ENERGY CONSUMPTION, CO_2 EMISSIONS AND ECONOMIC GROWTH: A REVISIT OF THE EVIDENCE FROM INDIA

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Abstract

We examined the causality in both static and dynamic framework between energy consumption, CO_2 emissions and economic growth in India using Granger approach in VAR framework. We found from the VAR analysis that energy consumption, capital and population Granger-cause economic growth not the vice versa. IRFs and VDs analysis results indicate that CO_2 emissions has positive impact on energy use and capital but negative impact on population and GDP. Energy consumption has positive impact on CO_2 emissions and GDP but its impact is negative on capital and population. This implies that, in the framework of production function, capital and population/labour has been rapidly substituted by energy use in the production process. We argue that since energy consumption generates GDP, therefore, reduction in the energy consumption will have negative impact on the economic growth and Indian economy may standstill to developing economy only. We suggest to the policy makers and Industrialists of India that since energy consumption increases CO_2 emissions too therefore, to the best energy consumption which is generated through the use of fossil fuels and other nonrenewable resources should be reduced and there should be an effort to exploit the renewable sources of energy for consumption and production purposes, which would economies the use of these natural resources in the economy and so economic growth will not be retarded and CO_2 emissions will be less.

Keywords: Carbon dioxide emissions, Energy consumption, Economic growth, Causality, IRFs, VDs.

JEL Classification: Q40, Q43, Q53, Q56

1. Introduction

Since the Industrial Revolution, nations of the world are running to achieve higher and higher economic growth at the cost of utilizing the existing, particularly, nonrenewable natural resources. This race of nations has resulted increase in greenhouse gases emissions, particularly CO_2 emissions, which plays a major role in global warming and ozone depletion. Conceiaco (2003) mentioned that during 20th century average global surface temperature increased by 0.6˚C, snow cover and ice extent fell by 10 percent, sea level rose by 10 to 20 centimeters. It has been anticipated that global average temperature will continue to rise throughout the 21st century by an additional 1.0°–3.5°C. Greenhouse gas emissions (GHGs), particularly carbon dioxide (CO_2) emissions, are considered to be the main causes of global warming. Recognizing the importance of taking corrective measures to condense global warming several countries have signed the Kyoto Protocol and agreed to meet the target set under the Kyoto Protocol, particularly to reduce

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greenhouse gas emissions by an average of five percent below the 1990 levels by 2008-12.

The increasing threat of global warming and climate change has focused attention on the relationship among economic growth, energy consumption and environmental pollutants. Many studies have examined the relationship between environmental degradation and economic growth.[1] The main focus of this line of research has been on the Environmental Kuznets Curve (EKC) or what is called as Carbon Kuznets Curve (CKC) hypothesis. The supposition of the hypothesis is such that initially as per capita income rises environmental degradation exaggerates, but after achievement of a critical level of economic growth it tends to fell down. Therefore, as Rothman and de Bruyn (1998) argues that economic growth may become a solution rather than a source of the problem. This may be either due to increase in the demand for environmental quality as economies grow (Lantz and Feng, 2006) or the possible energy saving because of the increasing awareness among the people regarding the harmful impact of environmental pollution. However, limited attempt has been made to empirically investigate the relationship between energy consumption, environmental degradation or pollution emissions and economic growth. Most of these studies are suffering from the problem of omission of relevant macroeconomic variables. For example, Ang (2007) for France and Soytas et al. (2007) for United States, Zhang and Cheng (2009) for China, Ang (2008) for Malaysia and Halicioglu (2009) and Soytas and Sari (2009) for Turkey, Sari and Soytas (2009) for oil-rich OPEC countries and for India, Tiwari (2011). Further, results from these studies are mixed. For example, Soytas et al. (2007) and Soytas and Sari (2009) found unidirectional Granger causality running from energy consumption to pollution emissions in the long run, while Halicioglu (2009) found bidirectional Granger causality in the long run and short run between economic growth and pollution emissions. Zhang and Cheng (2009) found unidirectional Granger causality running from economic growth to energy consumption and energy consumption to pollution emissions in the long run, while Ang (2007) found unidirectional Granger causality running from economic growth to energy consumption and pollution emissions in the long-run. Sari and Soytas (2009) provides conflicting results for five OPEC countries - Algeria, Indonesia, Nigeria, Saudi Arabia and Venezuela.

