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THE DRIVING FORCES OF CO2 EMISSIONS AND ITS RESPONSIVENESS IN ETHIOPIA: AN INTEGRATED ANALYSIS USING VECTOR ERROR CORRECTION MODEL

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ABSTRACT:

The main objective of this study is to examine the driving factors of CO2 emissions in Ethiopia to promote sustainable development. This study, employees an integrated approach of the multiplicative product of Population, Affluence, and Technology (IPAT) identity as a framework using Vector Error Correction Model (VECM). The results indicate the long-run responsiveness of CO2 emissions for the population is positive and significant and fits with the Malthusian perspective, which holds that population growth increases environmental impacts and showing the combined move of social and environmental sustainability is not bearable. To measure the effect, a one percentage change increase in population leads to a 1.9 percentage increment in the CO2 emission in Ethiopia, significantly and adversely affecting the human and environment system in the long run. Therefore, the government seeks to devise a sound policy to manage population pressure and reduce its adverse effect on human and environment system to promote the green growth strategy and sustainable development.

Keywords: Environmental Impacts, CO2 Emissions, Integrated Approach (IA), Human-Environment Interactions, IPAT And Ethiopia

INTRODUCTION

One of the most notable global agendas is sustainable development in the Millennium Development Goals (MDG) over the period 2000-2015 and Sustainable Development Goals (SDG) over the period 2016-2030. It is designed to meet the demands of the present generation without affecting the future generations by balancing economic, social and environmental development. In particular, environmental supremacy promotes sustainability as the highest concern in handling all human activities so that the environmental dimensions of the SDG agenda for securing sustainable development have been received a special attention.

Among environmental dimensions, CO2 emission is now key sustainable development issues to balance the relationship between human and environment in the framework of sustainable development and sustainability. However, the crucial challenge of a sustainability oriented environmental management is to find the proper balance between humans and the impacts their activities have on ecosystems. Every country shares the responsibility to reduce the rapid growth of greenhouse gas emissions in order to alleviate global climate change worldwide. However, limited research has been conducted in evaluating the driving forces of CO_2 emissions in developing countries, particularly in Sub-Saharan Africa (SSA) (Mulatu 2014,Fan et al. 2006,,Campbell et al. 2005),where about 60% of the population depends on agriculture for livelihood, making it the region most vulnerable to climate variability(IAASTD 2009). One key limitation to a precise understanding of such anthropogenic impacts is the absence of a set of refined analytic tools (York, Rosa, and Dietz 2003). The human-environmental impacts interaction has been conceptualized mathematically as the multiplicative product of Population, Affluence, and Technology (IPAT) (Perman et al. 2005). The IPAT framework is a worthwhile analytic tool for guiding environmental policy because of its combination of simplicity and parsimonious specification with the robustness its application. Although IPAT is also widely criticized, primarily for its simplistic formulation, but it is applied widely and captures the important driving forces behind environmental impacts (York, Rosa, and Dietz 2002).

In some cases, research related to the drivers of environmental impacts has used statistical correlations to simply indicate relationships without considering the responsiveness of environmental impacts to changes in the driving forces and their long- and short-run relationships (Wilson and Lindsey 2005, Yin et al. 2010, Xie et al. 2005). However, in our study, a Vector Error Correction Model (VECM) is applied to estimate and analyze the long-and the short-run dynamic relationships between CO_2 emissions and the driving forces. Therefore, this study contributes to the knowledge gap on the linkages between the economy and the environment by using IPAT identity as an integrated approach to assess the driving forces and the response ofCO_2 emissions in the Ethiopian context. The main objective of this research is to evaluate the driving forces of CO_2 emissions in Ethiopia and to contribute to the country's sustainable development strategy by mitigating the level of CO_2 emissions.

Environmental degradation in Ethiopia threatens physical and economic survival and reduces the environment's ability to provide ecosystem services. Mismanagement of natural resources and their underutilization has undermined their contribution to the country's overall development. Moreover, the growth of the population influences the degradation of environmental assets (EPA 2007). To overcome these challenges and to ensure sustainable development, the government of

Ethiopia has initiated different strategies, policies, and institutional arrangements. Therefore, research concerning which driving factors has an impact on the environment and CO_2 emissions and the extent of their impact have been of great importance, since these driving factors will directly influence policies to improve environmental impacts and CO_2 abatement (Fan et al. 2006). Besides, current economic activities inevitably induce more energy consumption and CO_2 emissions, and are also heavily dependent on natural resources. Therefore, it is vital for governments in Sub-Saharan Africa (SSA) to consider the responsiveness of CO_2 in order to influence behavior. The findings in this paper contribute to identifying environmental impacts which have to be considered, to create cohesion indicators to be used to inform decision-making for a wide range of purposes. To analyze the responsiveness or sensitivity of environmental impacts to a change in any of the driving forces, the reformulated stochastic form of IPAT model, i.e. the stochastic estimation of Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model is applied in the context of promoting sustainable development and sustainability.

LITERATURE REVIEW

Human beings are not autonomous and quarantined. They are part of a multifarious network of natural phenomena, leads to more interaction and interdependencies. Among these, problems associated with environment are emerging issues following the increased complexity of the world. In this regard, the concept of sustainable, sustainability and sustainable development received a great attention to attain the idea of a sustainable human-environment relationship. Thought they are striking and timely, the above three concept lacks an axiomatic principle, opening for theoretical and empirical criticism.

In more general sense, sustainable is accountable for solutions to the worsening relationship between human and environment with the aid of sustainability and sustainable development. The idea of sustainable development starts with satisfying today's need without compromising future in the complexity of environment, social and economic development (Brown, 1981). Sustainable development conveys a long term strategy of environmental, social and economic aspects to improve the wellbeing of society. In sum, the success of having social and economic sustainability can be leveled as equitable, that of social and environment earns bearable, and that of economic and environment sustainability produces viable development. Sustainable development is only achieved when there is balance or a trade-off between these three aspects.

Sustainability measures the level of quality of human and environment system in order to estimate its remoteness from the sustainable by measuring final objective based on scientific criteria in order to quantity and trace the results generated by sustainable development strategies. In summary, it depends on sustainable development, meaning that sustainable development is the crucial to realize sustainability (HOVE, 2004). Finally, the correspondence between sustainability and sustainable development tends to a complex and connectedness of system of human and environment.

