U.S. A similar evidence is obtained by a paper written by Shahiduzzaman and Layton (2015) in which those authors find no systematic

[5] For more details of these studies, refer to Al-Mulali and Ozturk (2016) and Tiba and Omri (2017).
[6] There are also the recent studies to analyze the validity of the EKC hypothesis using panel data for the states (regions) of the U.S. For example, see Apergis et al. (2017) and Atasoy (2017)

relationship between per capita income and carbon emissions over the business cycle phases for the period from 1949 to 2011.[7] Ajmi et al. (2015) also analyze the determinants of carbon emissions in six developed countries, including the U.S. Their empirical strategy controls for the effects of per capita income and per capita energy consumption in the EKC function for the period from 1960 to 2010. Their empirical findings also demonstrate the presence of a bi-directional causal relationship between per capita energy consumption and per capita carbon emissions. However, there is no significant causality between per capita income and per capita carbon emissions in the U.S.

Furthermore, considering the EKC hypothesis, Baek (2016) analyzes the effects of per capita income and energy consumption on CO_2 emissions in the U.S. for the period from 1960 to 2010. A special interest is given to the effects of nuclear energy and renewable energy consumption in the EKC function. Using the autoregressive-distributed lag (ARDL) model, the author finds that per capita income and energy consumption increase the level of carbon emissions. In addition, there is a suppressing effect of renewable energy consumption on carbon emissions in the short-run; while there is a significant overpowering effect of nuclear energy consumption in both the short-run and the long-run. Dogan and Turkekul (2016) also consider the EKC hypothesis to analyze the determinants of carbon emissions in the U.S. for the period from 1960 to 2010. Their empirical models not only consider per capita income and its squared value, but also energy consumption, financial development, trade openness, and urbanization rate. Their empirical analysis also indicates the presence of a bi-directional causal relationship between carbon emissions and economic growth as well as between CO_2 emissions and energy consumption. The authors also report that the EKC hypothesis is not valid in the U.S. economy since the expected

[7] Their empirical models also use the disaggregated level energy intensity (i.e., coal, electricity, gas, and oil).

signs could not be obtained, and a neutral effect exists between trade openness and CO_2 emissions in this country. Finally, Shahbaz et al. (2017) analyze the validity of the EKC hypothesis in the U.S. for the period 1960-2016. Their paper considers not only the impact of economic growth on carbon emissions, but also the effects of biomass energy consumption, oil prices, and trade openness on carbon emissions. Their empirical results illustrate that there is an "Inverted-U shaped" relationship between economic growth and carbon emissions. Moreover, biomass energy consumption and trade openness reduce carbon pollutants.

To conclude the literature review, this paper appertains to the third group of studies. In line with this group, it uses trade openness and FDI inflows as additional determinants (control variables) of carbon emissions while decomposing environmental Kuznets curve into scale, technique and composition effects. However, there is a lack of evidence of the existing literature of the effects of FDI and trade openness on CO_2 emissions in the U.S. Finally; there is a lack of studies on the decomposing the role of income into scale, technique and composition effects within a multivariate carbon emission function.

3. Modeling and Data Collection

This paper decomposes the environmental Kuznets curve into scale, technique and composition effects by considering the vital role of trade openness and FDI effects in carbon emission function for the U.S economy. The decomposition of environmental Kuznets curve into scale, technique and composition effects is based on the arguments raised by Tsurumi and Managi (2010) and Ling et al. (2015). It is argued by Tsurumi and Managi (2010) that economic growth affects carbon emissions via the scale effect, technique effect, and composition effect. Economic growth underpins the scale effect which increases CO_2 emissions and impedes environmental quality. The scale effect reveals that more production needs more energy usages, which in turn emits more carbon emissions.

On the other hand, the economic growth effect may impact carbon emissions positively or negatively via the technique effect. This effect implies that income or preferences changes may lead to policy changes, which leads to an improvement in the production techniques that enhance domestic production with fewer carbon emissions per unit. Economic growth can also impact carbon emissions positively or negatively via the composition effect. This effect reveals that the structure of an economy changes with an increase in income. With time, an increase in income may lead to dirtier or cleaner economic activities. Generally, carbon emissions may rise during the transformation from the agricultural to industrial sectors.

Similarly, a structural change from the industrial sector or an energy-intensive economy to the services economy may lead to a decline in carbon emissions, depending on the level of services and knowledge. Trade openness may affect carbon emissions via economic growth. It is argued by Cole (2006) that trade openness may affect carbon emissions through inducing an energy efficient technology transfer, awareness, increasing the demand for a cleaner environment and a shift of government policies towards the environmentally friendly economic policies.

Furthermore, the relationship between trade openness and carbon emissions depends on the association between trade openness and economic growth (Ling et al., 2015). Foreign direct investment impacts carbon emissions through economic growth and may affect economic growth via a technology transfer, a positive externality such as spillover effects and gains in productivity and by introducing new production processing with improved managerial skills. This increased economic growth induces energy demand, which in turn increases carbon emissions (Shahbaz et al., 2015). It implies that foreign direct investment promotes not only economic growth but also hampers environmental quality by increasing carbon emissions. On the contrary, foreign direct investment may improve environmental quality if an energy efficient technology is implemented in production in the recipient country with technical management skills and environment-friendly economic policies (Cole, 2006). Based on this theoretical background, we extend the general form of the carbon emission function as follows:

$$C_t = f(S_t, T_t, K_t, E_t, O_t, F_t) \quad (1)$$

where $C_t, S_t, T_t, K_t, E_t, O_t$ and F_t represent CO_2 emissions, scale effect, technique effect, composition effect, energy consumption, trade openness, and foreign direct investment.

We transform the general form of carbon emission function in Equation (1) by converting all the variables into natural-log. The log-linear specification may provide consistent and reliable empirical evidence. Furthermore, the transformation of the data of all the variables helps to reduce the sharpness in the time series data (Shahbaz et al., 2017). Various studies in the existing literature seem to use multiple proxies for the scale, technique and composition effects. For instance, Antweiler et al. (2001) and Panayotou (1997) propose to use GDP per square kilometer, GDP per capita and industrial value-added to GDP as measures of the scale, technique and composition effects, respectively. Later on, Cole (2006) used the lagged GDP per capita to capture the scale and technique effects. Cole (2006) further argues that "*there is no way to separate income and technique effects*" (P. 110). This issue is addressed by Tsurumi and Managi (2010) who suggest the use of real GDP and GDP per capita as proxies for the scale and technique effects, which are separable. Ling et al. (2015) measure the scale and technique effects by real GDP per capita and real GDP per capita squared. Composition effect is measured by the capital-labor ratio (Cole 2006, Ling et al., 2015; Tsurumi and Managi, 2010). We follow the Tsurumi and Managi (2010) model strategy by incorporating trade openness and foreign direct investment as additional determinants in the carbon emission function.

In doing so, the empirical equation is generated from the general carbon emission function and modeled as follows:

$$\ln C_t = \beta_0 + \beta_1 \ln S_t + \beta_2 \ln T_t + \beta_3 \ln K_t + \beta_4 \ln E_t + \beta_5 \ln O_t + \beta_6 \ln F_t + \mu_i \qquad (2)$$

Where $\ln$ is the natural-log and μ_i is the residual term assumed to be normally distributed. We measure the scale effect and the technique effect by real GDP and real GDP per capita. The capital-labor ratio is used to measure the composition effect. Energy consumption is measured by energy use. The sum of exports per capita and imports per capita is used to measure trade openness. The foreign direct investment is the FDI net inflows. More production needs more energy consumption, which results in increases in carbon emissions and we expect $\beta_1 > 0$. However, $\beta_2 < 0$ since energy efficient technology produces domestic production with fewer carbon emissions. We expect $\beta_3 > 0$ or $\beta_3 < 0$ as it depends on whether the economy is more energy-intensive or more technology-intensive. More energy consumption adds to carbon emissions, and we thus expect $\beta_4 > 0$. Though, trade openness reduces CO_2 emissions if trade policies are environmentally friendly, then $\beta_5 < 0$; otherwise $\beta_5 > 0$. Moreover, $\beta_6 > 0$ if FDI impedes environmental quality by increasing carbon emissions; otherwise $\beta_6 < 0$.

This study covers the period 1965-2016. We collect the data on CO_2 emissions (in metric tons), GDP (in constant 2010 US$) and energy use (in kg of oil equivalent) from the World Development Indicators (CD-ROM, 2018). Capital proxy for the capital stock at the current Purchasing Power Parity (PPP) (in a million 2011 US$) are sourced from the Penn World Table (Version 9.0) (Feenstra et al., 2015). The data on FDI net inflows (in constant 2010 US$) and labor force (total) are also obtained from the World Development Indicators (CD-ROM, 2018). We have transformed all the variables into per capita by dividing all the variables by total population (data collected from the World Development Indicators).

