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Tourism, Energy Consumption and Climate Change in OECD Countries

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ABSTRACT: The study analyzed dynamics of the relationship between tourism, energy consumption, and climate change for 25 OECD countries during 1995-2005. For the analysis, Panel VAR (PVAR) model was used. Results of panel unit root-tests show that tourism is nonstationary in the level form but stationary in first difference form and energy consumption and climate change are stationary variables in the level form. Analysis of bivariate model shows that results are sensitive with change in the measurement of the tourism variable, change in order of variable and inclusion of the third variable. However, results of our trivariate model are found to be insensitive with either the change in the measurement of our tourism variable or change in the ordering of the variables. Our results of IRFs shows that response of tourism in one SD shock in climate change and energy consumption and response of climate change emissions to tourism is marginally positive. Further, we find that response of climate change in one SD shock in energy consumption and response of energy consumption in one SD shock in tourism and climate change is zero.

Keywords: Tourism; energy consumption; climate change; OECD countries; panel VAR
JEL Classifications: L83; O13; Q4; Q5

1. Introduction

Environmental issues since the evidence of first green house effect have received considerable interest of researchers and policy makers of the world. Stern et al. (2006) found that the costs of taking action to reduce GHG emissions now are relatively less in comparison to the costs of economic and social disruption from unmitigated climate change. Our lifestyles, economies, health, and social wellbeing are all affected by climate change, and although the consequences of climate change will vary on a regional basis and tourism is no exception.

International tourism is not only an important industrial sector but also it is considered as important source of economic development all over the world, with an annual volume of 940 million arrivals in 2010 (www.unwto.org) and a projection that this number will continue growing to 1.6 billion worldwide by 2020.

The relation between climate change and tourism is bidirectional i.e., climate change impacts on tourism and tourism influence climate change. The first relation may ask for adaptation measures,[1]

[1] According to Braun *et al.* (1999), environmental factors are key components when tourists choose a holiday destination. There is convincing evidence to show that the world's climate will continue to change during this

like shifting destinations, seasons, and activities and investing in new air condition systems.[2] The second relation may ask for mitigation measures aimed at reducing greenhouse gas (GHG) emissions. Since, the tourism sector is a non-negligible contributor to climate change through GHG emissions derived especially from the transport and accommodation of tourists.[3] Tourism must seek to significantly reduce its GHG emissions in accordance with the international community. It was recognized at the Vienna Climate Change Talks (2007)[4] that global emissions of GHG need to peaked in the next 10 to 15 years and then be reduced to very low levels, well below half of levels in 2000 by midcentury.

Tourism can play a significant role in addressing climate change if the innovativeness and resources of this vital global economic sector are fully mobilized, and oriented towards this goal. The concern of the tourism community regarding the challenge of climate change has visibly increased over the last eight years. The World Tourism Organization (UNWTO) and several partner organizations, including United Nations Environment Programme (UNEP), convened the First International Conference on Climate Change and Tourism in Djerba, Tunisia in 2003. This was the first event in terms of raising awareness about the implications of climate change within the international tourism community. Further, the conferences recognized the complex inter-linkages between the tourism sector and climate change and established an adaptation and mitigation framework for future research and policymaking.

However, the role of energy consumption by the tourism sector is nearly ignored in the research work, which is also required for sustainable tourism. Sustainable tourism principles are applicable to all forms of tourism (either it is traditional mass tourism or niche tourism segments, such as ecotourism) and calls for the optimal use of natural resources, environmental protection, respect for the socio-cultural aspects of host communities, long-term economic viability of the tourism businesses, and the fair distribution of socio-economic benefits to all stakeholders. Management of energy supply and consumption, therefore, is a critical component of any sustainable tourism industry.

Apart from the use of the energy in transport, lodging facilities for tourist are major source of final energy consumption. Hotels use two types of energy namely electricity and thermal energy. Electricity is mainly used (disregarding the nature of the source) for illumination and to power motor-driven equipment and electronic devices. Example of electricity includes air conditioning units, fans and air-handlers, lighting fixtures, refrigeration equipment, water pumps, large appliances (for example, clothes and dish washing machines), small appliances (for example, toasters, microwave ovens, hair dryers), electronic devices (for example, television sets, stereos, computers), and communications equipment (for example, cellular telephones, computers). Thermal energy is used (disregarding the nature of the source) as a source of energy in heating applications for example, space heaters, water heaters, cooking equipment (such as stoves and ovens), and laundry dryers.

With this background, we set three objectives in our study. First, we analyzed bivariate dynamics between tourism (measured by International tourism expenditures (current US$)) and climate change (measured through CO2 emissions), second we analyzed bivariate dynamics between tourism and energy consumption (measured by Energy use (kg of oil equivalent per capita)), and third we analyzed the dynamics between trivariate model which includes tourism, climate change and energy consumption. Further, we analyzed the sensitivity of results by using another measure of tourism that is International tourism receipts (current US$).

This study contributes in the existing literature in various ways. First, most of the studies conducted in the area of tourism and climate change are based on micro-analysis (see the literature

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century. Future variations in temperature and other aspects associated with climate change will have differing effects on different regions worldwide.

[2] An important issue is the impact of non-carbon contributions to climate change. For the world economy these emissions add 40% to the contribution in Global warming potential of CO_2 emissions alone (an 'equivalence factor' of 1.4, see also Gössling et al. 2005).

[3] Carbon dioxide is emitted in tourism through the operation of accommodations (heating, cooling, washing, cooking, etc), activities (energy use for transportation of tourists from their accommodations to the sites of activities, for operating restaurants, bars, disco's, cinemas, cable-cars, scenic tours, et cetera) and transport between the tourists homes and the destination areas (by car, coach, train, ferry, aircraft, etc.).

[4] Available at: http://unfccc.int/meetings/vienna_aug_2007/meeting/6320.php

review section) we contribute with the use of macro-analysis in the dynamic framework. Second, to the best of our knowledge this study is first attempt to analyze the dynamics of tourism and energy consumption. Third, we also analyzed the dynamics in trivariate framework in order to overcome from the problem of omitted variables bias of the bivariate model. Fourth, use of Panel VAR (PVAR) model in the area of energy economics, environmental economics, and tourism economics is relatively new.[5]

Rest of the paper is organized as follows. Second section presents a brief review on the literature. We present methodology and data sources in the third section. Fourth section presents the analysis of the data and fifth section concludes.