By incorporating labour and capital in the framework of production function besides energy consumption, CO_2 emissions (as a measure of pollution) and economic growth the present study makes an attempt to extend Tiwari (2011) who has used energy consumption, CO_2 emissions (as a measure of pollution) and economic growth only. Further, Tiwari (2011) has included electricity consumption as measure of energy consumption we replace it by total energy consumption as electricity consumption is just a part of energy consumption and it may not give correct picture of the existing situation. It is argued that higher economic growth rates pursued by developing countries are achievable only in association with the consumption of a larger quantity of commercial energy, which is one among the key factors of production and also which leads to environmental degradation. There is still dispute on whether energy consumption is a stimulating factor or a result of, economic growth. The increased share of CO_2 in the

[1] For an extensive review of literature see Tiwari (2011).

atmosphere as results of the unbridled use of fossil fuels has negative impacts on natural systems and is a main factor contributing to climate change. In this context, the consumption of coal and oil should be replaced with renewable alternatives, such as wind, solar and hydropower, which do not emit CO_2. However, in the present study we will focus on the causality relationship among economic growth (measured by gross domestic product), environmental degradation (measured by carbon dioxide (CO_2) emissions) and aggregate energy consumption in India. Firstly, we have tested the stationarity property of the variables and the cointegration analysis was carried out by using Johansen and Juselius (1990) procedure. Since we were unable to find cointegrating relationship, static and dynamic causality relationships among the variables have been examined in VAR framework.

As expected, we found that energy consumption Granger causes CO_2 emissions, but not vice versa. The results may have important implications and may provide useful insights for other developed countries in light of Munasinghe (1999) who argues that developing countries may learn how to shape their environmental policies from the experiences of developed countries. The remainder of the paper is organized as follows. Section 2 provides the data source, variables definition, objectives, discusses the time series properties of the variables and has drawn findings. Sections 3 conclude.

2. Data, objectives, and econometric methodology and findings

A. Data and objectives

In the present study we have taken time series data for the period 1971-2007 from World Development Indicators (WDI) from the official website of World Bank (WB).

The interest of studying of the relationship between energy consumption, CO_2 emissions, and economic growth arises from the need to understand the complex links between the three variables. Such an understanding is basic to regulators and investors in deregulated electricity markets, in order to design a system that ensures reliability and efficiency. The specific objective of this study is to investigate the direction of causal relationship between electricity consumption and economic growth in both static and dynamic frame work.

B. *Estimation methodology*

Before conducting static and dynamic analysis certain pre-estimations like unit root and cointegration are required without which, conclusions drawn from the estimation may not be valid. Therefore, in the first step we have carried out unit root analysis by applying three different tests namely, (Augmented) Dickey Fuller (hereafter, DF/ADF) test, Phillips and Perron (hereafter, PP) (1988) test and Ng and Perron (hereafter, NP) (2001) test. In all cases, we will test the unit root property of the variables by employing the model suggested by the graphical plot of the study variables. Augmented form of the DF test is used when there is problem of serial correlation and to choose appropriate lag length Schwarz Information Criteria (hereafter, SIC) has been preferred. Since, PP test has advancements over DF/ADF test in the sense that whereas DF/ADF test use a parametric autoregression to approximate the ARMA structure of the errors in the test regression, PP test correct for any serial correlation and heteroskedasticity in the errors. Therefore, it is also used for analysis. In PP test to select appropriate lag length we have adopted Newey-West using Bartlet kernel method. However, Ng and Perron (2001) has suggested that PP test suffers from severe size distributions properties when error term has negative moving-average root. When root is close to minus one (e.g., -.79) the rejection rate can be as high as 100%. (see, Schwert, 1989). Ng and Perron (2001) has proposed three tests which are based on Modified SIC and Modified AIC, while DF/ADF test and PP test are based on nonmodified information criteria. Two tests of Ng and Perron (2001) test are said to be more powerful namely MZ(α) and MZ(t) (Mollick, 2009). Hence, in this study results of these two statistics are reported in table 1 along with the values of other tests. In all tests, null hypothesis is that series is nonstationary that is series has a unit root and if critical value (which is based on Mackinnon, 1996 for ADF and PP test) exceeds the calculated value in absolute terms (less in negative terms) null hypothesis will not be rejected implying that that series is nonstationary.