Among this complex system, the reduction of carbon emission has been receiving a great attention from different corner of the world. This, it is an integral part of sustainable development with the objective of reducing environmental impacts and improves social and economic conditions. This has also a linkage with a concept of sustainability that describes a state where conditions and systems are balanced in the long term. This allows the most of ongoing environment initiatives are designed in the framework of sustainable development approach as easier to do so. However, limited number of them focuses on sustainability due to the fact that it is far more difficult and will require radical change. No matter how the area is full of unsettled issues, environmental problems and valuations are still points of debates.

At a micro level, environmental valuation studies reveal information on both the structure and functioning of ecosystems and the varied and complex roles of ecosystems in supporting human welfare (Howarth and Farber 2002). At a macro level, the environmental impacts of economic activity can be looked at in terms of extractions from or inserted into the environment and by the responsiveness of the environmental impacts due to changes in economic development (Perman et al. 2005). Considerable progress has been made in developing a better understanding of anthropogenic drivers, which means the range of human actions that cause environmental change and the factors that shape those actions (Rosa and Dietz 2012). IPAT has been utilized as an analytical framework for assessing human impacts on the natural environment (Rosa, York, and Dietz 2004). The IPAT model is an important theoretical and empirical framework for identifying the drivers of environmental impacts and for estimating potential changes in impacts due to changes in any of the driving forces/factors, including CO_2 emissions, (Fan et al. 2006)energy consumption, 'water footprint', air pollution (Rosa et al. 2004), and 'ecological footprint'(York, Rosa, and Dietz 2004). The land use land cover change (LULC) dynamics and other environmental impacts appear to track well with the IPAT model (Mulatu 2014, Turner, Lambin, and Reenberg. 2007). The IPAT model also recognizes that population growth is one of the major driving forces behind increasing CO_2 emissions worldwide over the last two decades (Shi 2001).

The IPAT model has been reformulated into a stochastic form as the Stochastic Estimation of Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model (Dietz, Va, and Rosa 1994). Despite its limitations, the IPAT model provides a useful starting point for developing a better framework and for structuring empirical tests of competing arguments. The high uncertainty with regard to the nature and extent of the driving forces of environmental impacts and CO_2 emissions means that, with current knowledge, it is not possible to develop probabilistic future environmental impacts and emission scenarios. Although it is possible to derive (subjective) probability distributions of the future evolution of individual variables (for example: population, economic growth, or technological changes), the nature of their relationship is known only qualitatively at best or remains uncertain (and controversial) in many instances (IPCC 2000).

There are two perspectives on the impact of demographic growth on environmental impacts: the Malthusian tradition and the Boserupian approach (Fan et al. 2006). IPAT-linked work invokes a neo-Malthusian or eco-centric vision-closed system with inflexible limits and an exogenous role of technology in determining these limits. This view claims that the environmental impacts take place due to population pressure and that solutions have to be found in limiting population, rather than in changing consumption and behavioral patterns. In contrast, Boserupian or anthropocentric view opens systems with flexible limits and an endogenous role for technology as population increases. This view, with the support of a significant number of case studies, interprets the role of population growth in the context of broader conditions, with potentially positive outcomes for welfare and the environment. Besides, at the case study and regional level, the IPAT formulation is insufficiently sensitive to capture the diversity, variability and complexity of real-world situations(Lambin et al. 2001). However, IPAT bridges the approach to describe how our growing population contributes to our environment, both positively and negatively(Ehrlich and Holdren 1971). Indeed, proper application of IPAT as an analytical tool requires attention to certain statistical issues. Variability is a necessary, but not sufficient, condition for assessing causality, and is, certainly, a requirement for statistical analyses(York et al. 2002).

The concept of ecological elasticity has been also introduced to analyze environmental questions. Ecological elasticity (EE) refers to the responsiveness or sensitivity of environmental impacts to a change in any of the driving factors/forces. The ecological elasticity of population, affluence and other factors for cross-national emissions of CO_2 from fossil fuel combustion and for the energy footprint, a composite measure comprising impacts from fossil fuel combustion, fuel wood, hydropower and nuclear power, are computed using the STIRPAT model (York et al. 2003). This approach can easily be used to calculate the EE of any of the driving factors of environmental impacts. However, the operational measure of technology is not free of controversy and is usually included in the error term because appropriate direct measures of technology are lacking and any specific indicator is highly disputed(Fan et al. 2006).Therefore, in this study energy intensity and carbon intensity considered as a technology indicator to understand the links between the economy and the environment using IPAT identity as an integrated approach. To assess the driving forces and the response ofCO_2 emissions in Ethiopia context and to estimate the long-and the short-run relationships between CO_2 emissions and the driving forces/factors, VAR model specification with co-integration and VECM are used.

IPAT EQUATION

The IPAT equation and related formulas have been discussed since the 1970s as part of the ongoing debate on the driving forces of environmental change(Rosa et al. 2004). Although first used to quantify the contributions to unsustainability, the formulation has been reinterpreted to assess the most promising path to sustainability(Chertow 2000). The first simple original formulation of the theoretical framework to analyze the environmental impact (I) was presented by(Ehrlich and Holdren 1971). This simple formulation of the IPAT model is:

$$I = P * F \qquad (1)$$

Where I is the total impact, F measures the per capita impact and P is population size. Impact increases as either P or F increases or if one increases faster than the other declines(Chertow 2000). This simple model does not consider the interdependence of factors due to multiplicative and non-linear relationships. To indicate that the equation is non-linear and the variables are interdependent, the model can be expanded as:

$$I = P(I, F) * F \qquad (2)$$

This variant shows that P depends on I and F. Technology (T) is not introduced explicitly at this stage, but its impact is hidden in F, as a per capita impact. More generally, the *IPAT* model specifies that environmental impacts (I) are the multiplicative product of population size, affluence (per capita production or consumption), and technology (impact per unit of production/consumption).