2. A Brief Literature Review

Literature in the area we did our study is negligible however, we provides some literature available in the area and related issue. Gray and Bebbington (1993) argued that to assess and improve sustainable development we need to not only account for a sector's performance in the economic contribution but also environmental and social dimensions of it. The contribution of tourism has been recognized as potentially considerable (Gössling, 2002) but it is now the researches and policy makers have started to study energy consumption by tourist activities and the resulting greenhouse gas emissions that contribute to the anthropogenic component of global warming (Cárdenas and Rosselló, 2008). It is being recognized that tourism industry is also one of the largest consumers of energy; particularly it is needed to facilitate transportation of travelers, as well as to provide amenities and supporting facilities at the destinations visited (Becken, 2002; Becken and Simmons, 2002, Becken et al., 2001, 2003; Gossling, 2000; Gossling et al., 2002). If we see the literature in the area of tourism, energy, and environmental degradation we find that there are studies, however, dating from the 1930s analyzing the relationship between weather and tourism (Scott *et al.* 2004). For example, Selke (1936) studied on the geographic aspects of the German tourist trade. Recently literature on tourism started to increase. Lise and Tol (2002) by using cross-section data of the tourists originating in OECD countries showed that the optimal temperature for their destination countries ranged from 21ºC to 24ºC. Hamilton *et al*. (2005) by using a simulation model investigated the effects of climate change on international tourism using the A1B scenario[6] and found that international tourism is expected to increase in the coming decades, but may become sluggish later on in the century. Berrittella *et al.* (2006) by using a computable general equilibrium model showed that, at the international level, changes in climate (in which temperature is considered to be the most important climate variable) would eventually lead to a loss in welfare, which would be disproportionately spread across the various regions of the world. Uyarra *et al.* (2005) examines the significance of environmental characteristics in influencing the choices made by tourists in there microanalysis, which used a self administered questionnaire on tourists visiting Bonaire and Barbados- 316 from Bonaire and 338 from Barbados. They found that visitors to Bonaire placed additional importance on marine wild life attributes, while tourists going to Barbados had a preference for certain beach characteristics. Mather *et al.* (2005) examined the attraction of the Caribbean as a tourist destination for travelers from North America. This study established that the Caribbean sub-region is likely to be less attractive to tourists due to factors such as increased temperatures, beach erosion, deterioration of reef quality and greater health risks.

3. Empirical Methodology

For analysing, the dynamics of the relationship between climate change and/or energy consumption and tourism we use a Panel-data Vector Autoregression (PVAR) approach. To the best of our knowledge, this kind of investigation has not been done till date and we are the first to use PVAR approach for this type of study. This technique combines the traditional VAR approach, which treats all the variables in the system as endogenous, with the panel-data approach, which allows for

[5] The only exception is Tiwari (2011) which analyzed the dynamics of renewable and nonrenewable energy sources, CO_2 emissions, and economic growth in Europe and Eurasian countries. This is the only one study, which used PAVR approach in the area of energy and environmental economics; however, use of PAVR in tourism in our study is completely new contribution.

[6] A1B incorporates a balanced weighting on all energy sources (for details see Hamilton *et al*., 2005)

unobserved individual heterogeneity. While estimation we have two choices: one in which we can includes many variables that may have important economic effects on each other, and other which can be based on the uses fewer degrees of freedom and hence, enables more efficient estimation. Given the aim of estimating the impact of GDP and environmental degradation shocks on happiness volatility, this study has chosen a small, three-variable VAR model.

The structural model takes the form of a first-order tri-variate VAR system as follows:

$$\begin{aligned} EU_t &= k_1 - a_{12}CO_t - a_{13}TE_t + b_{11}EU_{t-1} + b_{12}CO_{t-1} + b_{13}TE_{t-1} + \varepsilon_t^{EU} \\ CO_t &= k_2 - a_{21}EU_t - a_{23}TE_t + b_{21}EU_{t-1} + b_{22}CO_{t-1} + b_{23}TE_{t-1} + \varepsilon_t^{CO} \\ TE_t &= k_3 - a_{31}EU_t - a_{32}CO_t + b_{31}EU_{t-1} + b_{32}CO_{t-1} + b_{33}TE_{t-1} + \varepsilon_t^{TE} \end{aligned} \tag{1}$$

where TE_t denotes tourism expenditure, EU_t denotes energy use, and CO_t denotes environmental degradation (i.e., CO_2 emissions). ε_t^{EU}, ε_t^{CO}, and ε_t^{TE} are three structural shocks (or pure innovations).[7] They are white noise disturbances with zero means, and constant variances, all individually serially uncorrelated. The system of Eq. (1) can be written in the compact form:

$$AX_t = K + B_1X_{t-1} + \varepsilon_t \tag{2}$$

where $A = \begin{bmatrix} 1 & a_{12} & a_{13} \\ a_{21} & 1 & a_{23} \\ a_{31} & a_{32} & 1 \end{bmatrix}$, $X_t = \begin{bmatrix} EU_t \\ CO_t \\ TE_t \end{bmatrix}$, $K = \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix}$, $B_1 = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$ and $\varepsilon_t = \begin{bmatrix} \varepsilon_t^{EU} \\ \varepsilon_t^{CO} \\ \varepsilon_t^{TE} \end{bmatrix}$.

Following reduced form of VAR is obtained by premultiplying both sides of (2) by A^{-1}:

$$X_t = \Gamma_0 + \Gamma_1 X_{t-1} + e_t \tag{3}$$

where $\Gamma_0 = A^{-1}K$, $\Gamma_1 = A^{-1}B_1$, and $e_t = A^{-1}\varepsilon_t$.

It is important to note that we can not use ordinary least squares estimation technique either for the structural VAR (1) or for the reduced form of VAR (3), since the regressors are correlated with the error term in each equation of the structural VAR (1) and equation of the reduced form of VAR (3). Nonetheless, estimation of VAR (3) only can provide estimates of 18 parameters,[8] whereas the structural VAR (1) contains 21 parameters,[9] so that it is impossible to recover all of the information present in (1) from (3). Putting differently, the reduced form of VAR (3) is under-identified and therefore, to overcome this under-identification problem we impose restrictions on the structural VAR (1) in such a way that the matrix A become a lower triangular with $a_{12} = a_{13} = a_{23} = 0$. Meaning thereby, we assumed that the variables that come earlier in the ordering affect the following variables contemporaneously, as well as with a lag, while the variables that come later affect the previous variables only with a lag. This implies that the variables that come first in the systems are more exogenous and the ones that appear afterward are more endogenous.[10]

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[7] This tri-variate VAR can be reduced to bi-variate VAR model also however, we have preferred to present a more general case of our analysis. Further, in the analysis to see the robustness of our results we have replaced TE_t by TR_t. In our specification, we assume, in our bi-variate model, that current shocks to the Climate change (i.e., CO_2 emissions) have an effect on the contemporaneous value of TE or tourism receipts (TR) or vice-versa, TE/TR has an effect on the contemporaneous value of EU. Similarly, in our trivariate model we assume that TE/TR has an effect on the contemporaneous value of EU and on Climate change (i.e, CO_2 emissions) with a lag, and TE/TR has an effect on the contemporaneous value of Climate change (i.e., CO_2 emissions) and on the value of EU with a lag. These our assumptions are based on simple logical reasoning and the discussion made in the introduction and literature review.

[8] The parameters include 12 coefficients of variables, 3 variances of e_t, and 3 covariances of e_t.

[9] The parameters include 18 coefficients of variables, and 3 variances of ε_t

[10] In simple words, if a variable, say x, appears earlier in the system than another variable, say y, then x is weakly exogenous with respect to y in the short run.