4. Empirical Strategy

Firstly, this paper employs the standard unit root tests such as the Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) tests. However, these unit root tests are unable to take into account structural breaks. Ignorance of unknown structural breaks in time series makes the empirical results based on the ADF and PP unit root tests biased and unreliable. Secondly, this issue is addressed by applying the Kim and Perron (2009) unit root test, while accommodating information of a single unknown structural break in the series.[8] The empirical strategy will also include using the ARDL approach to test for cointegration and the VECM approach to examine Granger causality in the short and long run.

4.1 The ARDL Bounds Testing Approach to Cointegration

In line with the results of the unit root tests, we apply the bounds testing approach to cointegration to examine whether a long run relationship is present between CO_2 emissions and their determinants. The existing applied economics literature provides numerous cointegration tests such as the EG residual-based test by Engle and Granger (1987), Phillips and Ouliaris (1990), Maximum Eigenvalue test by Johansen and Juselius (1990), and Gregory and Hansen (1996) in the presence of structural breaks. These cointegration tests require that all the variables should have a same order of integration.

[8] We also consider the endogenous multiple structural breaks method in the unit root test and the results are similar.

The ARDL bounds test is flexible whether the regressors or independent variables are I(1) or I(0). For this reason, the dependent variable should be I(1) to be able to use the ARDL, and it indeed is according to the unit root tests. This cointegration approach is suitable for a small sample dataset such as ours. The bounds testing approach to cointegration provides short-run and long-run results without a loss of information about the long-run empirical results. The issue of serial correlation along with endogeneity is solved automatically by the ARDL bounds testing for cointegration. The ARDL cointegration test provides consistent and reliable empirical results since a single cointegrating vector (cointegration association) is present between the variables. Pesaran et al. (2001) tabulated critical bounds (upper and lower) to decide on rejecting or accepting the null hypothesis of no cointegration. This null hypothesis is based on the asymptotic upper and lower critical bounds regardless of whether the variables are integrated at I(1) or I(0). At this point, the critical values of the bounds test, which are reported in Narayan (2005) and Pesaran et al. (2001), are used in the analysis. Third, after rejecting the null hypothesis of the bounds test that is "there is no cointegrating relationship among the variables," the short-run coefficients and the long-run coefficients are obtained by the ARDL model of Pesaran and Shin (1999).

Accordingly, our paper estimates the following the unrestricted error correction regression that considers the natural logarithm of the per capita carbon dioxide emissions as the dependent variable in the U.S:

$$
\begin{aligned}
\Delta \ln C_t = \alpha_0 &+ \sum_{i=1}^{n} \alpha_1 \Delta \ln C_{t-ij} + \sum_{i=0}^{n} \alpha_2 \Delta \ln S_{t-ij} + \sum_{i=0}^{n} \alpha_3 \Delta \ln T_{t-ij} + \sum_{i=0}^{n} \alpha_4 \Delta \ln K_{t-ij} \\
&\sum_{i=0}^{n} \alpha_5 \Delta \ln E_{t-ij} + \sum_{i=0}^{n} \alpha_6 \Delta \ln O_{t-ij} + \sum_{i=0}^{n} \alpha_7 \Delta \ln F_{t-ij} + \beta_1 \ln C_{t-1} + \beta_2 \ln S_{t-1} \\
&+ \beta_3 \ln T_{t-1} + \beta_4 \ln K_{t-1} + \beta_5 \ln E_{t-1} + \beta_6 \ln O_{t-1} + \beta_7 \ln F_{t-1} + \varepsilon_i
\end{aligned}
\tag{3}
$$

In Equation (3), *Δ* symbolizes the change in the variables and ε_{1t} is an error term. The parameters for α_{ij} (j= 1,2, 3,…7, *i* = 1, 2, 3,...n) represent the short-run coefficients and the parameters for β_i (i = 1, 2, 3, 4, 5, 6, and 7) are the long-run coefficients of the ARDL model. Pesaran et al. (2001) propose a joint significance ADRL-F test on the coefficients of the lagged level variables to decide for the long run relationship between the variables. It is opined by Pesaran et al. (2001) that the ARDL-F test is sensitive to the lag order selection. An ARDL requires applying the F-test for the lagged level independent variables and the t-test for the lagged dependent variable for cointegration. Failure to meet the two requirements raises the possibility of degenerate cointegration relationships among the variables (Pesaran et al., 2001: 296). Hence, we report the t-statistics along with the F-statistics in Table 3. We select the lag order of the variables following the Akaike Information Criterion (AIC). The AIC provides better information to choose the lag order compared to the Bayesian Information Criterion (BIC) (Ling et al., 2015; Shahbaz et al., 2017). We define the null hypothesis of no cointegration based on Equation (3):

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0,$$

against alternative hypothesis

$$H_0 : \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq \beta_7 \neq 0.$$

We may opt for cointegration if the ARDL statistic should be higher than the upper critical bounds. The decision is for no cointegration if the lower critical bounds are more than the calculated ARDL-F statistic. We are in the indecisive zone if the calculated ARDL-F statistic is found between the upper and lower critical bounds. In the ARDL estimations, the paper checks the necessary diagnostic tests for autocorrelation, heteroscedasticity, specification of the model, and stability of the regressions (i.e., using the CUSUM and CUSUMSQ tests).

4.2 The VECM Granger Causality Approach

In addition, we apply the vector error correction model (VECM) Granger-based causality test to examine long-run and the short-run causal relationship between CO_2 emissions and their determinants. It is argued by Granger (1969) that there should be causality between the variables should be at least from one-side if cointegration is confirmed by the single order of integration of the variables. The empirical equation of the VECM Granger causality is modeled as follow as:

$$(1-L)\begin{bmatrix} \ln C_t \\ \ln S_t \\ \ln T_t \\ \ln K_t \\ \ln E_t \\ \ln O_t \\ \ln F_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \\ \alpha_7 \end{bmatrix} + \sum_{i=1}^{p}(1-L)\begin{bmatrix} \beta_{11,i} & \beta_{12,i} & \beta_{13,i} & \beta_{14,i} & \beta_{15,i} & \beta_{16,i} & \beta_{17,i} \\ \beta_{21,i} & \beta_{22,i} & \beta_{23,i} & \beta_{24,i} & \beta_{25,i} & \beta_{26,i} & \beta_{27,i} \\ \beta_{31,i} & \beta_{32,i} & \beta_{33,i} & \beta_{34,i} & \beta_{35,i} & \beta_{36,i} & \beta_{37,i} \\ \beta_{41,i} & \beta_{42,i} & \beta_{43,i} & \beta_{44,i} & \beta_{45,i} & \beta_{46,i} & \beta_{47,i} \\ \beta_{51,i} & \beta_{52,i} & \beta_{53,i} & \beta_{54,i} & \beta_{55,i} & \beta_{56,i} & \beta_{57,i} \\ \beta_{61,i} & \beta_{62,i} & \beta_{63,i} & \beta_{64,i} & \beta_{65,i} & \beta_{66,i} & \beta_{67,i} \\ \beta_{71,i} & \beta_{72,i} & \beta_{73,i} & \beta_{74,i} & \beta_{75,i} & \beta_{76,i} & \beta_{77,i} \end{bmatrix} \times \begin{bmatrix} \ln C_{t-1} \\ \ln S_{t-1} \\ \ln T_{t-1} \\ \ln K_{t-1} \\ \ln E_{t-1} \\ \ln O_{t-1} \\ \ln F_{t-1} \end{bmatrix}$$

$$+\begin{bmatrix} \delta \\ \gamma \\ \lambda \\ \phi \\ \varphi \\ \theta \\ \rho \end{bmatrix} ECT_{t-1} + \begin{bmatrix} \mu_{1i} \\ \mu_{2i} \\ \mu_{3i} \\ \mu_{4i} \\ \mu_{5i} \\ \mu_{6i} \\ \mu_{7i} \end{bmatrix} \tag{4}$$

Those lagged level variables represent the long run. In Equation (4), $(1-L)$ is the difference operator and ECT_{t-1} is the lagged error-correction term, which is obtained from the long-run equilibrium model. In addition, $\varepsilon_{1,t}$, $\varepsilon_{2,t}$, $\varepsilon_{3,t}$, $\varepsilon_{4,t}$, $\varepsilon_{5,t}$ $\varepsilon_{6,t}$, $\varepsilon_{7,t}$ represent the independent and identically distributed (*i.i.d*) random errors within a finite covariance matrix with its mean is zero. The causality in the long run is investigated by the significant value of ECT_{t-1} by employing the t-test statistic. For the changes between carbon emissions and their determinants is examined by applying the F-statistic for the first-difference lagged explanatory variables.