$$I = P * A * T \qquad (3)$$

Waggoner and Ausubel(2002)revised the IPAT model by disaggregating T into consumption per unit of GDP (C) and impact per unit of consumption (T) and renamed the model as IMPACT. Schulze (2002)proposed and modified the IPAT model as I=PBAT model, where *B* are behavioral choices. However, Diesendorf (2002)argued that in I=PBAT model the aspects of behavior are implicitly involved in each factor on the right-hand side of the equation I=PAT. Thus, behavioral choices could only include aspects of behavior that are not already included in *P, A* and *T*, and as such, *B* is also very difficult to define precisely. (York et al. 2002) introduced the concept of Ecological Elasticity (EE) that refers to the responsiveness or sensitivity of environmental impacts to a change in any of the driving factors and the elasticity of IPAT model. Dietz et al.(1994) reformulated the IPAT model into a stochastic form as the stochastic estimation of Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model in order to analyze the effects of driving forces on a variety of environmental impacts. The basic STIRPAT model formulation is:

$$I_i = aP_i^b A_i^c T_i^d \varepsilon_i \quad \text{......} (4)$$

Where *a* is the constant scale of the model, *b*, *c* and *d* are the exponents of *P, A,* and *T*, respectively and ε is the error term. The subscript *i* varies across observations over units, over time or both. The original IPAT model assumes proportionality and sets $a=b=c=d=\varepsilon_i=1$, while STIRPAT treats these as parameters/coefficients to be estimated(Dietz et al. 1994)·(Rosa et al. 2004). The STRIPAT model is the most standard formulation of IPAT model for quantitative social research and can be estimated using regression techniques(York et al. 2002). The STRIPAT model can also be transformed in to logarithmic function, which measures the responsiveness or sensitivity of environmental impacts to a change in any of the driving forces(Dietz et al. 1994). The model then takes the following form:

$$\ln I_i = a + b(\ln P_i) + c(\ln A_i) + d(\ln T_i) + \varepsilon_i \quad \text{......} (5)$$

Where *a* and ε_i are the natural logarithms of *a* and ε_i in Equation 5, respectively. In the STIRPAT model, it is possible to substitute a vector of cultural, political and social structural variables for technology (*T)* and examine the net effect of each on environmental impacts(York et al. 2004,Mulatu 2014). In our analysis, energy intensity and carbon intensity are considered as a sign of technology to suggest the impact of technology on the environment. Thus, we employ STIRPAT as an integrated approach to better understanding the responsiveness of CO_2 emissions as an environmental impact due to changes in driving forces in the Ethiopian economy context using the following estimation technique.

METHODOLOGY

Data

Time-series data of Ethiopia on socioeconomic variables (population and GDP per-capita) for the period 1971-2011 have been collected from Ethiopia Ministry of Finance and Economic Development (MoFED) and from the database of the World Bank (WB) for Ethiopia economic indicators. Data on CO_2 emissions, energy intensity and carbon intensity for the period

1971-2011 have been collected from International Energy Agency (IEA). The definitions of variables used and their unit of measurement presented in Table 1.

Estimation Techniques

Once the model is specified, the study will use a vector autoregressive model to examine the responsiveness of CO_2 emissions, using the STIRPAT model as a base and the interactions of all variables in the specification. This estimation technique does not require restriction on the variables as exogenous and endogenous. Johansen (1988) procedure for vector autoregressive (VAR) model specification with co-integration and error correction techniques to estimate long-and short-run coefficients that indicate the relationship of the variables, if the variables are stationary after differencing.

A VAR system of equation may be specified as:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + u_t \quad \text{...} \quad (6)$$

Where the A_i's are (nxn) coefficient matrices, Y_t are all variables mentioned in the model specification, and $u_t = (u_{1t}, u_{2t}, ..., u_{nt})'$ are n dimensional vectors of multivariate random errors with zero mean and covariance matrix, that is, the innovation or the error term. The optimal lag length (p) will be determined by Akaike Information Criteria, AIC=T.log(SSR)+2n, Schwarz and Risanen Criteria SBC=T.log(SSR)+n.log(T) also called Schwartz and Hannan-Quinn Criteria HQC=T. log(SSR)+2n.log(log(T)).

The study also applies an endogenous structural breaks unit root test of both Zivot and Andrews(1992)test and Clemete, Montanes, and Reyes(1998)test in order to address problems that are associated with single break and two breaks, respectively. If there is no structural break in time series data, the result generated from these tests and from the Augmented Dickey-Fuller (ADF) test should be the same. However, the Zivot and Andrews (ZA) model considers one structural break and uses many dummy variables for each structural break year(Zivot and Andrews 1992). As the exact endogenous break is unknown, the ZA model then assumes every point as a potential break. Therefore, it sequentially conducts a regression for every structural break point, in which the minimum t-statistic indicates where the endogenous structural break point is found. The following equation gives the ZA model.

$$y_t = \alpha + \beta t + \gamma DU1_t + \omega DT1_t + \mu y_{t-1} + \sum_{i=1}^{k} \lambda \Delta y_{t-i} + \varepsilon_t \quad \text{................................} \quad (7)$$

$$DU1_t = \begin{Bmatrix} 1\, if\ t > T_B \\ 0, otherwise \end{Bmatrix} and, DT1_t = \begin{Bmatrix} 1, if\ t > T_B \\ 0, otherwise \end{Bmatrix}$$

Where y_t is a time series variable, t is the time trend, and $DU1_t$is the intercept dummy variable indicating the mean shift (change in the level), $DT1_t$and stands for the slope dummy representing change in the slope of the trend function. T_B represents a potential break point and k denotes lag length. The null hypothesis states that the time series that excludes any structural break is non-stationary whereas the alternative hypothesis indicates that the series that includes one structural break is stationary. Clemete et al.(1998)alternatively in the presence of two breaks, the time Clemete Montanes and Reyes (CMR) test of Stationarity proposed two models:- Additive outlier (AO) model and Innovative outlier (IO) model in order to address instantaneous structural breaks and gradual change, respectively. The following equation gives the IO model as below.

$$y_t = \alpha + \beta y_{t-1} + \delta_1 DT_{1t} + \delta_2 DT_{2t} + \omega_{1t} DU_{1t} + \omega_{2t} DU_{2t} + \sum_{i=1}^{k} \gamma_i \Delta y_{t-i} + \varepsilon_t \quad \ldots\ldots\ldots\ldots(8)$$

The AO model has two stages in order to test for Stationarity. The first step removes the deterministic part of the variable by modeling:

$$y_t = \alpha + \omega_{1t} DU_{1t} + \omega_{2t} DU_{2t} + \overline{y_t} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