Further, in place of pooling data from different countries to estimate the VAR model (3), we introduced country fixed effects (μ_i) and country-specific time dummies, $d_{i,t}$ to capture the differences in behavior across countries and period. Hence, VAR model (3) becomes:

$$X_{i,t} = \Gamma_0 + \Gamma_1 X_{i,t-1} + \mu_i + d_{i,t} + e_t \ , \qquad i=1,\ldots 25. \qquad (4)$$

where *i* denotes i^{th} country. [11] Since the fixed effects are correlated with the regressors due to lags of the dependent variables, the mean-differencing procedure commonly used to eliminate fixed effects would create biased coefficients. To avoid this problem we use forward mean-differencing (following Love and Zicchino, 2004), also referred to as the 'Helmert procedure' (see Arellano and Bover, 1995). This procedure removes only the forward mean, i.e., the mean of all the future observations available for each country-year. This transformation preserves the orthogonality between transformed variables and lagged regressors, so we can use lagged regressors as instruments and estimate the coefficients by system GMM[12]. More, our model also allows for country-specific time dummies, $d_{i,t}$ to capture aggregate, country-specific macro shocks that may affect all countries in the same way. We eliminate these dummies by subtracting the means of each variable calculated for each country-year.

Further, to calculate the impulse-response functions that describe the reaction of one variable to the innovations in another variable in the system, while holding all other shocks equal to zero, we need to decompose the residuals in a such a way that they become orthogonal as the actual variance-covariance matrix of the errors is unlikely to be diagonal. The usual convention is to adopt a particular ordering and allocate any correlation between the residuals of any two elements to the variable that comes first in the ordering.[13] The impulse response functions for (3) are:

$$X_t = \lambda + \sum_{s=0}^{\infty} \Theta_s \varepsilon_{t-s} \qquad (5)$$

where $\Theta_s = \Gamma_1^s A^{-1}$ is the orthogonalized impulse response of the j^{th} column to a one-unit shock of ε_{t-s}. Thus, the impact of a energy use and environmental degradation shock (i.e., ε_t^{EU} and ε_t^{CO}) can be studied while holding other shocks (i.e., ε_t^{TE}) constant. Additionally, to analyze the impulse-response functions we need an estimate of their confidence intervals. Since the matrix of impulse-response functions is constructed from the estimated VAR coefficients, their standard errors need to be taken into account. We calculate standard errors of the impulse response functions and generate confidence intervals with 1000 Monte Carlo simulations.[14] Finally, we also present variance decompositions, which show the percent of the variation in one variable that is explained by the shock to another variable, accumulated over time. The variance decompositions show the magnitude of the total effect. We report the total effect accumulated over the 10 years.

Worth to be mentioning that different ordering of variables gives different results of the orthogonalized impulse response function. The residuals e_t are expressed as follows:

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[11] Countries incorporated for the analysis in the study are: Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States of America.

[12] In our case the model is "just identified", i.e. the number of regressors equals the number of instruments, therefore system GMM is numerically equivalent to equation-by-equation 2SLS.

[13] The procedure is known as Choleski decomposition of variance-covariance matrix of residuals and is equivalent to transforming the system in a "recursive" VAR for identification purposes. See Hamilton (1994) for the derivations and discussion of impulse-response functions.

[14] In practice, we randomly generate a draw of coefficients for equation (4) using the estimated coefficients and their variance covariance matrix and re-calculate the impulse-responses. We repeat this procedure 1000 times (we experimented with a larger number of repetitions and obtained similar results). We generate 5th and 95th percentiles of this distribution which we use as a confidence interval for the impulse-responses.

$$\begin{bmatrix} e_t^{EU} \\ e_t^{CO} \\ e_t^{TE} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix}^{-1} \begin{bmatrix} \varepsilon_t^{EU} \\ \varepsilon_t^{CO} \\ \varepsilon_t^{TE} \end{bmatrix} \quad (6)$$

The ordering stated in (6) implies that a change in a energy use shocks (i.e., ε_t^{EU}), directly affects e_t^{CO} and e_t^{TE}, which in turn affect the time paths of CO_t and TE_t. Similarly, a change in a environmental degradation shocks (i.e., ε_t^{CO}), directly affects e_t^{TE}, which in turn affect the time paths of TE_t. In this sense, the energy use shock is exogenous because the CO_t shock, ε_t^{CO}, or TE_t shock, ε_t^{TE}, has no effect on the energy use, and it is justified to come first in the system of equations.[15] Annual data of all the analyzed variables is accessed from the on line data base of World Bank Development Indicators. Study period is 1995-2005 which is limited by the availability of the data in order to have balanced panel model. All variables were transformed in to their natural logarithms form hence a prefix, Ln, before the variables denoted natural logarithms of the variables considered.

4. Results and Discussion

Before going ahead with PVAR approach, we analysed the stationarity property of the data by using a battery panel unit root tests. Panel unit root tests, we used are the LLC test (Levin, Lin and Chu, 2002), IPS test (Im, et al., 2003) and ADF and PP type Fisher Chi-square tests of MW (Maddala and Wu, 1999). Results of panel unit root tests of variables analysed are presented in Appendix 1. We find form the analysis of panel unit root tests that LnCO_2 emissions and LnEU are stationary in the level form whereas LnTE/TR stationary at first difference from when model includes constant and/or trend. Therefore, in order analyse the dynamics between the test variables we transformed the nonstationary variables into first difference form because it is important to obtain efficient results in PVAR framework. Next, we estimate the coefficients of the system given in (1) after the fixed effects and the country time dummy variables have been removed. In Table 1, we report the results of two variables vector D(LnTE/TR) and LnCO_2 emissions in model 1-4 and D(LnTE/TR) and LnEU in model 5-6.

It is evident from the model 1 in Table 1 that response of CO_2 to CO_2 is positive and significant; model 2 shows that response of CO_2 and TR respectively is positive and significant to CO_2 and TR. The model 3 and model 4 are based on changing the ordering of the variables entered in the model 1 and 2, which shows similar results. The model 5 shows that response of TE to EU is positive and significant and response of EU to EU is positive and significant whereas, model 6 shows that response of TR to TR and EU is positive and significant and response of EU to EU is positive and significant.

Hence, from Table 1 we can summarise that when we analyse either the dynamics of CO_2 and TE or TE and EU, in both cases results are sensitive to the change in the measurement of the variable (in our case we use two variables TE and TR for measuring tourism). However, results of the dynamics of CO_2 and TE/TR are not sensitive to the change in the order of the variables entered in the PVAR equation.

[15] One might question on the ordering of the variables which might affect our results. We have also altered the ordering of the variable to see the robustness of our results, however, for each case we have not put the model but it can be easily derived from the present one. We reported results of IRFs in appendix.