5. Empirical Results and Discussion

5.1 Descriptive Statistics and Correlation Matrix

Table (1) shows the descriptive statistics of the variables. Among those variables, the technique effect has the highest mean value (in log terms). The scale effect, trade openness and energy consumption emerge next with the highest mean values (in log terms). The mean value for the carbon emission remains the smallest. In terms of the degree of variability in the variables from their mean values, it is the highest in the technique effect, and this is followed by the variability of foreign direct investment and trade openness. The variabilities in carbon emissions and energy consumption remain the smallest. Thus, while the degree of spread is high in the technique effect, foreign direct investment and trade openness, it is less in energy consumption and carbon emissions, comparatively. The distribution patterns show that, except for trade openness that has a positive skewed distribution, the rest of the variables are negatively skewed. Thus, while there is a higher tendency for increases than decreases in trade openness, it is the opposite for the rest of the variables. The values of the kurtosis and the Jarque-Bera test confirm all the variables are normally distributed except for carbon emissions.

The pairwise correlation matrix shows that while the scale effect and energy consumption have a positive correlation with carbon emissions, the technique effect, composition effect, and trade openness are negatively correlated with carbon emissions. The correlation between foreign direct investment and CO_2 emissions is positive. In terms of the correlation among the regressors, there seems to be a higher degree of correlation between the composite effect and the scale effect, trade openness and the scale effect, and foreign direct investment and the scale effect. This evidence seems to suggest a possible collinearity problem which could affect the identification of parameters in the model. However, correlations do not imply causalities. Therefore, subsequently, in this study, we test for the short-run and long-run causalities.

Table 1: Descriptive Statistics and the Correlation Matrix

Variables	$\ln C_t$	$\ln S_t$	$\ln T_t$	$\ln E_t$	$\ln K_t$	$\ln O_t$	$\ln F_t$
Mean	2.9440	10.5665	111.7000	8.9363	4.8516	8.9627	5.8362
Median	2.9630	10.5758	111.8483	8.9494	4.8161	8.9873	6.0619
Maximum	3.0898	10.8627	117.9991	9.0405	5.1426	9.7311	7.3353
Minimum	2.7086	10.1361	102.7422	8.8180	4.4416	8.1736	3.6358
Std. Dev.	0.0873	0.2235	4.7089	0.0553	0.1859	0.4452	1.0137
Skewness	-1.0029	-0.3277	-0.3074	-0.5386	-0.1439	0.0230	-0.5917
Kurtosis	3.7602	1.7548	1.7353	2.6426	2.0381	1.8165	2.4133
Jarque-Bera	8.0535	3.4651	3.4606	2.2541	1.7639	2.4547	3.0534
Probability	0.0178	0.1768	0.1772	0.3239	0.4139	0.2930	0.2172
$\ln C_t$	1.0000						
$\ln S_t$	0.3340	1.0000					
$\ln T_t$	-0.4309	0.4509	1.0000				
$\ln E_t$	0.4504	0.4595	-0.4617	1.0000			
$\ln K_t$	-0.5135	0.5404	0.5427	-0.3298	1.0000		
$\ln O_t$	-0.4064	0.3710	0.4790	-0.5329	0.4169	1.0000	
$\ln F_t$	0.5124	0.4045	0.4026	0.3615	0.5108	0.3819	1.0000

5.2. Results of the Unit Root Tests with/without Structural Breaks

Table 2 contains the results of the tests of unit roots by first using the traditional augmented Dickey-Fuller and Phillip-Perron tests which do not take into account structural breaks. For these tests, it is evident that all the variables contain a unit root in the levels, which an indication that these series might be I(1) variables. However, as pointed out by Perron (1989), the traditional unit root tests that do not take into account structural breaks give biased results, and thus they reduce the ability to reject a false null hypothesis. In the lower part of Table 2, we use the ADF test with structural break developed by Kim and Perron (2009).

Generally, we cannot reject the null hypothesis of a unit root with structural breaks in the levels. These structural breaks are relevant and the outcome of environmental, economic, energy and trade policies implemented in the United States over the study period. The structural break periods are 2008, 1992, 2007, 1996 and 1992 for the CO_2 emissions, scale effect, technique effect, energy consumption, composition effect, trade openness, and foreign direct investment, respectively. The structural breaks may reflect the Kyoto protocol that was signed in 1997 after hefty discussions in the year before. This agreement is a protocol to the United Nations Framework Convention on Climate Change (UFCCC), to decrease greenhouse gases that cause climate change. The break-in CO_2 emissions show the implementation of the 'Pollution Prevention Law and Policies (PPLP)' in 2007, which has significantly affected environmental quality in 2008.

Table 2: Results of the Unit Root Analysis

Variable	**ADF at Level**		**PP at Level**	
	T. Statistic	P. Value	T. Statistic	P. Value
$\ln C_t$	-1.1398 (2)	0.9091	-1.0366 (3)	0.9273
$\ln S_t$	-1.6546 (3)	0.7138	-1.2307 (3)	0.8813
$\ln T_t$	-1.6980 (2)	0.7336	-1.2577 (3)	0.8843
$\ln E_t$	-1.5570 (1)	0.7924	-2.0107 (3)	0.5782
$\ln K_t$	-3.0144 (2)	0.1414	-2.3006 (3)	0.4242
$\ln O_t$	-1.7689 (1)	0.6451	-1.6711 (3)	0.6545
$\ln F_t$	-2.9801 (2)	0.1511	-3.1053 (3)	0.1186
Variable	**ADF at Level with Break**		**ADF at 1st Diff. with Break**	
	T-statistic	**Break Year**	**T-statistic**	**Break Year**
$\ln C_t$	-3.2311 (1)	2008	-5.3862 (2) ***	2009
$\ln S_t$	-1.6584 (2)	1992	-5.8537 (3) ***	2005
$\ln T_t$	-1.6574 (1)	1992	-6.0052 (2) ***	2005
$\ln E_t$	-2.9042 (3)	2007	-5.2492(1) **	2000
$\ln K_t$	-4.0537 (2)	1996	-5.8854 (3) ***	1991
$\ln O_t$	-2.9602 (2)	1992	-6.6058 (2) ***	2009
$\ln F_t$	-3.6827 (1)	1992	-7.2291 (3) ***	1991
Note: *** and ** show significance at the 1% and 5% levels, respectively. The optimal lag lengths used are shown in ().				

However, after the first difference, we reject the null hypothesis of unit roots with a structural break. Thus, the ADF unit root test with a structural break confirms that we have variables which are integrated of degree one, I(1). This evidence is a crucial requirement for cointegration or the long-run equilibrium analysis.

5.3. Results of the Bounds Cointegrating Test

In Table 3, we apply the cointegrating bounds test with structural breaks to examine the presence of multiple cointegrating vectors, as we do not impose the assumption of one cointegrating equation. Except for the models for the scale effect and the technique effect, the calculated F-statistic for the rest of the variables is higher than the upper bound critical values at either one percent or five percent significance levels. Thus, there is evidence of multiple cointegration relationships between carbon emissions and their determinants. In particular, for the CO_2 emissions equation, the evidence of cointegration implies that the identified regressors can indeed be treated as the 'long-run forcing' variables that explain the changes in CO_2 emissions in the U.S.

Table 3: Results of the Bounds Cointegration Test

Bounds Testing Approach to Cointegration				Diagnostic tests					
Estimated Models	Optimal Lag Length	Break Year	F-statistic	χ^2_{NORMAL}	χ^2_{ARCH}	χ^2_{RESET}	χ^2_{SERIAL}	CUSUM	CSUSUMSQ
$C_t = f(S_t, T_t, E_t, K_t, O_t, F_t)$	2, 2, 1, 2, 1, 2, 2	2008	11.150***	0.7363	1.4849	2.1352	0.9007	Stable	Stable
$S_t = f(C_t, T_t, E_t, K_t, O_t, F_t)$	2, 2, 1, 2, 1, 2, 2	1992	2.187	0.4403	2.002	0.4351	1.1007	Unstable	Stable
$T_t = f(C_t, S_t, E_t, K_t, O_t, F_t)$	2, 2, 2, 2, 2, 1, 2	1992	2.191	0.1090	1.6101	1.1303	2.1050	Stable	Unstable
$E_t = f(C_t, S_t, T_t, K_t, O_t, F_t)$	2, 1, 2, 2, 1, 2, 1	2007	9.155***	2.1342	2.1051	0.3765	0.1594	Stable	Stable
$K_t = f(C_t, S_t, T_t, E_t, O_t, F_t)$	2, 1, 1, 2, 1, 2, 2	1996	11.190***	1.3623	4.1825	2.1535	0.3043	Stable	Stable
$O_t = f(C_t, S_t, T_t, E_t, K_t, F_t)$	2, 1, 2, 2, 2, 1, 1	1992	7.087**	1.2628	2.2802	2.1051	0.3010	Stable	Stable
$F_t = f(C_t, S_t, T_t, E_t, K_t, O_t)$	2, 1, 2, 1, 1, 2, 2	1992	7.190**	2.0989	1.9087	2.0084	0.1780		
Significance Level	Critical values (T = 52)								
	Lower bounds $I(0)$	Upper bounds $I(1)$							
1 percent Level	7.317	8.70							
5 percent Level	5.360	6.373							
10 percent Level	4.437	5.377							

Note The asterisks *** and ** denote significant at the 1% and 5% levels, respectively. The AIC determines the optimal lag length.