The study uses and tests the following model after removing the deterministic part of the variable as explained in equation 9:

$$\overline{y_t} = \rho \overline{y_{t-1}} + + \omega_{1i} DT_{1t-i} + \omega_{2i} DT_{2t-i} + \sum_{i=1}^{k} \varphi \Delta \overline{y_{t-i}} + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

Where

$$DU_{1t} = \begin{Bmatrix} 1, if\ t > T_B \\ 0, otherwise \end{Bmatrix}, \quad DU_{2t} = \begin{Bmatrix} 1, if\ t > T_B \\ 0, otherwise \end{Bmatrix}$$ for representing intercept dummy

$$DT_{1t} = \begin{Bmatrix} 1, if\ t > T_B \\ 0, otherwise \end{Bmatrix}, \quad DT_{2t} = \begin{Bmatrix} 1, if\ t > T_B \\ 0, otherwise \end{Bmatrix}$$ for representing the slop dummy

After presenting the VECM results, the Granger Causality Test (GCT) can be run for testing the Granger causality using the Wald test that involves the effect of past values of all other variables on the current value of the remaining variable. Moreover, it checks the stability condition of the model and analysis of one-time shock to apply forecasting techniques for some specified target year. The requirement of satisfying the stability condition of the model indicates that the unit roots or the solutions of the system are below one, or all the Eigenvalues lie inside the unit circle, which is the necessary and sufficient condition for stability. Note that one of the Eigen value is imposed to unit in the VECM. Otherwise, the impact of the impulse (shock) in some variables might not decrease/increase with time. A crucial condition for the VAR model to be valid and consistent requires the covariance to be stationary in order to avoid the formation of explosive roots. This confirms that using the model satisfies the stability condition and can be used for forecasting.

As the model is stable, the next points will be to discuss the impulse response functions and the variance decomposition in response to a one-time shock in the system. The impulse response function presents the dynamic interactions among endogenous variables and traces the effect of a one-time shock on current and future values of the endogenous variables. It sheds light for empirical causal analysis and policy effectiveness. The variance decomposition also presents the separation of the variation in an endogenous variable into the component shocks during the forecast period.

RESULTS AND DISCUSSION

Results

Descriptive Analysis

This part of the result gives the general features of the data in terms of both central tendency and variation measures of the distribution as well as shape of the distribution over the period 1971-2011. The statistical summary of the variables is presented in Table 2. Except Energy intensity, the measures of skewness indicate that all variables have tails on the right side longer than the left ones and bulk of values falls to the left of the mean. On top of this, Kurtosis also explains the peakedness of the probability distribution of each variable so that energy intensity behaves in the way of having a mesokurtic distribution while per capita income is being characterized by leptokurtic shape. All other variables are indicating a platykurtic shape of the distribution as indicated in Table 2.

Looking at Table 3, the partial correlation of CO_2 emission with energy intensity is negative and statistically insignificant while all others are positive and statistically significant. This holds information of the regression results in a case of Ordinary Least Regression (OLS).

Stationarity Test

All time-series data must be stationary, meaning constant mean and variance over time, in the regression model. Otherwise, the regression result becomes spurious. This paper uses Zivot-Andrews unit root test that assumes one structural break and Clemente-Montanes-Reyes unit-root test that accounts for two structural breaks in the time-series. These tests have a comparative advantage over the DF test and ADF test that presume there is no structural break in the time-series. Table 4 provides the Zivot-Andrews unit root test and all variables are non-stationary at level form (before making the data at first difference form). However, except energy intensity, all of them are stationary at first difference form.

One of the interesting points in this test is that the year chosen for structural break for each variable is not uniform. The ZA test points out that energy intensity is non-stationary in the existence of one structural break. This claims the CMR unit-root test that enables to examine the stationarity condition in the existence of two structural breaks in the time series for both additive outlier (AO) and innovation outlier (IO). The result presented in Table 5 confirms that energy intensity is stationary at the first difference form, as *t*-value calculated is greater than *t*-value tabulated. Note that both *t*-values are considered in absolute value in order to compare for decision.

Finally, all variables that are expressed in the first difference form are stationary when the study considers structural break using by ZA unit root test and its complement, the CMR unit root test. Once it is confirmed that all variables are stationary at first difference, the next step is to conduct co-integration and Error correction model with the optimal lag length.

Selection and Determination of Lags Order Criteria

Before selecting the lag length, two situations should be identified. First, the too short lag length in the VAR may not capture the dynamic behavior of the variables (Chen and Patel 1988),thus, the optimal lag length would be selected by the smallest lag shown under the criteria. Second, (DeJong et al. 1992) (1992)points out that too long lag length will distort the data and lead to a decrease in power of explaining the dynamic behavior of the variable. One of the most common practices in the system of equations is to select the optimal lagged term using some criteria such as Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SBIC), Bayesian information criterion (BIC), and Hannan-Quinn information criterion (HQIC). Therefore, they indicate a lag length of one and four. However, lag length one is considered in the VAR model for having well defined co-integration vector to the interest of satisfying post estimation tests.

Johansen Tests for Co-Integration

In order to check whether there is co-integration or long-run relationship among variables, it is common to apply the Johansen tests based on the co-integration rank that shows the number of co-integrating vectors (Johansen 1988). The co-integration analysis also provides a framework for estimation, inference, and interpretation when each variable is not stationary individually while has a stationary linear relationship together. If there is a stationary linear combination of non-stationary variables, the variables combined are said to be co-integrated. The best way of testing co-integration is by using the system Maximum Likelihood (ML) estimator of Johansen test (Table 7).

As the rule of thumb, as the log-likelihood of the unconstrained model with the co-integrating equations is significantly different from the log-likelihood of the constrained model that excluded the co-integrating equations, we reject the null hypothesis of no co-integration. Besides, the above result shows that the trace statistic value (42.73022) is less than the critical value (47.85613) as moving from the rank zero in ascending order. This leads to accept the null hypothesis that states the maximum rank is one and thereby one co-integration equations is used in the model. This allows conducting the Vector Error Correction Model (VECM) in order to evaluate the both long-run and short-run relationships.

The Long Run Dynamics

The Vector Error Correction Model (VECM) is a special case of the VAR for variables that are stationary in their first differences after taking into account any co-integrating relationships. The focus of this paper is the long-run response of CO_2 emissions due to changes in the driving forces over the period of 1971-2011.