Table 1. Results of a two-variable PVAR model

Independent variables	Dependent variables				
	$LnCO_{2(t-1)}$	$D(LnTE_{(t-1)})$		$LnCO_{2(t-1)}$	$D(LnTR_{(t-1)})$
Model 1: CO2 and TE			Model 2: CO2 and TR		
$LnCO_{2(t-1)}$	1.0942739** (2.7583388)	3.5340624 (1.5636303)	$LnCO_{2(t-1)}$	1.0468264*** (2.9173676)	1.7943156 (1.4334016)
$D(LnTE_{(t-1)})$	.00776834 (.25012533)	.14980395 (.64319658)	$D(LnTR_{(t-1)})$	.02788992 (.94961066)	.29281182** (2.6911079)
Model 3: TE and CO2			Model 4: TR and CO2		
	$D(LnTE_{(t-1)})$	$LnCO_{2(t-1)}$		$D(LnTR_{(t-1)})$	$LnCO_{2(t-1)}$
$D(LnTE_{(t-1)})$	.14980395 (.64319658)	.00776834 (.25012533)	$D(LnTR_{(t-1)})$	.29281182** (2.6911079)	.02788992 (.94961066)
$LnCO_{2(t-1)}$	3.5340624 (1.5636303)	1.0942739** (2.7583388)	$LnCO_{2(t-1)}$	1.7943156 (1.4334016)	1.0468264** (2.9173676)
Model 5: TE and EU			Model 6: TR and EU		
	$D(LnTE_{(t-1)})$	$LnEU_{(t-1)}$		$D(LnTR_{(t-1)})$	$D(LnEU_{(t-1)})$
$D(LnTE_{(t-1)})$	.20346738 (1.5957502)	.00388656 (.29424897)	$D(LnTR_{(t-1)})$	.31760399*** (4.2507868)	.0286644 (1.5822114)
$D(LnEU_{(t-1)})$	1.285208** (2.74223)	.69251068*** (5.4556552)	$D(LnEU_{(t-1)})$	.66323454* (2.0099563)	.66656053*** (5.1699032)
Two variable PVAR model is estimated by GMM, country-time and fixed effects are removed prior to estimation. Reported numbers show the coefficients of regressing the row variables on lags of the column variables. Heteroskedasticity adjusted *t*-statistics are in parentheses. ***, ** and * indicates significance at 1%, 5% and 10% level, respectively.					

Next, we present our results trivariate model in Table 2 below.

Table 2. Results of a three-variable PVAR model

Independent variables	Dependent variables						
	$D(LnTE_{(t-1)})$	$LnCO_{2(t-1)}$	$LnEU_{(t-1)}$		$D(LnTR_{(t-1)})$	$LnCO_{2(t-1)}$	$LnEU_{(t-1)}$
Model 1: TE, CO2 and EU				Model 2: TR, CO2 and EU			
$D(LnTE_{(t-1)})$	.1900635 (1.1893095)	.00730585 (.23293791)	.00422393 (.31351712)	$D(LnTR_{(t-1)})$	.31186423*** (3.7084307)	.02682919 (.915423)	.02905712 (1.54785)
$LnCO_{2(t-1)}$	1.0805469 (.93301073)	1.1224596** (2.5145018)	-.02719678 (-.10698048)	$LnCO_{2(t-1)}$	.64701488 (.7403042)	1.11070** (2.58164)	-.0442704 (-.176184)
$LnEU_{(t-1)}$	.93937266* (1.9472016)	-.01079138 (-.07107032)	.70121517*** (6.5309807)	$LnEU_{(t-1)}$	.44938183 (1.3555596)	-.02501902 (-.160312)	.681193*** (6.27029)
Model 3: TE, EU and CO2				Model 4: TR, EU and CO2			
	$D(LnTE_{(t-1)})$	$LnEU_{(t-1)}$	$LnCO_{2(t-1)}$		$D(LnTR_{(t-1)})$	$LnEU_{(t-1)}$	$LnCO_{2(t-1)}$
$D(LnTE_{(t-1)})$	.1900635 (1.1893095)	.00422393 (.3135171)	.00730585 (.23293791)	$D(LnTR_{(t-1)})$	.31186423*** (3.7084307)	.02905712 (1.54785)	.02682919 (.91542322)
$LnEU_{(t-1)}$	.93937266* (1.9472016)	.70121517*** (6.530981)	-.01079138 (-.0710703)	$LnEU_{(t-1)}$	.44938183 (1.3555596)	.681193*** (6.27029)	-.02501902 (-.1603121)
$LnCO_{2(t-1)}$	1.0805469 (.93301073)	-.02719678 (-.10698048)	1.1224596** (2.5145018)	$LnCO_{2(t-1)}$	.64701488 (.7403042)	-.0442704 (-.176184)	1.110701** (2.5816354)
Three variable PVAR model is estimated by GMM, country-time and fixed effects are removed prior to estimation. Reported numbers show the coefficients of regressing the row variables on lags of the column variables. Heteroskedasticity adjusted *t*-statistics are in parentheses. *** , ** and * indicates significance at 1%, 5% and 10% level, respectively.							

It is evident from model 1 in Table 2 that lagged EU has positive and significant impact on TE and EU, lagged value of CO_2 has positive and significant impact CO_2, and TE has insignificant impact on all the three variables. However, model 2, which is used to see the sensitivity of the results of model 1 by replacing TE with TR, shows that results are sensitive as now lagged TR shows positive and significant impact on TR and other findings are same. Results reported in model 3 and 4 respectively are obtained by changing the ordering of the variables of model 1 and 2, which shows same results as of model 1 and 2. Hence, results reported in Table 2 also show that results are sensitive to the change in the dependent variable in one case.

Further, to see the more clear results we moved ahead to analyze the variance decomposition. We present the results of variance decompositions of bivariate models in Table 3.

Table 3. Variance decomposition of a two-variable PVAR model

	$LnCO_{2(t-1)}$	$D(LnTE_{(t-1)})$	$LnCO_{2(t-1)}$	$D(LnTR_{(t-1)})$	$D(LnTE_{(t-1)})$	$LnCO_{2(t-1)}$	$D(LnTR_{(t-1)})$	$LnCO_{2(t-1)}$
Model 1: CO2 and TE			Model 2: CO2 and TR		Model 3: TE and CO2		Model 4: TR and CO2	
$LnCO_{2(t-1)}$	.99897438	.00102562	.99213394	.00786606	.47188539	.52811461	.39435658	.3283495
$D(LnTE/TR_{(t-1)})$	.96113516	.03886484	.93245387	.06754613	.43084566	.56915434	.60564342	.6716505
Model 5: TR and EU			Model 6: TR and EU					
	$D(LnTE_{(t-1)})$	$D(LnEU_{(t-1)})$	$D(LnTR_{(t-1)})$	$D(LnEU_{(t-1)})$				
$D(LnTE_{(t-1)})$	.79069787	.08365311	.85527285	.04390584				
$D(LnEU_{(t-1)})$	.20930213	.91634689	.14472715	.95609416				
Percent of variation in the row variable (10 periods ahead) explained by column variable.								

It is evident from model 1 and 2 of Table 3 that CO_2 and TE/TR explain more than 90% of variation in them. However, when we changed the ordering of the variables i.e., when TE/TR comes first and CO_2 later in the PVAR model, CO_2 is found to be explaining 53% of variation in CO_2 and 57% of variation in TE (see model 3). Model 4 shows that CO_2 and TR explains more than 60% of variation in them.

Model 5 shows that 79% of variation in TE is explained by TE itself and about 92% of variation EU is explained by EU itself. If we see the results of model 6 we find that most the variation in both the variables is explained by themselves. Hence, we find form the results of our bivariate models that all variables explains most of the variation in themselves and explanatory power of the variables had been affected by change in the ordering of the variables[16].

Further, we computed VDs of trivariate model and present results in Table 4.