For these models, we also perform several diagnostic statistics. All the models pass the normality, heteroscedasticity, model misspecification, serial correlation, and stability tests. Cointegration implies that there exists a long-run equilibrium. In this study, we show the long-run and short-run models for the carbon emissions function and test for causality in the short-run and long-run.

5.4. Results of the Long-run and the Short-run Analyses

Tables 4 and 5 contain the long-run and short-run estimates. In both cases, it is evident that, while the scale effect (measured by real GDP) increases carbon emissions, the technique effect (measured by real GDP per capita) decreases it. This finding confirms the existence of the EKC hypothesis. However, this identified relationship is significant only in the long-run. Thus, in the U.S, the EKC is more of a long-run phenomenon. This evidence makes sense since, in the short-run, both input substitution options and the investments in advanced technologies are limited. However, in the long-run, the time is long enough to propel input substitution and investment in advanced technologies.

In the U.S, there is evidence to suggest that environmental awareness has improved among the population. Demand for renewable energy sources like solar panels has increased as well as the demand for electricity-based cars. These shifts in the demand patterns change the input composition in favor of less energy-intensive inputs, hence inducing a lower energy requirement and its associated carbon dioxide emissions in the long-term. Moreover, the growth of the U.S economy has moved in tandem with investment in the technical aspect of production, and this has improved energy use efficiency in the country. This finding is consistent with the results of Atasoy (2017) who confirms the existence of EKC in the long-run but not in the short-run. Dogan and

Seker (2016), by using a panel of top renewable energy-using countries that included the U.S., also confirm the existence of the EKC in the long-run. However, the results contrast with the findings of Dogan and Turkekul (2016) and Dogan and Ozturk (2017) who reveal evidence of no EKC in the short-run and long-run in the U.S.

Energy consumption in the short-run and long-run has a significant positive effect on carbon emissions in the U.S. According to the estimates, an increase in total energy consumption by 10% would cause carbon emissions to increase by 8.8% in the short-run but 1.3% in the long-run. The positive effect of energy consumption on CO_2 emissions in the U.S. could be attributed to the energy source structure. In the U.S., renewable energy sources which decrease energy-related emissions are dominated by non-renewable energy sources that increase energy-related emissions.[9] For example, in 2016, total energy consumption was 97.4 thousand trillion Btu. Starting with the non-renewable energy sources, natural gas accounted for 33%, petroleum for 28%, coal for 17%, and nuclear electric power for 10%, thereby provided about 88% of this total consumption, while the remaining 12% came from renewable energy sources.

The dominance of non-renewable energy sources over renewable energy sources implies that in the U.S. increasing the consumption of energy will create more pollution. However, a comparison between the short-run and long-run coefficients reveal that the energy-induced carbon effect is higher in the short-run than in the long-run. As mentioned earlier, in the short-run, input substitutability options and the investments in advanced technologies that are more energy efficient are limited. As a result, the energy-induced carbon effect is higher in the short-run.

[9] Dogan and Seker (2016) reveal that in the U.S., while non-renewable energy sources increase carbon dioxide emissions, renewable energy sources decrease carbon dioxide emissions. Dogan and Ozturk (2017) also confirm this result for the U.S. Paramati et al. (2017) also find this result for both developed and developing economies in G20, but find that non-renewable energy increases carbon dioxide emissions, renewable energy decreases carbon dioxide emissions.

However, in the long-run, input substitution and advanced energy saving technologies become available. Therefore, the energy-induced carbon effects decline in the long-run. Atasoy (2017) also finds that the energy-induced carbon effect is higher in the short-run than in the long-run for the U.S. In contrast, Dogan and Turkekul (2016) find that energy-induced carbon effect is higher in the long run than in the short-run in the U.S.

The effect of the composition effect, i.e., capital intensity (which is measured by the capital-labor ratio) is significantly negative in the short-run and long-run. As suggested by Cole et al. (2005), the effect of capital intensity is ambiguous. While the higher capital intensity may indicate the growth of energy-intensive industries and hence higher carbon emissions, it could imply a growth of capital energy-efficient industries, consequently, lower carbon dioxide emissions. The negative effect of capital intensity or the composition effect on CO_2 emissions in the long-run and short-run suggests that, in the case of the U.S., the effect of the latter explanation may dominate the former. The elasticity suggests that an increase in the composition effect by 10% will cause carbon dioxide emissions to go down by 0.9% in the long-run and by 1.5% in the short-run. Thus, the short-run effect seems to dominate the long-run effect. This could be linked to the depreciation of capital over time. As capital installed in the short-run begins to wear down, energy productivity of the equipment and machinery decreases in the long-run. Thus, without significant investment in capital consumption, the carbon-reducing effect of capital declines in the long-run. By implication, investment in capital consumption has to be intensified to improve the carbon-reducing impact of installed machinery and equipment in the U.S. in the long-run.

Figure 1 shows the total current depreciation cost for aggregate equipment of private nonresidential fixed assets for different sectors. Generally, depreciation costs for total equipment in all sectors continue to rise, which indicates that there is a high degree of equipment depreciation.

Indeed, this implies that without significant investment in capital consumption, the energy productivity of equipment in these sectors will fall, and hence minimizing the carbon-reducing effect of equipment in these sectors.

Figure 1: Current-cost Depreciation of Private Nonresidential Fixed Assets (Total Equipment)

Data Source: Bureau of Economic Analysis, the U.S. Department of Commerce

Trade openness has a negative effect on CO_2 emissions in the short-run and the long-run, but the effect is statistically significant only in the latter case. Thus, the tendency for trade openness to reduce emissions is likely to materialize more in the long-run than in the short-run in the U.S. In the long-run, an increase in trade openness by 10% will cause carbon emissions to fall by 1.45%. Dogan and Turkekul (2015) also find that trade openness reduces carbon dioxide emissions in the U.S. only in the long-run. Dogan and Seker (2016) also confirm the negative effect of trade openness on carbon dioxide emissions in the U.S. in the long-run. The tendency for trade openness to decrease emissions more in the long-run than the short-run can be explained as follows. In the short-run, countries that are initially exposed to trade openness may not have the technical capacity to compete favorably in the international market. Hence, production is likely to be pollution-intensive. However, in the long-term, the technical capacity of the economy might improve due to the opportunities of the inflow of foreign capital, local investment in technology, and exposure to better international management practices. Consequently, production is likely to be less pollution-intensive in the long-run.

In the short-run and long-run, foreign direct inflows increase carbon dioxide emissions, and the effect is higher in the long run than in the short-run. According to the estimated elasticities, an increase in foreign direct investment by 10% will cause carbon dioxide emissions to increase by 0.19% in the long-run and by 0.08% in the short-run. While the positive effect of FDI on emissions may seem to confirm the existence of the *Pollution Haven Hypothesis*, we are cautious to explain this as such since the U.S economy is one of the countries in the world with stringent environmental regulations, especially on foreign capital. As found by Kelly and Levinson (2002), an increase in pollution-abatement cost reduces FDI in manufacturing and chemical industry, though in an economic sense, the effect is minimal. On the contrary, we contribute this phenomenon to the scale-dominant impact of FDI. FDIs impose a higher energy requirement on the host country via the scale effect since more capital implies more energy required to run this capital equipment and machinery. Thus, through the scale effect, FDI is positively related to carbon dioxide emissions. However, FDIs also present the local economy with opportunities of learning and imitating technology in abroad and technological spillover, which could improve the technical processes of production in the country, hence leading to improvements in energy efficiency and lower energy-related emissions. Thus, through the technical effect, FDIs reduce carbon dioxide emissions in the host country.

In conclusion, the positive effect of FDI on carbon dioxide emissions suggests an oppressive influence of the scale effect of FDI over the technical effect of FDI. Lee (2013) examines the effect of FDI on economic growth, energy consumption and clean energy use for the G-20 countries. This author finds that FDI actively leads to economic growth and higher energy consumption, which confirms the dominance of the scale effect of FDI. However, there is no evidence to suggest that FDI promote clean energy use in these economies, and consequently could lower carbon dioxide emissions, which also confirms the limited nature of the technical effects of FDI.

Paramati et al. (2017) also examine the effect of stock market growth and renewable energy use on carbon dioxide emissions, while controlling for the impact of FDI for the G-20 economies. Their result shows that while FDI reduce carbon emissions for the developing economies sub-group, it increases carbon dioxide emissions for the developed economies sub-group, which includes the U.S. According to them, two possible explanations could underlie the positive FDI-environment relationship for the developed economies sub-group. First, the authors claim that these economies do not rely on FDI for technological transfer, and second, they may have converted these FDIs into productive activities without due course to the environment.