According to the cointegrating equation presented below, the long- run estimate for the log of carbon intensity and population are positive, while the long-run estimate for the log of energy intensity and per capita income is negative. The long run dynamic relationships between the driving forces and the CO2 emission are statistically significant by t-tests for all variables (indicated in the parenthesis). An increase in carbon intensity and population induces CO2 emission to increase more in the long run. However, an increase in energy intensity and per capita income has an inverse relationship with CO2 emissions in the long run (Table 8).

The Short-Run Dynamics and Speed of Adjustment

Having a result on the long-run equilibrium dynamic relationships among variables, the short-run dynamic relationship should be the subsequent point of presentation. Given that there is a stable long-run relationship among the relevant variables, it is possible to estimate an error correction model that captures both the short-and long-run behavior. The changes in the relevant variables represent short-run elasticities, while the coefficient on the CointEq1 (error correction term) term represents the speed of adjustment towards the long-run equilibrium point. Treating the percentage change in CO2 emissions as the "dependent" variable, estimates are reported in terms of logarithmic differences of the variables in Table 9.

The short-run estimates indicate that population is the only statistically significant variable and negatively influences CO2 emission, unlike the long run case. As the theory predicts, the error correction term is negative and statistically significant. However, its value is under question mark. The magnitude of ECM term should be interpreted in appropriate sense. There are two distinct thoughts: The rigid proponents believe that it should fall within a range of zero to negative one while the other says nothing wrong if it is less than negative one (Narayan Kumar, 2006). It is well known that the ECM coefficient theoretically is expected to be between -1 and 0. If there is positive ECM, the process it not converging in the long run, attributing to model specification problems, data issues including structural break and the presence of autocorrelation. On the other hand, the value of ECM that falls between -1 and -2 indicates the existence of dampened fluctuation about the equilibrium instead of monotonically converging to the equilibrium path directly. In short, the correction process fluctuates around the long-run value in a dampening manner. However, once this process is complete, convergence to the equilibrium path is rapid (Narayan Kumar et.al. 2006 and Norman et.al, 2005).

Test for Weak Exogeneity and Granger Block Causality

Due to the above limitation, the study needs to go further by testing exogeneity and causality of variables in order to set some restriction on the model. This can be one by identifying whether variables are endogenous or exogenous, addressing the main problem in most econometrics analysis. Therefore to identify variables those are endogenously determined and conditional up on the other variables in the VAR, the test for weak exogeneity is conducted. This requires imposition of zero restriction on the loading or speed of adjustment coefficients.

A very useful property of the VECM framework is that it enables the investigator to impose zero restrictions on the adjustment coefficients of each equation, thus determining which variables can be treated as weakly exogenous in the system, thereby omitting them from the interdependent system of variables in the way of either treating as exogenous or total excluded from the model.

Based on this weak exogeneity test, the Table 10 indicates that the energy intensity, per capita income and population can be omitted from the system (treated as weakly exogenous) because the null hypothesis of a zero restriction is not rejected for these variables at least at the 5 percent level. This means that only CO2 emission and carbon intensity are treated as endogenous variables.

In order to investigate further the "causal" relationship among these variables, the study also performed a Granger Block Causality test with the restrictions. This test examines all five equations and tries to determine whether the presumed exogenous variables can be omitted from each equation. As attached at annex II, this test examines the existence causality or precedence and finds that population granger causes both CO2 emission and carbon intensity with a unidirectional relationship. In general, the test for weak exogeneity and granger block causality tests allow applying a restriction on the VECM with treating them as exogenous or excluding them from the model.

Restricted VEC Model

Approach I: VECM restriction of treating as exogenous variables

The first approach is to consider both CO2 emission and energy intensity as endogenous variables and all others are treated as exogenous variable. The result is presented in Table 11. The findings indicate that there is no significant relationship between CO2 emission and energy intensity in the long run. However, the exogenous variables namely population, carbon intensity and per capita income positively and significantly influence the CO2 emission in the short run.

Approach II: VECM restriction of excluding from the model

Taking the result of exogeneity test, it is possible to produce the restricted VECM Model that combines both the long run and short run dynamics analysis. The long run dynamics tells us that the increase in population puts on a pressure and aggravates the CO2 emissions in Ethiopia. This means that a one percent increase in population is associated with a 1.90 percent increase in CO2 emission in Ethiopia as indicated in Table 12.
Looking at Table 13, the short run dynamics reveals that there is no significant relationship between CO2 emission and population. The speed of adjustment now satisfies the theoretical framework about its sign and magnitude by which the study controls the weakness mentioned above. Accordingly, the system of equation would take around 28 percent per annum where there is a single shock within the system of the equations, indicating how fast CO2 responds in response to a single shock in the system

VEC Stability Condition Test

Checking the stability of the model is an important test in time-series econometrics. The stability of the VECM requires the modulus of the Eigen values to lie within the unit circle, setting one of the roots equal to one in case of having one cointegration vector. Otherwise, the system is not stationary. Rather it is explosive or non-convergent. The result in Table 14 reveals that the VECM satisfies the stability condition of the model. As the VECM is stable, it is possible to present the impulse response functions and variance decomposition in response to a one-time shock in the system.

Impulse Response Function

Impulse response functions is the response function of each variable to the shock exogenously emerged out from error terms (exogenous shock). Table 15 indicates that an exogenous shock in population growth directly affects the population growth and thereby influences other variables in the model. This can detect the dynamic relationships over time among endogenous variables and traces the effect of a one-time shock on current and future values of the endogenous variables. If the system of equations is stable, any shocks should decline to zero, and if it is an unstable system, it would produce an explosive time path. Therefore, the finding indicates that the response of CO2 emission shows that shocks are dying slowly over the forecast 10 periods. As can be seen, the response of CO2 emission can be 0.09 S.D (standard deviation) to a one S.D change in shock in period one and it would become 0.01 at the end of period 10, indicating showing that shocks are dying slowly and confirms convergence toward the long run equilibrium. However, the response of CO2 emission seems an oscillating type and behaves a constant move in the long run.

Variance Decomposition with Optimal Lag Length

Variance Decomposition or forecast error indicates the amount of information each variable contributes to the other variables in a model. It measures the extent to which each shock contributes to unexplained movements and forecast errors in each variable. In other word, it determines how much of the forecast error variance of each of the variable can be explained by exogenous shocks to other variables over a series of time horizons. Accordingly, the Table 16 indicates that the variation in CO_2 emission is majorly explained by its own lagged values, followed by population pressure.