Table 4. Variance decomposition a three-variable PVAR model

	$D(LnTE_{(t-1)})$	$LnCO_{2(t-1)}$	$LnEU_{(t-1)}$		$D(LnTR_{(t-1)})$	$LnCO_{2(t-1)}$	$LnEU_{(t-1)}$
Model 1: TE, CO2 and EU				Model 2: TR, CO2 and EU			
$D(LnTE_{(t-1)})$	.43077606	.54554168	.02368227	$D(LnTR_{(t-1)})$	.37497344	.61199527	.01303129
$LnCO_{2(t-1)}$	.27408969	.72586235	.00004796	$LnCO_{2(t-1)}$	.17905162	.8205712	.00037719
$LnEU_{(t-1)}$	.03526903	.07475576	.88997521	$LnEU_{(t-1)}$	.01451974	.08527185	.90020841
Model 3: TE, EU and CO2				Model 4: TR, EU and CO2			
	$D(LnTE_{(t-1)})$	$LnEU_{(t-1)}$	$LnCO_{2(t-1)}$		$D(LnTR_{(t-1)})$	$LnEU_{(t-1)}$	$LnCO_{2(t-1)}$
$D(LnTE_{(t-1)})$	.43077606	.09520822	.47401573	$D(LnTR_{(t-1)})$	.37497344	.09168882	.53333774
$LnEU_{(t-1)}$	.03526903	.92403044	.04070053	$LnEU_{(t-1)}$	.01451974	.93820422	.04727604
$LnCO_{2(t-1)}$	.27408969	.04737491	.6785354	$LnCO_{2(t-1)}$	.17905162	.06069358	.7602548
Percent of variation in the row variable (10 periods ahead) explained by column variable.							

It is evident from model 1 in Table 4 that TE, CO_2 aand EU explains about 43%, 55% and 2% of total variation in TE. Similarly, TE, CO_2 and EU explains 27%, 73% and 0% of toatal variation in CO_2 and in case of EU these variables explain 3.5%, 7.5% and 89% of variation. From model 2 we find similar results as obtained in model 1 in terms of relative degree of the rxplanatory power of the variables, of course, in terms of percentage varaition there is little difference.

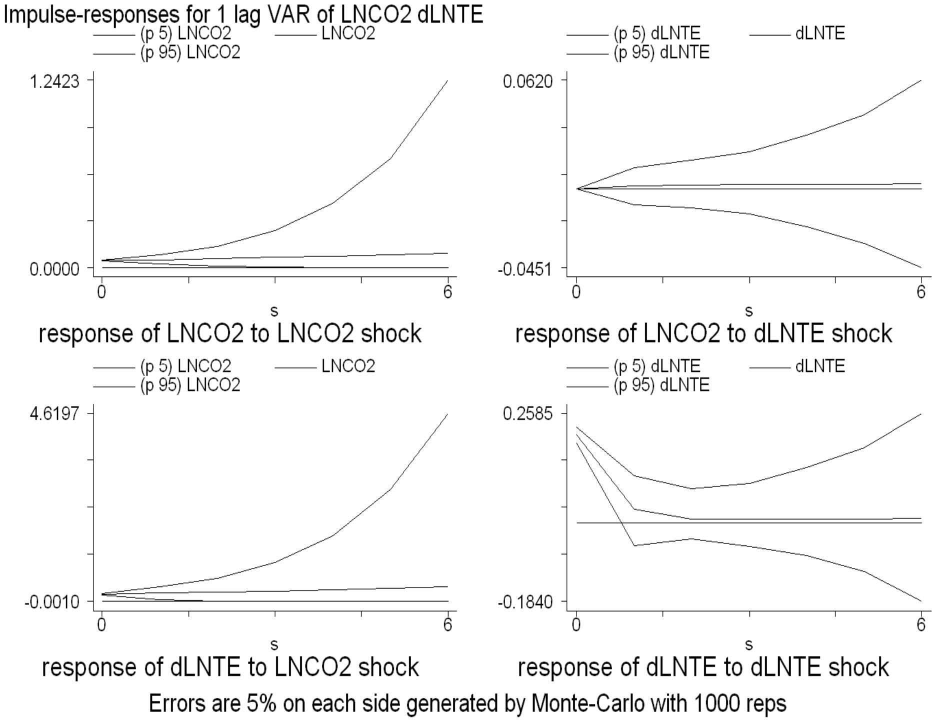
Next we change the ordering of the variables and presnt results in model 3 and 4 in Table 4. From the results of model 3 we find that explanatory power that TE, EU and CO_2 explains 43%, 9.5% and 47% of total variation in TE, 3.5%, 92% and 4% of total variation in EU and 27%, 4.7% and 68% of total variation in CO_2 emissions. From model 4 we find similar results as obtained in model 3 in

[16] It is important to mention that we cannot draw the conclusion simply based on the explanatory power of the variables as one variable is measured in terms of growth rate and another is measured in level form only.

terms of relative degree of the rxplanatory power of the variables however, in terms of percentage varaition there is little difference.

In the final step, we present the IRFs of our bivariate models analyzed above. Figure 1, shows that response of CO_2 emissions in one standard deviation (SD) shock in TE is negligible whereas response of TE in one SD shock CO2 emissions is marginally positive. Further, by changing the ordering of the variables (i.e., when variables entered in the equation are of order dLnTE and $LnCO_2$ instead of $LnCO_2$ and dLnTE) we find that response of TE in one SD shock in CO_2 emissions and response of CO_2 emissions in one SD shock in TE is marginally positive (see the Figure 1 in Appendix 2). Figure 2, shows that response of CO_2 emissions in one SD shock in TR and response of TR in one SD shock in CO_2 emissions is marginally positive and this holds good even after changing the ordering of the variables (see Figure 2 in Appendix 2).

<u>Figure 1. LnCO2 and dLnTE</u>



<u>Figure 2. LnCO2 and dLnTR</u>

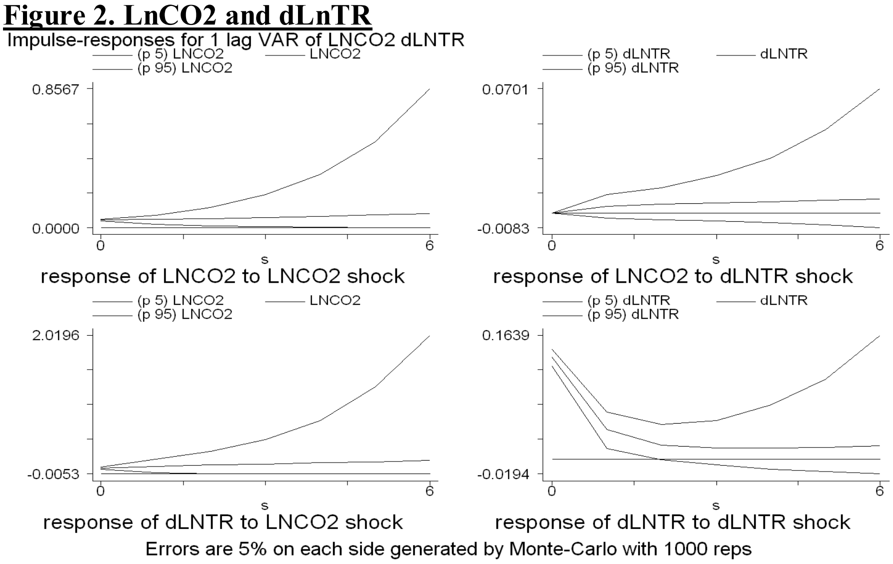


Figure 3, shows that response of TE in one SD shock in EU is first positive and very high and thereafter it starts declining whereas response of EU in one SD shock in TE has a rapid declining trend.