The dummy variable has a negative and significant effect on carbon emissions. This evidence confirms that the implementation of PPLP has improved environmental quality by lowering carbon emissions in the U.S. in short-run and the long-run. Environmental regulations impose additional costs on firms, thus shrinking production and limits entry into the industry. Consequently, the associated carbon dioxide emissions fall. Also, environmental regulations could stimulate investment in technological innovation; this might increase production and employment and attract new entrants into the industry. In this regard, the overall effect of the regulations might depend on the extent of economies of scale enjoyed in the industry. Our findings of the negative policy effect could be attributed to either of the reasons stated above or even both in the case of the U.S.

Finally, the error-correction term in the short-run model is negative and significant. The estimated value suggests that for any initial one percent error in carbon dioxide emissions, approximately 38% of this error will be corrected in the first year. The negative sign, thus indicates that disequilibrium in carbon dioxide emissions is temporal. The model diagnostics suggest that for the short-run and long-run equations, there are no misspecification, heteroscedasticity, and serial correlation problems. Also, the errors are normally distributed, and the estimated short-run and long-run parameters are stable (see Appendix A for the graph plot). The stability of empirical model implies that the coefficients are not susceptible to structural breaks. Hence reliable forecasts can be derived based on these estimates.

5.5 Results of the Short-run and the Long-run Causality Tests

We report the results of short-run and long-run causality based on the VECM with structural break approach. First, we performed the short-run and long-run causality test independently and then later tests them jointly. All these results are shown in the upper and lower parts of Table 6, respectively. First, we implement the stability tests for all the equations based on the CUSUM and CUSUMSQ plots. The results, as shown in Table 6, indicate that the models are stable.

Table 4: Results of the Long-Run Analysis

Dependent Variable = $\ln C_t$				
Variables	Coefficient	Std. Error	T-Statistic	Prob. Value
Constant	17.1046**	8.5638	1.997301	0.0536
$\ln S_t$	4.7364***	1.6315	2.9029	0.0064
$\ln T_t$	-0.2331***	0.0793	-2.9376	0.0058
$\ln E_t$	0.1284***	0.0051	24.9775	0.0000
$\ln K_t$	-0.0929**	0.0442	-2.0915	0.0438
$\ln O_t$	-0.1450***	0.0316	-4.5786	0.0001
$\ln F_t$	0.0192***	0.0062	3.1111	0.0037
D_{2008}	-0.0040***	0.0130	-3.0769	0.0039
R^2	0.8801			
Adj-R^2	0.8767			
F-Statistic	28.7554***			
Durbin Watson	1.8878			
Stability Test				
Test	F. Statistic	Probability Value		
χ^2_{Normal}	1.2902	0.5245		
χ^2_{serial}	1.8568	0.2080		
χ^2_{ARCH}	0.6024	0.4308		
χ^2_{Hetero}	2.1091	0.1107		
χ^2_{Remsay}	0.7054	0.4701		
CUSUM	Stable			
CUSUMSQ	Stable			
Note: *** and ** show significance at the 1% and 5% levels, respectively.				

For carbon dioxide emissions, we only find evidence of short-run causality running from the composition effect to carbon dioxide emissions. However, in the long-run, there is evidence to suggest that the scale effect and the technique effect Granger cause carbon emissions in the U.S. The significance of the error-correction term shows this. Next, the lower part of Table 6 shows evidence of all the regressors independently causing carbon dioxide emissions in the short-run and long-run.

Table 5: Results of the Short-Run Analysis

Dependent Variable = $\Delta \ln C_t$				
Variables	Coefficient	Std. Error	T-Statistic	Prob. Value
Constant	-0.0096***	0.0036	-2.6318	0.0128
$\Delta \ln S_t$	1.9091	2.9959	0.6372	0.5284
$\Delta \ln T_t$	-0.1100	0.1460	-0.7535	0.4565
$\Delta \ln E_t$	0.8784***	0.1037	8.4670	0.0000
$\Delta \ln K_t$	-0.1465**	0.0661	-2.2143	0.0338
$\Delta \ln O_t$	-0.0041	0.0350	-0.1182	0.9066
$\Delta \ln F_t$	0.0077*	0.0044	1.7545	0.0886
D_{2008}	-0.0089**	0.0035	-2.5662	0.0152
ECM_{t-1}	-0.3778**	0.1375	-2.7472	0.0097
R^2	0.6068			
Adj- R^2	0.5970			
F-Statistic	7.890***			
Durbin Watson	1.7063			
Stability Test				
Test	F. Statistic	Probability Value		
χ^2_{Normal}	1.50526	0.4308		
χ^2_{serial}	0.2065	0.8070		
χ^2_{ARCH}	0.2005	0.9607		
χ^2_{Hetero}	1.2107	0.5605		
χ^2_{Remsay}	0.2323	0.8399		
CUSUM	Stable			
CUSUMSQ	Stable			
Note: ***, ** and * show significance at the 1%, 5%, and 10% levels, respectively.				

For energy consumption, we find that only carbon emissions and foreign direct inflows Granger cause energy consumption in the short-run. However, in the long-run, there is evidence to suggest that carbon dioxide emissions, scale effect, technique effect, composition effect, trade openness and foreign direct inflows Granger cause energy consumption. However, the joint test reveals that independently these variables Granger cause energy consumption in the short-run and long-run.

For the composition effect, the independence test shows that only the scale effect Granger causes the composition effect in the short-run. But in the long run, all the variables Granger cause the composition effect, as indicated by the significance of the error-correction term. The joint test, however, shows that independently these variables Granger cause the composition effect in the short-run and long-run. In the case of trade openness, only the composition effect and foreign direct inflows Granger cause trade openness in the short-run. The significance of the error-correction term suggests the presence of long-run causality. The lower part of Table 6 confirms that carbon dioxide emissions, scale effect, technique effect, composition effect, and energy consumption Granger cause trade openness in the short-run and long-run.

In the short-run, the independent test reveals that carbon dioxide emissions, scale effect, energy consumption, and trade openness Granger cause foreign direct investment. There is evidence of long-run causality indicated by the significance of the error-correction term. The joint test, instead shows that independently all the variables Granger cause foreign direct investment in the short-run and long-run.

We conclude that there is a bi-causal relationship between energy consumption and foreign direct investment and also between trade openness and foreign direct investment in the short-run. All other causality patterns can be described as unidirectional in the short-run. There is evidence of unidirectional causality from trade openness to foreign direct investment in the short-run and long-run. All other identified causal relationships are bi-directional in the short-run and long-run.

Table 6: Results of the VECM Granger Causality Analysis

Dependent Variable	Short Run								Long Run	CUSUM	CUSUMSQ
	$\sum \Delta \ln C_{t-1}$	$\sum \Delta \ln S_{t-1}$	$\sum \Delta \ln T_{t-1}$	$\sum \Delta \ln E_{t-1}$	$\sum \Delta \ln K_{t-1}$	$\sum \Delta \ln O_{t-1}$	$\sum \Delta \ln F_{t-1}$	Break Year	ECM_{t-1}		
$\Delta \ln C_t$	…	0.6422 [0.5349]	0.1652 [0.8487]	0.6666 [0.5227]	10.2089*** [0.0003]	0.4229 [0.6599]	1.5928 [0.2241]	2008	-0.2229*** [-4.007]	Stable	Stable
$\Delta \ln S_t$	0.2792 [0.7588]	…	3.9826** [0.0321]	9.3701*** [0.0019]	0.3111 [0.7355]	0.0066 [0.9934]	0.2430 [0.7861]	1992	….	Stable	Stable
$\Delta \ln T_t$	0.3781 [0.7408]	4.0086** [0.0317]	…	7.0053** [0.0110]	0.1701 [0.8109]	0.2074 [0.8092]	0.2040 [0.8109]	1992	….	Stable	Stable
$\Delta \ln E_t$	24.9636*** [0.0000]	0.4060 [0.6706]	0.6369 [0.5373]	…	0.6334 [0.5391]	0.7598 [0.4782]	3.0299* [0.0514]	2007	-0.1178*** [-3.9097]	Stable	Stable
$\Delta \ln K_t$	1.0799 [0.3555]	23.0644*** [0.0000]	0.3520 [0.7068]	0.3190 [0.7298]	…	0.3504 [0.7079]	0.1961 [0.8232]	1996	-0.3208*** [-2.8017]	Stable	Stable
$\Delta \ln O_t$	0.3986 [0.6756]	0.0763 [0.9267]	0.9053 [0.4178]	0.7526 [0.4819]	3.2161* [0.0579]	…	2.6039* [0.0947]	1992	-0.3236** [-2.3001]	Stable	Stable
$\Delta \ln F_t$	3.0152* [0.0679]	5.1761** [0.0136]	1.1395 [0.3367]	3.9224** [0.0336]	1.7923 [0.1882]	2.5561* [0.0985]	…	1992	-0.0814*** [-3.1576]	Stable	Stable
Joint Long-run and Short-run Causality									CUSUM	CUSUMSQ	
$\Delta \ln C_t$	…	15.8161*** [0.0000]	13.3242*** [0.0000]	26.1319*** [0.0000]	9.1516*** [0.0003]	12.9157*** [0.0000]	14.5678*** [0.0000]	2008	Stable	Stable	
$\Delta \ln S_t$	….	….	….	….	….	….	….	1992	….	….	
$\Delta \ln T_t$	….	….	….	….	….	….	….	1992	….	….	
$\Delta \ln E_t$	21.2311*** [0.0000]	9.8090*** [0.0002]	7.6017*** [0.0010]	….	12.2071*** [0.0000]	21.5060*** [0.0000]	20.1989*** [0.0000]	2007	Stable	Stable	
$\Delta \ln K_t$	5.5401*** [0.0036]	3.6014** [0.0276]	4.0702** [0.0183]	10.7030*** [0.0001]	….	5.1704** [0.0155]	18.9018*** [0.0000]	1996	Stable	Stable	
$\Delta \ln O_t$	17.2011*** [0.0000]	11.8191*** [0.0001]	6.6710*** [0.0019]	5.9879** [0.0123]	19.0989*** [0.0000]	….	12.7890*** [0.0000]	1992	Stable	Stable	
$\Delta \ln F_t$	15.0681*** [0.0000]	14.3440*** [0.0000]	22.1217*** [0.0000]	12.1013*** [0.0000]	12.9053*** [0.0000]	13.1231*** [0.0000]	….	1992	Stable	Stable	