Discussion

The STIRPAT formulation is amenable to examining the effects of driving factors on impacts along with alternative conceptualizations of the driving forces of environmental impacts (Dietz et al. 1994). In this study, the STIRPAT model is estimated by considering the time dimension of the data, stationarity test, causality, stability and the dynamic interactions of endogenous variables. In addition, energy intensity and carbon intensity considered as technology (T) in our formulation to comprehend the responsiveness of CO_2 emissions in Ethiopian economy. We treat CO_2 emissions as the dependent variable and establish the STIRPAT model to analyze the driving forces of CO_2 emissions. The main focus of the discussion is the regression coefficients that show the long-run responsiveness of CO_2 emissions due to changes in the driving forces of CO_2 emissions. However, the study refined this findings by impose some restrictions on the VECM in order to reflect the reality and to satisfy the post estimation tests of the model. To do so, the weak exogeneity and granger block causality tests allow applying a restriction on the VECM with treating population, carbon intensity and per capita income as exogenous at the first glance based on weak exogeneity test and taking population as the only variable that causes CO2 emission based on Granger causality test as the second alternative approach.

Approach based on weak exogeneity test finds that insignificant relationship between CO2 emission and energy intensity in the long run. But, population pressure, carbon intensity and per capita income are positive and significant driving forces of CO2 emission in the short run. The second approach of taking population as the granger cause of CO2 emission finds different result with the satisfaction of convergence towards the long run equilibrium position of the model. There is a long run relationship between an increase in population and CO2 emissions in Ethiopia. This finding fits with the Malthusian perspective, which holds that population growth increases environmental impacts and against the Boserupian view that the impact of population on the state of the environment is likely either a non-relationship between two variables, or even a negative elasticity. The adverse effect of this population pressures on the environment creates imbalance between human and environment system, putting challenges to achieve sustainability. This result also supports the findings of Rosa et al. (2004) that indicated the high level of consumption even in slow population growth in developed nations is at least as great threat to the environment as rapid population growth elsewhere. It is also inconsistent to the argument that global climate change clearly belongs to the developed world and its moderately sized population, not to the less developed world and its large population(York et al. 2002).

As a result, measures should be taken to sustain the driving forces of environmental impacts in order to maintain the level of CO_2emissions in order to create a bearable sustainable development by creating a balance between environment and population pressure. In addition, evidence from this empirical analysis suggests that a detailed understanding of the underlying driving forces of CO_2 emissions is required prior to any policy interventions in Ethiopia in order to achieve the initiatives of Climate Resilience Green Economy (CRGE) (i.e. to achieve the country's development goals while limiting greenhouse gas emissions to around today's 150 Mt CO_2 in 2030) (FDRE 2014) to promote sustainable development and sustainability.

The importance of informed decision on environmental policies has highlighted the need for a deeper scientific understanding of the driving forces/factors impacting environment (York et al. 2004). However, the scientific knowledge of the driving forces behind environmental impacts is meager in Ethiopian economy context. Anthropogenic greenhouse gas (GHG) emissions are mainly driven by population size, economic activity, lifestyle, energy use, land-use patterns, technology and climate policy(IPCC 2014).Thus, improved understanding of CO_2 emissions elasticities due to changes in GDP per capita, population and technology is vital both for climate change policy interventions and negotiations; and for generating projections of CO_2 emissions. Indeed, the so-called Kaya Identity-essentially IPAT with energy intensity (energy consumption over GDP) and carbon intensity of energy (carbon emissions over energy consumption) in place of technology (T)-plays a core role in the Intergovernmental Panel on Climate Change (IPCC) estimates of future CO_2 emissions(Liddle 2012). Our efforts to study the driving forces of CO_2 emissions in a more analytical and systematic manner are also greatly improved the acceptance of integrated approach studies.

CONCLUSION AND POLICY IMPLICATIONS

The scientific knowledge of the driving forces behind environmental impacts is meager in Ethiopia economy context. Thus, improved understanding of CO_2 emissions elasticities due to changes in GDP per-capita, population and technology is vital both for climate change policy interventions and negotiations, and for generating projections of CO_2 emissions. This study explores the human-environment interactions using an integrated approach in order to analyze the driving forces of CO_2 emissions and its responsiveness in Ethiopia. The environmental impacts are the multiplicative product of Population, Affluence, and Technology (IPAT) identity applied as a framework to assess the driving forces of CO_2 emissions in the context of sustainable development. The approach illustrated in this paper serves as a demonstration of the integrated research, combining the environmental approach and time-series data analysis in a coherent manner that is interactive and comprehensive for seeking better understanding of a unique environmental concern. The long- run and the short-run relationships between CO_2 emissions and the driving forces/factors analyzed using Vector Error Correction Model (VECM). Consequently, we anticipate that our analytical and integrated approach increases the relevance of studies to better understanding of human-environment interactions.

The finding indicates that the long-run responsiveness of CO_2 emissions to the existing population pressure is positive and statistically significant, leading to exposed the Ethiopian development to unbearable interaction between environment and social (population) aspects. On average, the responsiveness CO2 emission to a one percentage increase in population is estimated around 1.9 percent. This is due to unchecked population growth rate of 2.7 percent per annum, approaching to 100 million populations. And, the adverse effect is accentuated as there are not defined implemented development strategies to absorb the pressure population growth. The finding is contrary to Boserupian view and fits with the Malthusian perspective, which holds that population growth increases environmental impacts. Therefore, considering the driving forces and the responsiveness of CO_2 emissions would enable us to inform decision-makers to make emission reduction measures and to maintain sustainable development and sustainability for lower-income level or developing countries in general and Ethiopia in particular.

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Annexes:

Table 1: Definitions of variables used in this paper

No	variable	Definition	Unit of measurement
1	CO_2 emissions	Carbon dioxide emissions from the burning of fossil fuels and the manufacture of cement. It includes carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring.	Mt
2	Population	Mid-year population	Number
3	GDP per-capita	Gross domestic product divided by midyear population constant local price year 2000	Constant local price year 2000
4	Energy intensity	It is calculated using the ratio of total primary energy supply (TPES) per PJ (including biofuels and other non-fossil forms of energy) per GDP. Energy intensity of the economic output.	TPES per GDP
5	Carbon Intensity	CO_2 emissions per unit of total primary energy supply (TPES). Carbon intensity of the energy mix.	CO_2 emissions per unit TPES

Note: The logarithm of each variable presented as log in the regression models.