Figure 3. dLnTE and EU

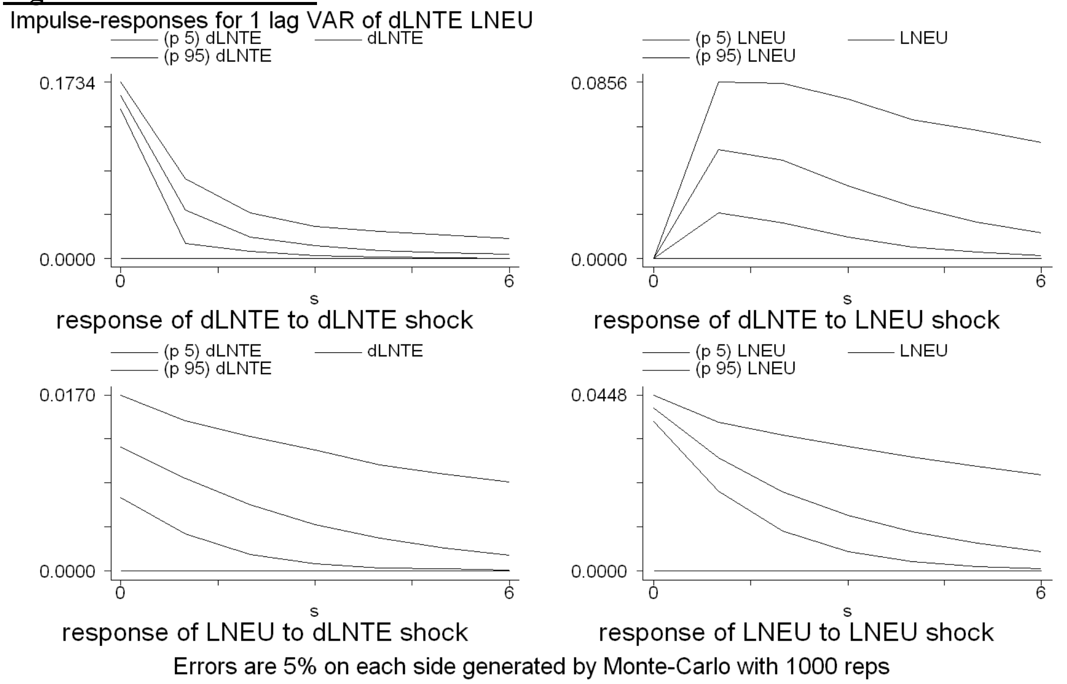


Figure 4, shows that response of TR in one SD shock in EU is first positive and very high and thereafter it starts declining gradually. Similarly, response of EU in one SD shock in TR is first shows positive trend and thereafter a gradual declining trend.

Figure 4. dLnTR and LnEU

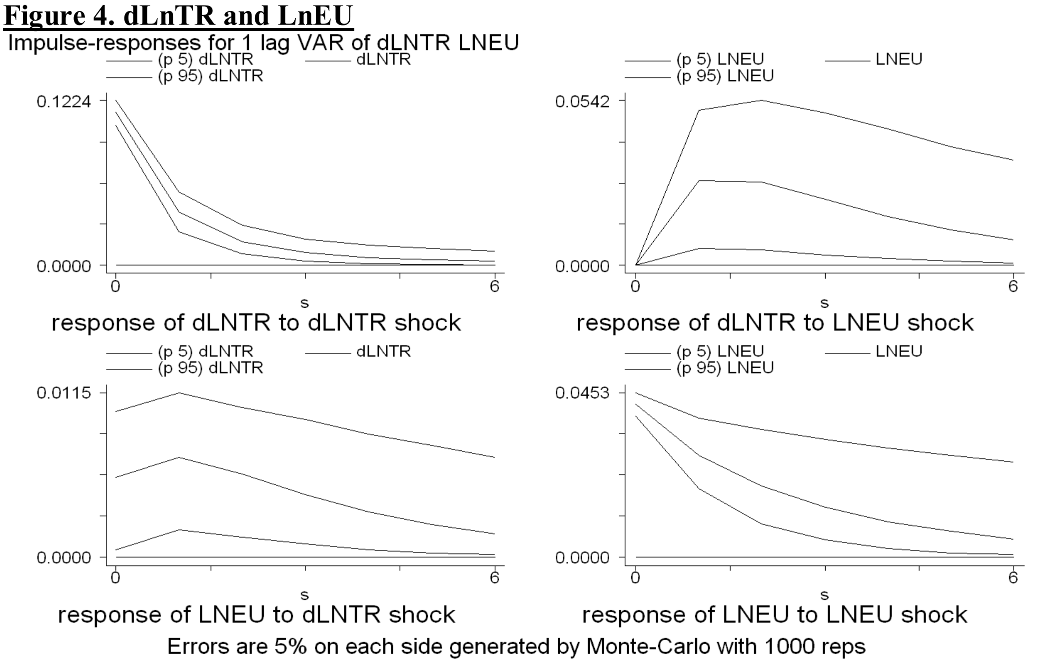


Figure 5, shows that response of TE in one SD shock in CO_2 emissions and EU is marginally positive, response of CO_2 emissions to TE is marginally positive and response of CO_2 emissions to EU is zero, and response of EU in one SD shock in TE and CO_2 emissions is also zero.