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

5.6. Results of the Variance Decomposition Analysis

This section ascertains the future contributing roles of each variable in explaining one standard deviation shock in each variable. The first part of Table 7 shows the variance decomposition of carbon dioxide emissions. In the first year, one standard deviation shock in carbon dioxide emissions is explained by itself. However, this reduces in year two as the significance of other variables in terms of their contribution increases. For instance, trade openness accounts for about 22% of the future variations in carbon dioxide emissions in year 2. On the whole, trade openness seems to account for the larger share of future changes in carbon dioxide emissions in the U.S. However, this begins to fall, albeit with a marginal size after the 7th year.

Similarly, the contributions of the scale effect, the composition effect and foreign direct investment in explaining future variations in carbon dioxide emissions begin to diminish respectively after the 5th and 6th years. On the contrary, the contributions of the technique and energy consumption in explaining future changes in carbon dioxide emissions increase with time. For example, the contribution of the technique effect increases by 12.8 percentage points in the first five-year period and further by 5.8 and 3.4 percentage points in the next two five-year periods. For energy consumption, the upturn in the contribution increases by 1.62, 5.42 and 3.03 percentage points for the three to five-year windows. In all, trade openness, the scale effect and energy consumption are the dominant contributors to future variations in carbon dioxide emissions in the U.S.

The second part of Table 7 shows the variance decomposition for the scale effect. In the first year, the carbon dioxide emissions and the scale effect explain the changes in the scale effect. However, the contribution of carbon dioxide emissions to further changes in the scale effect decreases significantly. The contribution of carbon dioxide emissions decreases from 44% in the 1st year to approximately 9% in the 15th year, which represents a fall of 35 percentage points. Likewise, the contributions of trade openness and the technique effect have also declined after some period; precisely the 6th period for trade openness and the7th period for the scale effect. On the contrary, foreign direct investment, energy consumption and the composition effect grow in importance with time. In general, carbon dioxide emissions and trade openness explain much of the future variations in the scale effect in the U.S.

The scale effect, carbon dioxide emissions and trade openness account for much of the future variations of the technical effect. However, while the contribution of the scale effect grows with time, the effect of carbon dioxide emissions and trade openness decreases with time. The other variables (FDI, energy consumption and composition effect) account relatively for a smaller share in the future variations of the technical effect. However, their importance grows with time.

In the case of energy consumption, carbon dioxide emissions, trade openness and the technique effect contribute primarily to the future variations in energy consumption. While the contribution of trade openness and the technique effect grows with the time that of carbon dioxide emissions diminishes. The contributions of scale effect, composition effect, and foreign direct inflows remain small and decrease with time.

The technique effect, trade openness and carbon dioxide emissions explain much of the variation in the composition effect, but the contribution of carbon dioxide emissions diminishes, while that of trade openness and the technique effect increases with time. The contributions of the scale effect, energy consumption, and foreign direct investment remain the smallest but increase with time. The scale effect, technique effect, energy consumption, and carbon dioxide emissions are the major contributors to future changes in trade openness. While the importance of the scale effect and the technique effect grows with time, whereas that of energy consumption and carbon dioxide emissions declines with time. The composition effect and FDI are the least contributors, but the importance of FDI grows with time and that of the composition effect declines with time. Lastly, the carbon dioxide emissions, scale effect, and trade openness explain much of the future variations in FDI, while the importance of the scale effect grows with time, and that of carbon dioxide emissions and trade openness declines with time. The composition effect, energy consumption, and the technique effect are the least contributors. While the contribution of the composition and technique effects increases with time, the contribution of energy consumption drops with time.

Table 7: Results of the Variance Decomposition Analysis

Variance Decomposition of $\ln C_t$							
Period	$\ln C_t$	$\ln S_t$	$\ln T_t$	$\ln E_t$	$\ln K_t$	$\ln O_t$	$\ln F_t$
1	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	69.1125	0.0447	4.2504	2.7152	0.7026	22.4019	0.7724
3	46.3330	0.1100	8.0965	2.6452	1.1805	39.7100	1.9245
4	34.1871	0.1433	10.7816	1.8293	1.2510	49.0926	2.7150
5	27.3525	0.1436	12.7623	1.6236	1.1124	53.9344	3.0709
6	23.0916	0.1274	14.3027	2.2234	0.9295	56.2104	3.1146
7	20.1797	0.1091	15.5482	3.3543	0.7904	57.0312	2.9868
8	18.0463	0.0951	16.5972	4.6716	0.7204	57.0793	2.7897
9	16.4026	0.0850	17.5188	5.9330	0.7099	56.7697	2.5807
10	15.0863	0.0768	18.3569	7.0235	0.7380	56.3328	2.3855
11	13.9989	0.0695	19.1361	7.9169	0.7855	55.8799	2.2129
12	13.0774	0.0644	19.8678	8.6326	0.8398	55.4534	2.0643
13	12.2807	0.0647	20.5570	9.2049	0.8933	55.0612	1.9379
14	11.5811	0.0742	21.2056	9.6675	0.9428	54.6972	1.8312
15	10.9596	0.0969	21.8148	10.0479	0.9868	54.3520	1.7417
Variance Decomposition of $\ln S_t$							
Period	$\ln C_t$	$\ln S_t$	$\ln T_t$	$\ln E_t$	$\ln K_t$	$\ln O_t$	$\ln F_t$
1	44.3280	55.6719	0.0000	0.0000	0.0000	0.0000	0.0000
2	33.9963	56.3314	1.2535	0.5922	0.0513	7.7131	0.0618
3	26.3729	55.0745	2.5745	0.5924	0.1035	15.2293	0.0524
4	21.4753	54.6757	3.4768	0.4643	0.1037	19.7580	0.0459
5	18.2590	55.1748	3.9818	0.6641	0.0859	21.7736	0.0603
6	16.0128	56.1556	4.2004	1.2239	0.0983	22.1874	0.1213
7	14.3537	57.3114	4.2379	1.9536	0.1608	21.7390	0.2433
8	13.0814	58.4914	4.1735	2.6579	0.2647	20.9126	0.4182
9	12.0828	59.6383	4.0585	3.2268	0.3898	19.9790	0.6245
10	11.2860	60.7347	3.9219	3.6324	0.5173	19.0670	0.8404
11	10.6409	61.7754	3.7790	3.8921	0.6352	18.2262	1.0508
12	10.1112	62.7582	3.6373	4.0391	0.7379	17.4679	1.2480
13	9.6702	63.6809	3.5012	4.1053	0.8238	16.7884	1.4298
14	9.2983	64.5404	3.3738	4.1161	0.8938	16.1807	1.5966
15	8.9805	65.3324	3.2584	4.0895	0.9495	15.6390	1.7503