Table 2: Descriptive Analysis

Variable	Obs.	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
CO_2emissions	41	120.9	70.4	54.0	265	0.8	2.2
Energy intensity	41	89.7	14.4	55.0	117	-0.5	3.0
Carbon intensity	41	106.4	28.1	67.0	163	0.7	2.1
population	41	54.0	16.3	31.7	84.7	0.3	1.8
Per capita income	41	1063.1	219.7	855	1860	2.2	7.4

Table 3: Partial and Semi Partial Correlations of CO_2 emission

Variable	**Partial corr.**	**Semi partial corr.**	**Partial corr. ^2**	**Semi partial corr. ^2**	**Significant value**
Population	0.9246	0.1252	0.8550	0.0157	0.0000
Per Capita Income	0.4051	0.0229	0.1641	0.0005	0.0116
Energy Intensity	-0.1243	-0.0065	0.0154	0.0000	0.4573
Carbon Intensity	0.9308	0.1314	0.8664	0.0173	0.0000

Table 4: Zivot-Andrews unit root test for allowing for one break in intercept

Variables (in log)	At Level Form		At Difference	
	Break year	Minimum t-statistics	Break year	Minimum t-statistics
CO_2emissions	2000	-4.068	1994	-7.139*
Population	1986	-2.617	1982	-6.507*
Per Capita Income	2004	-0.476	2004	-6.846*
Energy Intensity	2004	-0.982	2004	-4.141
Carbon Intensity	2001	-4.189	2003	-7.221*

Critical Values: 1% level of significance (-5.43) and 5% level of significance (-4.80)

Table 5: Clemente-Montanes-Reyes unit-root test for two breaks with AO and IO models

Variable(log at level form)	At Level form		At Difference form	
	Min t	Optimal Breakpoints (year)	Min t	Optimal Breakpoints (year)
Energy Intensity (in AO model)	-2.827	1982 and 2005	-5.631*	1993 and 2004
Energy Intensity (in IO model)	-2.679	1982 and 2003	-6.555*	1994and 2004

N.B:- Min.'t' is the minimum t-statistics calculated. 5% critical value for the two breaks; -5.490

Table 6:-Selection of the Optimal Lag Length

Lag	LogL	LR	FPE	AIC	SC	HQ
0	263.0335	NA	6.03e-13	-13.94776	-13.73006	-13.87101
1	460.9337	331.6165*	5.34e-17*	-23.29371	-21.98756*	-22.83323*
2	482.6972	30.58663	6.88e-17	-23.11877	-20.72416	-22.27456
3	506.5078	27.02821	9.07e-17	-23.05448	-19.57141	-21.82653
4	547.7563	35.67435	5.96e-17	-23.93277*	-19.36125	-22.32110

Table 7: Johansen tests for co-integration

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.516781	70.36707	69.81889	0.0452
At most 1	0.426521	42.73022*	47.85613	0.1393
At most 2	0.270250	21.60095	29.79707	0.3212
At most 3	0.211193	9.628937	15.49471	0.3104
At most 4	0.016030	0.614074	3.841466	0.4333

Table 8: Long run Equation

Cointegrating Eq:	CointEq1
LOGCO2EMISSIONS(-1)	1.000000
LOGCARBONINTENSITY(-1)	-0.908021 (0.02031) [-44.7079]
LOGENERGYINTENSITY(-1)	0.320139 (0.05882) [5.44315]
LOGPIC(-1)	0.288802 (0.05927) [4.87239]
LOGPOP(-1)	-1.145371 (0.01916) [-59.7803]
C	0.643784

LCO2EMISSIONS =-0.64 – 0.32LENERGYINTENSITY + 0.90LCARBONINTENSITY – 0.28LPIC + 1.14 LPOP

(5.44) (-44.70) (4.87) (-59.78)

Table 9: Short-run Equilibrium and Feedback Coefficients

Error Correction:	D(LOGCO2EMISSIONS)	D(LOGCARBONINTENSITY)	D(LOGENERGYINTENSITY)	D(LOGPIC)	D(LOGPOP)
CointEq1	-6.040645	-5.732419	1.349197	-1.051839	-0.082323
	[-4.22504]	[-4.43915]	[1.31582]	[-1.17007]	[-0.45377]
D(LOGCO2EMISSIONS(-1))	2.040188	2.269722	1.581567	-1.773180	0.108644
	[0.96953]	[1.19420]	[1.04798]	[-1.34017]	[0.40688]
D(LOGCARBONINTENSITY(-1))	-1.890613	-2.132878	-1.679694	1.853218	-0.112733
	[-0.88485]	[-1.10522]	[-1.09615]	[1.37946]	[-0.41580]
D(LOGENERGYINTENSITY(-1))	0.115426	0.229080	-0.068087	-0.333063	-0.122331
	[0.23087]	[0.50730]	[-0.18989]	[-1.05952]	[-1.92827]
D(LOGPIC(-1))	0.019599	0.112607	-0.536258	0.265504	-0.127703
	[0.03853]	[0.24511]	[-1.47002]	[0.83016]	[-1.97855]
D(LOGPOP(-1))	-5.863989	-6.037069	0.602044	0.989251	-0.048123
	[-2.35106]	[-2.67985]	[0.33657]	[0.63080]	[-0.15205]
C	0.131359	0.103617	-0.057660	0.029357	0.023494
	[3.29223]	[2.87526]	[-2.01502]	[1.17020]	[4.64038]

Table 10: Test for Weak Exogeneity

H0: Weakly exogenous variable	Chi-Square Statistics	Probability
Logco2emissions A(1,1)=0	9.784644	0.001760
Logenergyintensity A(2,1)=0	1.458450	0.227177
Logpop A(3,1)=0	0.2444229	0.621168
Logpic A(4,1)=0	1.279886	0.257920
Logcarobonintensity A(5,1)=0	9.346725	0.002234