Figure 5. dLnTE, $LnCO_2$ emissions and LnEU

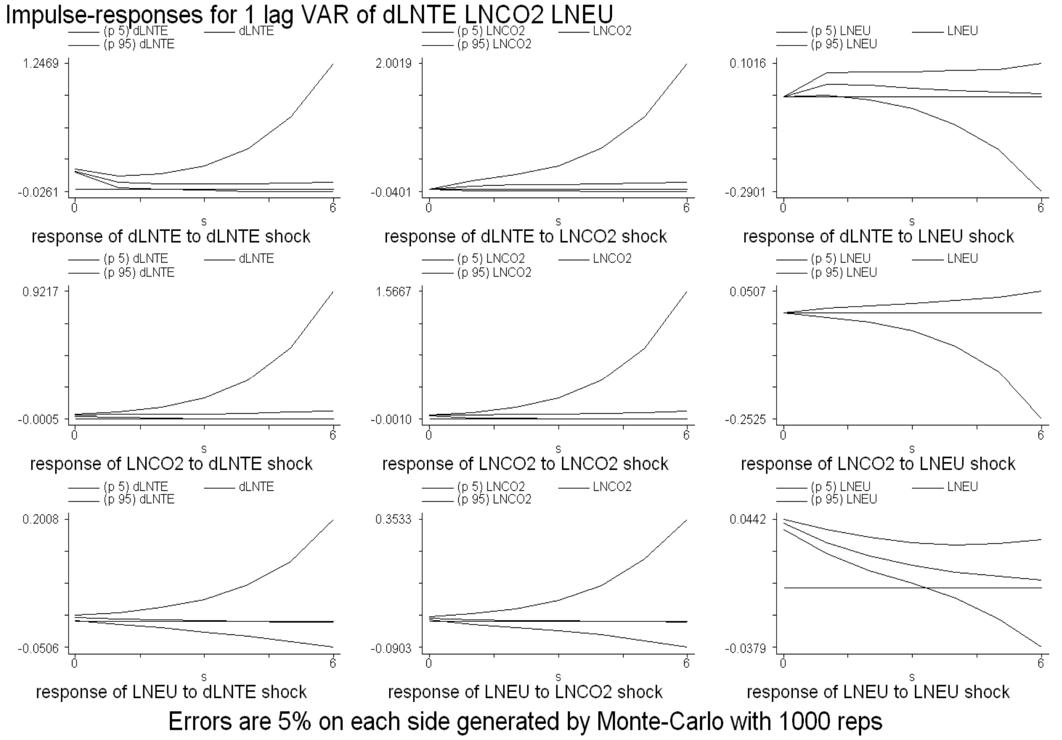
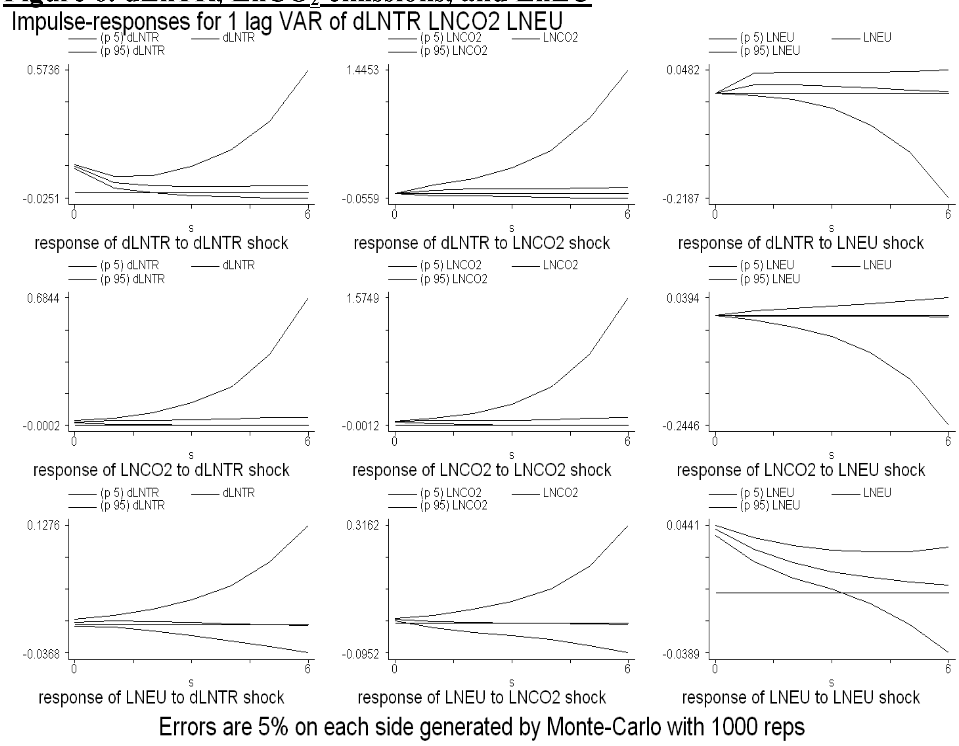


Figure 6, shows that of TR in one SD shock in CO_2 emissions and EU is marginally positive, response of CO_2 emissions to TR is marginally positive and response of CO_2 emissions to EU is zero, and response of EU in one SD shock in TR and CO_2 emissions is also zero. Hence, results reported in Figure 5 are not sensitive to the change in the measurement of one variable. Further, results of Figure 5 and 6 are also not sensitive to the change in the ordering of the variable (see Figure 3 and 4 in Appendix 2).

Figure 6. dLnTR, $LnCO_2$ emissions, and LnEU



5. Conclusions

This study attempted to analyze the dynamics of the relationship between tourism sector (TE/TR), energy consumption, and climate change for 25 OECD countries. Data used for analysis covers the duration of 1995-2005. For the analysis, we used Panel VAR (PVAR) model. Before going ahead with PVAR, we used a battery of panel unit root-tests that shows that TE and TR are nonstationary in their level form and CO_2 emissions and EU are stationary in level form. Hence, we transformed our nonstationary variables into first difference form so that variables entered in the system are stationary, which is also desirable to obtain efficient estimates. Thereafter, in the first, we analyzed bivariate model and we tested the sensitivity of the results in two ways. In one case, we changed the measurement of the Tourism variable and in the second case; we change the ordering of the variable. However, bivariate framework is found to be sensitive with these two cases. Further, we analyzed trivariate model and checked sensitivity of the results as we did in bivariate framework. However, results IRFs of trivariate model are not found to be sensitive with any of the case. We find from the results of IRFs analysis that response of TE/TR in one SD shock in CO_2 emissions and EU and response of CO_2 emissions to TE/TR is marginally positive. Further, we find that response of CO_2 emissions in one SD shock in EU and response of EU in one SD shock in TE/TR and CO_2 emissions is zero.

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Appendix 1: Results of unit root analysis of the variables analyzed

Constant and trend included in the model												
	$LnCO_2$		Ln(EU)		Ln(TE)		D(LnTE)		Ln(TR)		D(LnTR)	
Method	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
Levin, Lin & Chu t*	-7.61030	0.0000	-11.8990	0.4130	-2.65560	0.0040	-9.42030	0.0000	-3.44422	0.0003	-10.3993	0.0000
Im, Pesaran and Shin W-stat	-2.70736	0.0034	-3.51183	0.0002	2.18099	0.9854	-1.25964	0.1039	1.61274	0.9466	-1.48807	0.0684
ADF - Fisher Chi-square	84.7783	0.0015	100.240	0.0000	29.3394	0.9913	72.9405	0.0188	30.8775	0.9847	77.8233	0.0071
PP - Fisher Chi-square	114.884	0.0000	120.670	0.0000	13.1597	1.0000	120.377	0.0000	30.0691	0.9885	106.207	0.0000
Source: Authors' calculation												