Variance Decomposition of $\ln T_t$							
Period	$\ln C_t$	$\ln S_t$	$\ln T_t$	$\ln E_t$	$\ln K_t$	$\ln O_t$	$\ln F_t$
1	44.3090	55.6380	0.0528	0.0000	0.0000	0.0000	0.0000
2	34.1660	56.5606	0.9475	0.6171	0.0478	7.5957	0.0649
3	26.6088	55.4952	2.0612	0.6373	0.0971	15.0439	0.0562
4	21.7206	55.2298	2.8522	0.4934	0.0971	19.5568	0.0497
5	18.4955	55.8357	3.3000	0.6444	0.0805	21.5786	0.0649
6	16.2357	56.9083	3.4936	1.1389	0.0940	22.0021	0.1270
7	14.5620	58.1434	3.5252	1.8031	0.1570	21.5587	0.2503
8	13.2749	59.3901	3.4655	2.4506	0.2609	20.7306	0.4270
9	12.2620	60.5920	3.3603	2.9746	0.3857	19.7897	0.6356
10	11.4515	61.7329	3.2360	3.3460	0.5128	18.8658	0.8546
11	10.7934	62.8093	3.1065	3.5803	0.6301	18.0113	1.0687
12	10.2513	63.8202	2.9790	3.7083	0.7320	17.2388	1.2700
13	9.7989	64.7636	2.8580	3.7603	0.8170	16.5459	1.4559
14	9.4159	65.6365	2.7472	3.7604	0.8858	15.9268	1.6270
15	9.0875	66.4344	2.6502	3.7260	0.9401	15.3765	1.7850
Variance Decomposition of $\ln E_t$							
Period	$\ln C_t$	$\ln S_t$	$\ln T_t$	$\ln E_t$	$\ln K_t$	$\ln O_t$	$\ln F_t$
1	80.4443	1.5368	0.0015	18.0173	0.0000	0.0000	0.0000
2	55.5194	0.8010	2.7938	22.4652	0.8652	16.6920	0.8630
3	39.8670	0.5146	5.5705	19.5013	1.5666	30.8463	2.1333
4	31.6268	0.4206	7.7114	15.7309	1.8195	39.6091	3.0812
5	27.0140	0.3737	9.3883	13.1208	1.7779	44.7502	3.5746
6	24.1151	0.3351	10.7364	11.8880	1.6202	47.5937	3.7111
7	22.0678	0.3030	11.8498	11.6540	1.4651	49.0222	3.6379
8	20.4901	0.2799	12.8073	11.9403	1.3615	49.6489	3.4716
9	19.2043	0.2640	13.6714	12.3927	1.3118	49.8763	3.2793
10	18.1157	0.2508	14.4825	12.8224	1.2996	49.9379	3.0907
11	17.1670	0.2372	15.2612	13.1607	1.3078	49.9493	2.9166
12	16.3212	0.2229	16.0143	13.4022	1.3241	49.9552	2.7597
13	15.5551	0.2099	16.7419	13.5662	1.3421	49.9644	2.6201
14	14.8538	0.2015	17.4415	13.6758	1.3589	49.9714	2.4967
15	14.2076	0.2017	18.1111	13.7502	1.3734	49.9678	2.3880
Variance Decomposition of $\ln K_t$							
Period	$\ln C_t$	$\ln S_t$	$\ln T_t$	$\ln E_t$	$\ln K_t$	$\ln O_t$	$\ln F_t$
1	30.2478	52.4433	6.1091	0.0438	11.1557	0.0000	0.0000
2	25.3624	53.3545	4.6431	1.8124	10.762	3.5562	0.5088
3	21.7407	52.6971	3.8500	3.5049	9.9292	7.6007	0.6770
4	19.3167	52.2648	3.4850	4.5155	9.2909	10.4285	0.6982
5	17.7317	52.3624	3.3996	4.9802	8.9103	11.9151	0.7003
6	16.6672	52.8128	3.5225	5.1485	8.7087	12.4206	0.7194
7	15.9037	53.3741	3.8135	5.1911	8.6011	12.3525	0.7637
8	15.3081	53.8736	4.2396	5.1961	8.5260	12.0245	0.8318
9	14.8066	54.2209	4.7700	5.2049	8.4463	11.6342	0.9167

10	14.3598	54.3839	5.3774	5.2383	8.3440	11.2873	1.0090
11	13.9466	54.3605	6.0401	5.3067	8.2138	11.0315	1.1005
12	13.5551	54.1617	6.7421	5.4131	8.0572	10.8847	1.1857
13	13.1783	53.8020	7.4724	5.5550	7.8788	10.8513	1.2619
14	12.8117	53.2970	8.2226	5.7261	7.6837	10.9300	1.3285
15	12.4522	52.6615	8.9867	5.9187	7.4765	11.1176	1.3863
Variance Decomposition of $\ln O_t$							
Period	$\ln C_t$	$\ln S_t$	$\ln T_t$	$\ln E_t$	$\ln K_t$	$\ln O_t$	$\ln F_t$
1	20.0367	8.8359	14.0703	0.1021	0.0038	56.9509	0.0000
2	20.4133	12.5002	13.4936	4.5795	0.1206	48.6051	0.2874
3	19.2716	15.1697	12.6028	9.7614	0.5497	42.3289	0.3155
4	17.8803	17.3389	11.9286	13.0202	1.0837	38.4599	0.2881
5	16.7788	19.4852	11.5864	14.3660	1.4987	36.0147	0.2698
6	15.9400	21.7436	11.5072	14.5686	1.7236	34.2546	0.2620
7	15.2016	24.0388	11.5987	14.2159	1.7896	32.8621	0.2931
8	14.4598	26.2430	11.7923	13.6182	1.7578	31.7351	0.3934
9	13.6917	28.2584	12.0473	12.9248	1.6794	30.8321	0.5659
10	12.9160	30.0328	12.3425	12.2170	1.5846	30.1176	0.7892
11	12.1586	31.5473	12.6685	11.5452	1.4875	29.5580	1.0346
12	11.4376	32.8007	13.0224	10.9389	1.3937	29.1278	1.2787
13	10.7617	33.8008	13.4035	10.4099	1.3051	28.8112	1.5074
14	10.1333	34.5603	13.8121	9.9584	1.2223	28.5990	1.7142
15	9.5508	35.0951	14.2476	9.5779	1.1452	28.4854	1.8976
Variance Decomposition of $\ln F_t$							
Period	$\ln C_t$	$\ln S_t$	$\ln T_t$	$\ln E_t$	$\ln K_t$	$\ln O_t$	$\ln F_t$
1	24.5239	7.7759	2.3207	3.0102	0.1862	16.3697	45.8131
2	25.6221	14.2345	2.0964	3.1343	1.0267	14.6655	39.2202
3	25.0689	19.1057	1.9063	2.8715	2.0166	13.3611	35.6698
4	24.0799	22.2587	1.8161	2.7214	2.6222	12.9941	33.5072
5	23.1734	24.2973	1.7738	2.6683	2.9442	13.0769	32.0658
6	22.4805	25.7134	1.7400	2.6347	3.1278	13.2033	31.1001
7	21.9836	26.7786	1.7057	2.5988	3.2502	13.2254	30.4574
8	21.6260	27.6207	1.6779	2.5646	3.3422	13.1468	30.0215
9	21.3560	28.2990	1.6667	2.5359	3.4135	13.0182	29.7105
10	21.1383	28.8454	1.6790	2.5126	3.4663	12.8863	29.4718
11	20.9511	29.2815	1.7182	2.4950	3.5014	12.7793	29.2732
12	20.7817	29.6241	1.7849	2.4845	3.5203	12.7097	29.0945
13	20.6221	29.8867	1.8786	2.4834	3.5252	12.6807	28.9231
14	20.4669	30.0803	1.9981	2.4936	3.5186	12.6918	28.7504
15	20.3120	30.2141	2.1425	2.5160	3.5033	12.7410	28.5707

6. Conclusion and Policy Implications

This paper investigated the decomposition of the environmental Kuznets curve into the scale effect, technique effect and composition effects by incorporating energy consumption, trade openness and foreign direct investment as additional determinants of carbon emissions. In doing so, we have applied the unit root, and cointegration approaches in the presence of structural breaks in the series. We have also applied the VECM Granger-based causality to examine the causal relationships between carbon emissions and their determinants in the short-run and long-run.

The empirical results indicate the presence of a cointegration association between carbon emissions and their determinants. Moreover, the scale effect adds to carbon emissions, but the technique effect decreases it. The negative effect of the technical effect and the positive effect of the scale effect suggest the existence of the EKC hypothesis, but this hypothesis is more evident in the long run than in the short-run. Further, energy consumption has a positive effect on CO_2 emissions. The composition effect is negatively linked to carbon emissions, but the effect is less in the long-run due to the depreciation of capital. Trade openness improves environmental quality by lowering carbon emissions, while foreign direct investment has a positive impact on carbon emissions confirming the presence of the pollution haven hypothesis in the U.S. Environmental regulations also reduce carbon emissions.

In light of the positive impact of the scale effect on carbon emissions, economic growth in the world's largest economy increases carbon emissions, and thus hurts the global environment. This evidence suggests that it will be difficult for the world to significantly reduce CO2 emissions without the participation of the United States in global agreements related to climate change. This conclusion has relevance to the withdrawal of the United States from the COP 21 agreement which aims to strengthen the global response to the threat of climate change by keeping a temperature increase in the world in this century well below 2 degrees Celsius above pre-industrial levels.