Table 11: VECM Restriction of treating as exogenous variables

Cointegrating Eq:	CointEq1	
LOGCO2EMISSIONS(-1)	1.000000	
LOGENERGYINTENSITY(-1)	-0.014217	
	[-0.75118]	
C	-4.568777	
Error Correction:	D(LOGCO2EMISSIONS)	D(LOGENERGYINTENSITY)
CointEq1	-0.997132	0.173970
	[-100.035]	[1.75107]
D(LOGCO2EMISSIONS(-1))	0.000751	0.009671
	[0.07857]	[0.10154]
D(LOGENERGYINTENSITY(-1))	-0.008733	-0.075265
	[-0.44756]	[-0.38698]
C	-9.039469	2.549788
	[-80.8933]	[2.28931]
LOGPOP	1.026383	-0.251005
	[72.2100]	[-1.77174]
LOGCARBONINTENSITY	1.008208	-0.164947
	[105.393]	[-1.72997]
LOGPIC	0.046685	-0.114744
	[5.75053]	[-1.41280]

Table 12: VECM Restriction of excluding from the model

Cointegrating Eq:	CointEq1
LOGCO2EMISSIONS(-1)	1.000000
LOGPOP(-1)	-1.903699
	(0.18825)
	[-10.1126]
C	2.877570

LCO2EMISSIONS = -2.877570 +1.903699 LPOP

(10.1126)

Table 13: Restricted Vector Error Correction Model

Error Correction:	D(LOGCO2EMISSIONS)
CointEq1	-0.288394
	[-2.45585]
D(LOGCO2EMISSIONS(-1))	0.192961
	[0.95473]
D(LOGPOP(-1))	-3.321217
	[-1.59871]
C	0.115285
	[2.34096]

Table 14: VEC Stability Condition Test

Root	Modulus
1.000000	1.000000
0.780118	0.780118
0.107818 - 0.152181i	0.186504
0.107818 + 0.152181i	0.186504

VEC specification imposes 1 unit root(s).

Note that all other diagnostic tests are satisfied

Table 15 Impulse Response Function to Cholesky (d.f adjusted) one S.D innovation

	Response of LOGCO2EMISSIONS:	
Period	LOGCO2EMISSIONS	LOGPOP
1	0.097660	0.000000
2	0.067221	-0.020194
3	0.047872	-0.016109
4	0.037433	-0.007942
5	0.030141	-0.001187
6	0.024474	0.003993
7	0.020029	0.008000
8	0.016554	0.011123
9	0.013843	0.013559
10	0.011728	0.015460

Table 16: Variance decompositions with preferred ordering

	Variance Decomposition of LOGCO2EMISSIONS:		
Period	S.E.	LOGCO2EMISSIONS	LOGPOP
1	0.097660	100.0000	0.000000
2	0.120266	97.18066	2.819335
3	0.130442	96.07832	3.921685
4	0.135939	96.04777	3.952231
5	0.139245	96.22598	3.774021
6	0.141436	96.26230	3.737699
7	0.143071	96.03454	3.965457
8	0.144455	95.51724	4.482759
9	0.145748	94.73100	5.268998
10	0.147035	93.71725	6.282754

Annex 11: VEC Granger Causality/Block Exogeneity Wald Tests

VEC Granger Causality/Block Exogeneity Wald Tests
Sample: 1971 2011
Included observations: 39

Dependent variable: D(LOGCO2EMISSIONS)

Excluded	Chi-sq	df	Prob.
D(LOGCARBONINTENSITY)	0.814659	1	0.3667
D(LOGENERGYINTENSITY)	0.056217	1	0.8126
D(LOGPIC)	0.000355	1	0.9850
D(LOGPOP)	5.595059	1	0.0180
All	7.572236	4	0.1086

Dependent variable: D(LOGCARBONINTENSITY)

Excluded	Chi-sq	df	Prob.
D(LOGCO2EMISSIONS)	1.469358	1	0.2254
D(LOGENERGYINTENSITY)	0.262796	1	0.6082
D(LOGPIC)	0.050307	1	0.8225
D(LOGPOP)	7.256282	1	0.0071
All	9.461915	4	0.0505

Dependent variable: D(LOGENERGYINTENSITY)

Excluded	Chi-sq	df	Prob.
D(LOGCO2EMISSIONS)	1.071953	1	0.3005
D(LOGCARBONINTENSITY)	1.174582	1	0.2785
D(LOGPIC)	2.181678	1	0.1397
D(LOGPOP)	0.120240	1	0.7288
All	6.982645	4	0.1368

Dependent variable: D(LOGPIC)

Excluded	Chi-sq	df	Prob.
D(LOGCO2EMISSIONS)	1.749820	1	0.1859
D(LOGCARBONINTENSITY)	1.856386	1	0.1730
D(LOGENERGYINTENSITY)	1.073237	1	0.3002
D(LOGPOP)	0.378558	1	0.5384
All	2.706849	4	0.6080

Dependent variable: D(LOGPOP)

Excluded	Chi-sq	df	Prob.
D(LOGCO2EMISSIONS)	0.163694	1	0.6858
D(LOGCARBONINTENSITY)	0.171014	1	0.6792
D(LOGENERGYINTENSITY)	3.729876	1	0.0534
D(LOGPIC)	3.967756	1	0.0464
All	5.101400	4	0.2771

Post Estimation Tests

VEC Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)
Sample: 1971 2011
Included observations: 39

Joint test:

Chi-sq	df	Prob.
14.76371	18	0.6781

Individual components:

Dependent	R-squared	F(6,32)	Prob.	Chi-sq(6)	Prob.
res1*res1	0.101922	0.605278	0.7241	3.974974	0.6801
res2*res2	0.102150	0.606782	0.7229	3.983845	0.6789
res2*res1	0.100138	0.593503	0.7331	3.905390	0.6895

VEC Residual Heteroskedasticity Tests: Includes Cross Terms
Sample: 1971 2011
Included observations: 39

Joint test:

Chi-sq	df	Prob.
25.52190	27	0.5452

Individual components:

Dependent	R-squared	F(9,29)	Prob.	Chi-sq(9)	Prob.
res1*res1	0.125511	0.462468	0.8876	4.894917	0.8434
res2*res2	0.136270	0.508368	0.8563	5.314534	0.8061
res2*res1	0.133805	0.497753	0.8638	5.218409	0.8149

VEC Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at
lag order h
Sample: 1971 2011
Included observations: 39

Lags	LM-Stat	Prob
1	1.866952	0.7602

Probs from chi-square with 4 df.