Appendix 2: Results of analysis by changing the ordering of the variables

Figure 1. LnCO2 and dLnTE

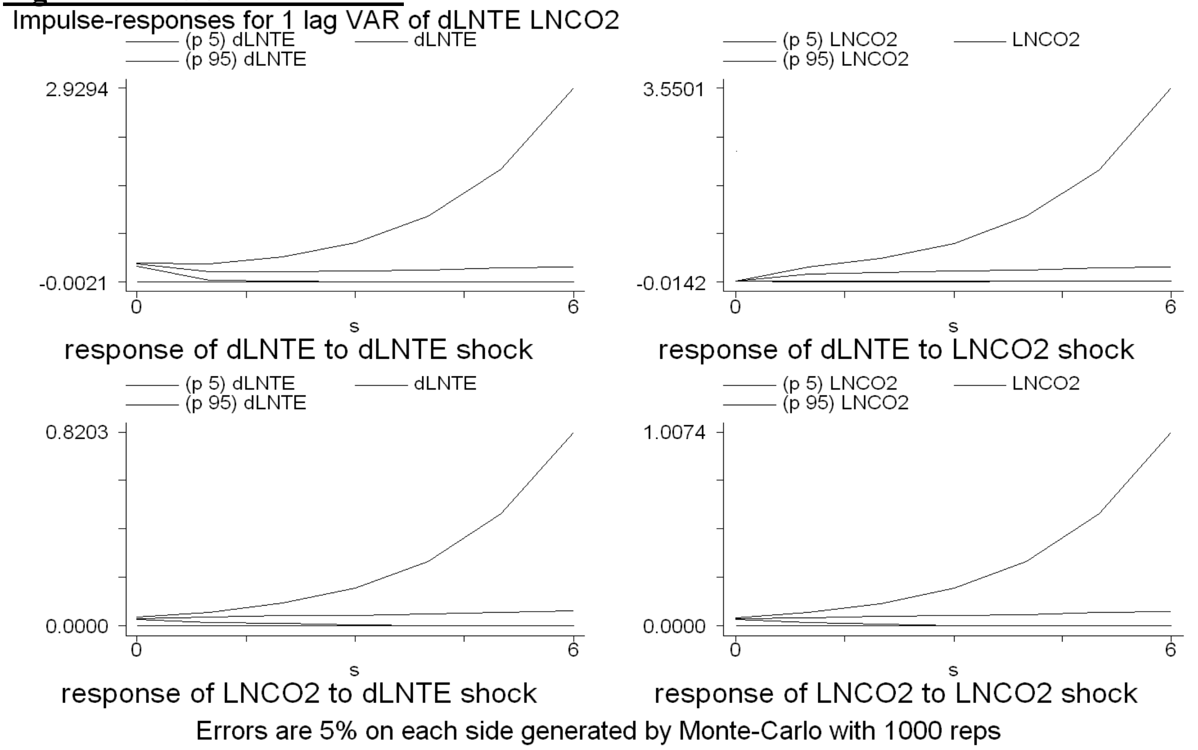

Figure 2: dLnTR and LnCO2

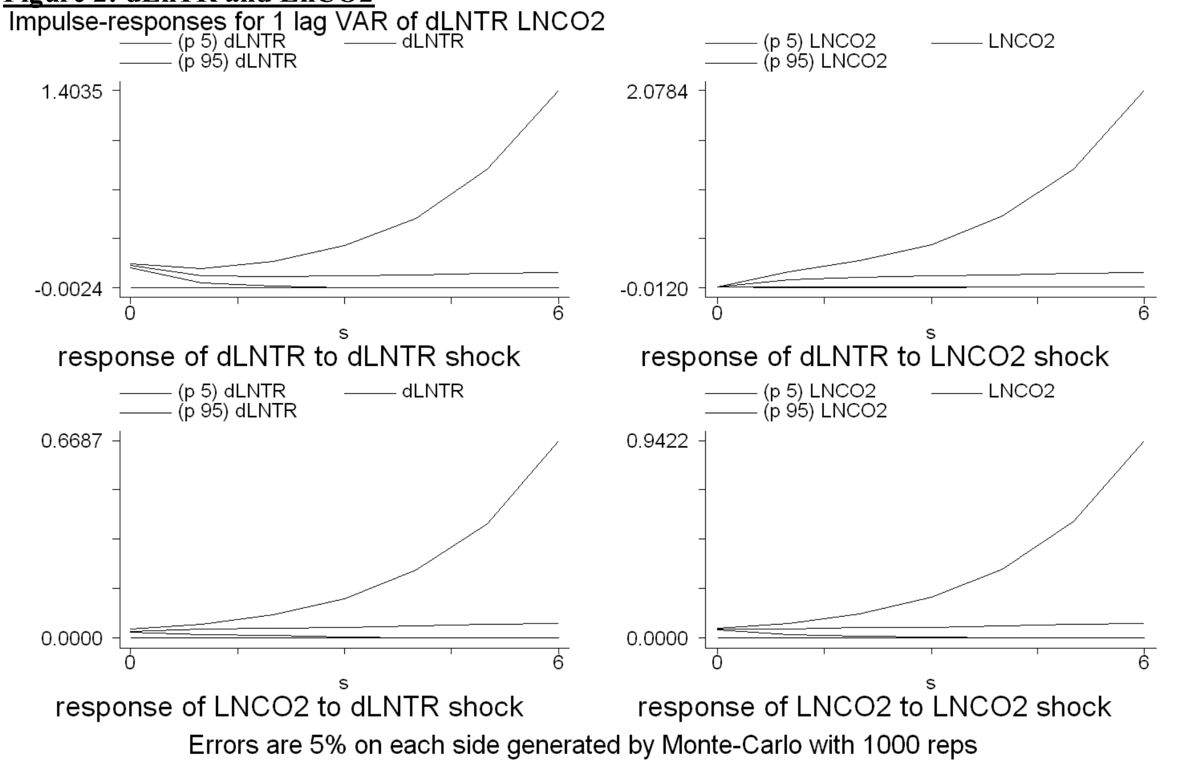

Figure 3: dLnTE, LnEU, and LnCO2

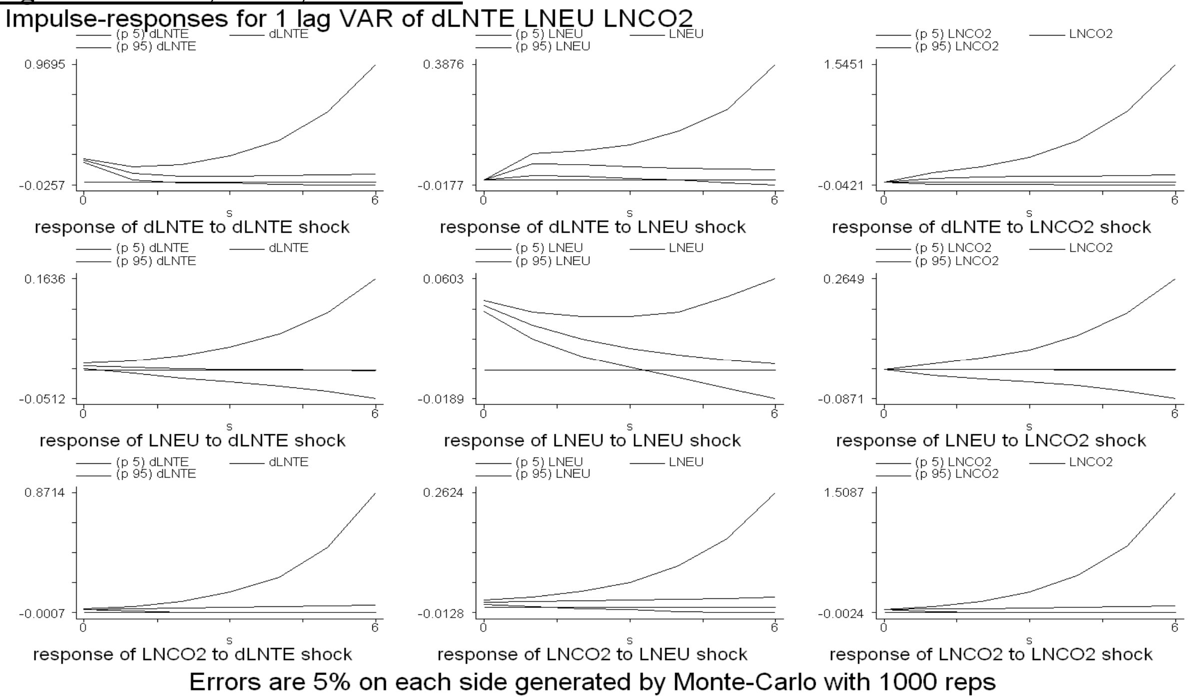

Figure 4: dLnTR, LnEU, and LnCO2