This task is challenging since the results show that the scale effect dominates the technical effect. Therefore, to reduce carbon emissions in the U.S, the technical processes of production should be improved. In this regard, investment in technological innovations and addressing capital consumption are prominent as well as advancing the knowledge of trade liberalization in national policy discourse and implementation. The U.S. companies should have a "social purpose" that determines how their investments and technology affect the environment and climate changes. Not very technology (e.g., electric cars) that produces new energy will help with climate change. The composition effect should work against the scale effect as the American economy keeps shifting towards more services and less manufactured goods. The share of the U.S. services sector to GDP is 78.9% in 2015, compared to 68.9% of the world. This fact also implies the composition effect in the U.S. has a limited range to run against climate change.

Policies that promote export quality and export diversification can reduce the production of highly energy-intensive products (Apergis et al., 2018; Fang et al., 2019; Gozgor and Can, 2017; Shahbaz et al., 2019). Upgrading the quality of export basket can be more effective than increasing the volume of exports to decrease the demand for fossil-fuels energy, and thus export quality can reduce the level of carbon emissions. The shift in production of electricity should target the use of renewable and cleaner sources of energy in producing cleaner electricity. The desirability of FDI to the environment should also be connected to the lower corruptibility of local governments. Governmental regulations should also be strong enough to discourage foreign companies from taking advantage of weak rules and moving their highly polluting activities to those countries with such laws. Governments can even subsidize foreign companies that bring in technologies that reduce pollutions. Eco-duties (e.g., taxes and tariffs) can also be used to protect the environment from those heavy polluters.

Stricter environmental regulations are also necessary since this will not only directly reduce carbon emissions but also help avert the potential occurrence of the pollution haven hypothesis. There should be strong support for the Climate Action Plan in the United States that addresses climate change through setting up effective standards. Besides, FDI may take advantage of weak regulations and use countries with weak regulations as a haven for their polluting activities. The same applies to governments where foreign companies can exploit to their advantage high levels of corruption. In such circumstances and others, FDI may not lead to less carbon-intensive technologies.

Lastly, shifting the energy consumption structure towards more renewable and cleaner energy sources is very crucial in this case. With the continuous decline in the cost of renewable energy in the U.S, investment in renewables is now cost competitive. According to the Energy Information Administration (EIA), renewable energy and natural gas are likely to increase their market share in the future. Even though the recent tariff imposition of 30% on imported solar panels seems a significant setback, this one-time tariff imposition is expected not to derail the long-term growth of the industry, given the massive public support of renewable energy by the people and businessess of the country.

We have positioned the paper as an invitation to the additional roles of FDI and trade openness vis-a-vis the CO2-intensive industries and demand sectors of US emissions Future research should consider the impact of export quality on CO2 emissions instead of just trade openness. This variable is different from export volume and export diversification and is not well explored. Research should also focus on coordination of the various energy and environmental policies at the state level in the United States and the province level in Canada (Popp, 2019). More research on electric grid management should be undertaken to smooth out increases in intermittent renewable power. There is a need to research the coordination at the federal level.

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Appendix I. Long-Run Analysis

Figure 2: CUSUM

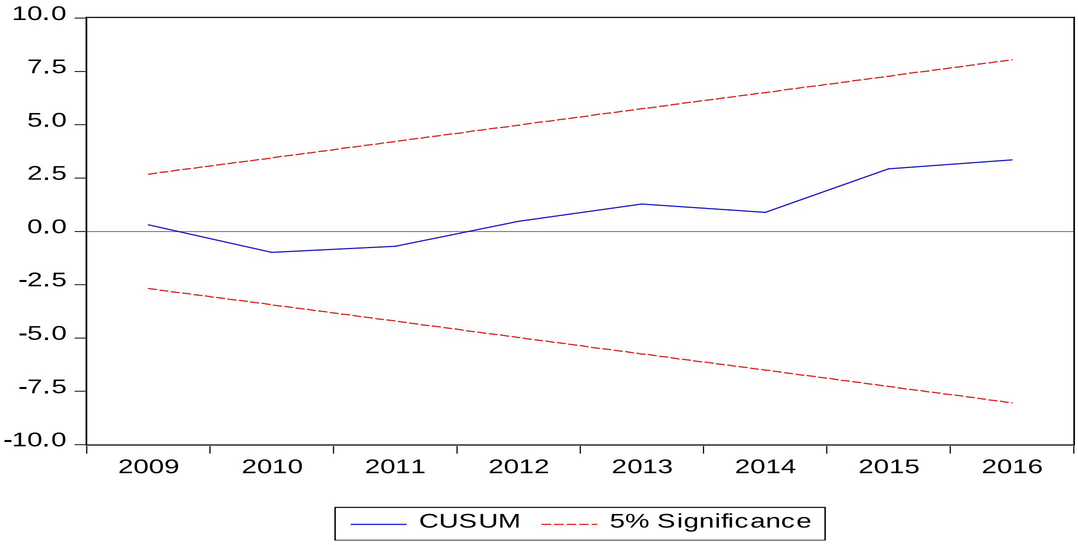
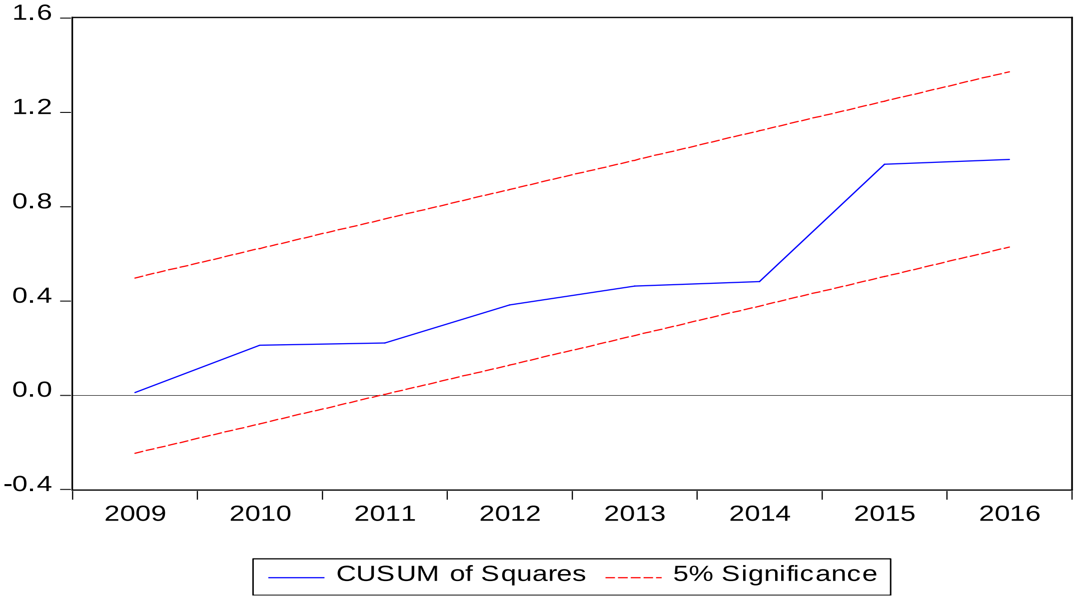


Figure 3: CUSUMSQ



Appendix II. Short-run Analysis

Figure 4: CUSUM

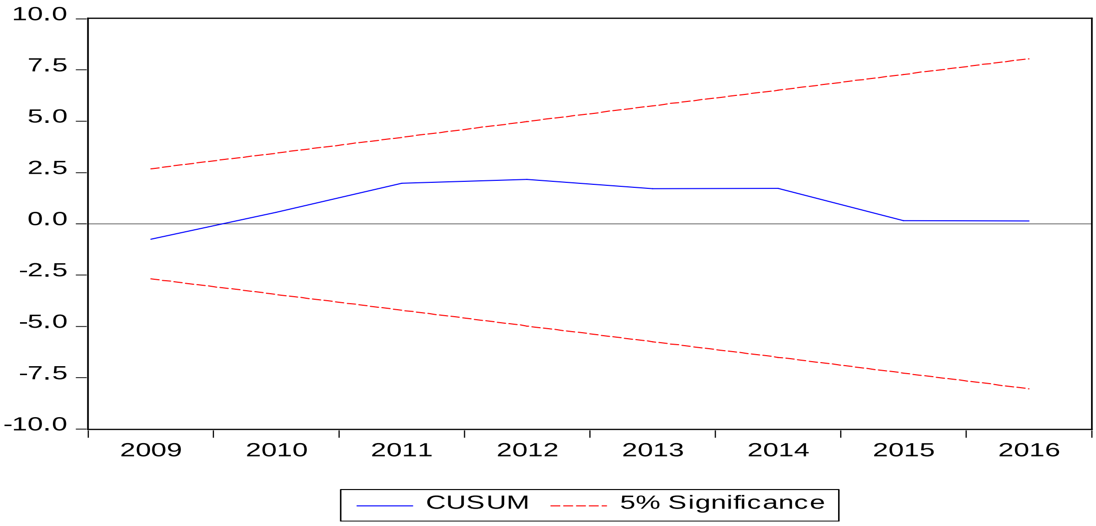


Figure 5: CUSUMSQ