It is evident from table (1) that all variables are nonstationary in their level form and are turns out to be stationary after first difference i.e., (I). Since all variable are integrated at first order, I(1) , we can proceed for cointegration analysis. To proceed for cointegration first step is selection of appropriate lag length.[2] Therefore, we have carried out a joint test of lag length selection which suggests (basing upon SIC) we should take one lag of each variable. Then we have chosen lag intervals (1, 1) and then joint test for cointegrating vector and model selection has been performed to determine the model/assumption[3] to be used for cointegration analysis. Joint test (which is commonly known as Pantula Principle) suggests that model 4 or 5 should be used for the cointegration analysis however, model 5 is treated as theoretically inappropriate therefore, with model 4

[2] Since JJ test is found to be sensitive to lag length chosen for the analysis. When the order of VAR i.e., lag length is too short, problem of serial correlation among the residuals arises and test statistic will become unreliable. Conversely, if lag length (order of VAR) is too high there will be an upward bias in the test statistics, again causing doubts on the reliability of the estimates of parameters. Therefore, it is very important to choose appropriate lag length in VEC modelling. For this purpose lag length selection test which was based on VAR analysis has been carried out. There are five lag length selection criteria's Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC), and Hannan-Quinn Information Criteria (HQIC). However, for analyses this study has employed in all models SIC, because it is found that it has performed well in Monte Carlo studies (Kennedy, 2003, 117).

[3] The JJ test also found to sensitive to the choice of deterministic assumptions used in testing the cointegration. There are basically five types of VARs that can be estimated using five different assumptions. Model.1 Assume no deterministic trend in data and no intercept or trend in the VAR and in the cointegrating equation. Model.2 Assume no deterministic trend in the data, but an intercept in the cointegrating equation and no intercept in VAR. Model.3 Assume a linear trend in the data an intercept in cointegrating equation and test VAR. Model.4 Assume a linear deterministic trend in the data, intercept and trend in cointegrating equation and no trend in VAR. Model.5 Assume a quadratic deterministic trend in the data, intercept and trend in VAR, and linear trend in VAR. Johansen (1991) suggest that to choose right model we should test the joint hypothesis of the rank order and the deterministic components. This test is known as Pantula Principal. As it is not very sure that in data used in this study whether deterministic trend is present and VAR also has linear trend or not we have carried out joint test for all five models. That model has been chosen which minimizes the value of SIC and in case if it is found that two models are giving the minimum value of SIC, the better (theoretically appropriate) has been chosen which minimizes the value of SIC of VEC modelling.

cointegration analysis has been carried out.[4] For cointegration analysis we have adopted Johansen and Juselius (1990) method which employs VAR system to test for numbers of cointegration vectors. Its estimation procedure is based on Maximum Likelihood (ML) method. Following Johansen and Juselius (1990) VAR representation of column vector X_t can be written as follows:

$$X_{(t)} = Bz_t + \sum_{i=1}^{k} \Pi_i X_{(t-i)} + \varepsilon_t \qquad (1)$$

Where X_t is column vector of n endogenous variables, z is a (n×1) vector of deterministic variables, ε is a (n×1) vector of white noise error terms and Π_i is a (n×n) matrix of coefficients. Since, most of the macroeconomic time series variables are nonstationary, VAR of such models are generally estimated in first-difference forms. Following Johansen and Juselius (1990), the first differencing of the equation 1 in form of VECM specification, can be specified as follows:

$$\Delta X_{(t)} = Bz_t + \sum_{i=1}^{k} \psi_i \Delta X_{(t-i)} + \Pi X_{t-i} + \varepsilon_t \qquad (2)$$

where $\psi_i = -\sum_{i=1}^{k-1} \Pi_i$ and $\Pi = \sum_{i=1}^{k} \Pi_i - I$

Equation 2 differs from standard first-difference version of a VAR model only by the presence of ΠX_{t-k} term in it. This term contains the information about the long run equilibrium relationship amongst the variable in X_t. Where, Δx_t are all I(0) endogenous variables, Δ indicates the first difference operator, Ψ_i is a (n×n) coefficient matrix and Π_i is a (n×n) matrix whose ranks determines the number of cointegrating relationships. The Johansen and Juselius (1990) cointegration test is to estimate the rank of the Π matrix (r) from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of Π. And if the rank of Π is reduced, even if all variables are individually I(1), the level-based long-run component would be stationary. The appropriate modelling methodology here is VECM. Further, in case of reduced rank of Π i.e., (0 < r < n) then there exists (n×r) matrix of α and β such that:

$$\Pi = \alpha\beta^T \qquad (3)$$

Where r represents the number of cointegrating relationships amongst the endogenous variables included in X_t, α is a matrix of error correction parameters that measures the speed of adjustment in ΔX_t. Which indicates the speed with which the system responds to last period's deviations from the equilibrium relationship and β is the matrix of long run coefficients which contains the element of r cointegrating vectors and has the property that the elements of $\beta' X_t$ are stationary.

[4] Cointegration analysis has been carried out for model 5 also and we found no evidence of cointegration in this case also. Results have not been presented but can be accessed from the author.

Johansen and Juselius (1990) have demonstrated that the β matrix which contains the cointegrating vectors can be estimated as the eigenvectors associated with the r largest eigenvalue of the following equation:

$$\left|\lambda S_{kk} - (S_{k0}S_{ko}) / S_{00}\right| = 0 \tag{4}$$

where S_{00} contains residuals from a least square regression of ΔX_t on $\Delta X_{t-1},\ldots, \Delta X_{t-k+1}$, S_{kk} is the residual matrix from the least square regression of X_{t-1} on ΔX_{t-k+1}, and S_{0k} is the cross-product matrix. These eigenvalues can be used to construct a Likelihood Ratio (LR) test statistic in order to find the number of cointegrating vectors.

JJ test provides two Likelihood Ratio (LR) test statistics for cointegration analysis. First test is trace (λ_{trace}) statistics and the second one is maximum eigenvalue (λ_{max}) statistics. These are specified as follows:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{N}\ln(1-\hat{\lambda}_i) \tag{5}$$

and

$$\lambda\max(r, r+1) = -T\ln(1-\hat{\lambda}_{r+1}) \tag{6}$$

Where r is the number of cointegrating vectors under the null hypothesis and $\hat{\lambda}_i$ is the estimated value for the i[th] ordered eigenvalue from the matrix Π. The trace statistics tests the null hypothesis that the number of cointegrating relations is r against of k cointegration relations, where k is the number of endogenous variables. The maximum eigenvalue test, tests the null hypothesis that there are r cointegrating vectors against an alternative of r+1 cointegrating vectors.

Table 2. Cointegration test Cointegration test [Trend assumption: Linear deterministic trend (restricted) Lags interval (in first differences): 1 to 1].

Unrestricted Cointegration Rank Test (Trace)					
H_o	H_a	Eigenvalue	Max-Eigen Statistic	5% Critical Value	Prob.**
None	At most 1	0.547063	27.72005	37.16359	0.3972
At most 1	At most 2	0.427985	19.55065	30.81507	0.5866
At most 2	At most 3	0.212286	8.351724	24.25202	0.9695
At most 3	At most 4	0.164921	6.308027	17.14769	0.7861
At most 4	At most 5	0.096113	3.536790	3.841466	0.0600
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)					
H_0	H_a	Eigenvalue	Trace Statistic	5% Critical Value	Prob.**
None	At most 1	0.547063	65.46723	79.34145	0.3476
At most 1	At most 2	0.427985	37.74719	55.24578	0.6331
At most 2	At most 3	0.212286	18.19654	35.01090	0.8130
At most 3	At most 4	0.164921	9.844817	18.39771	0.4955
At most 4	At most 5	0.096113	3.536790	3.841466	0.0600
Note: * denotes rejection of the hypothesis at the 0.05 level and **MacKinnon-Haug-Michelis (1999) p-values. Source: Author’s calculation					

To determine the rank of matrix Π, the test values obtained from the two test statistics are compared with the critical value from Mackinnon-Haug-Michelis (1999) which differs slightly from those provided by Johansen-Juselius (1990). For both tests if the test statistic value is greater than the critical value, the null hypothesis of r cointegrating vectors is rejected in favor of the corresponding alternative hypothesis. By choosing model 4 and lag interval (1, 1) we have carried out JJ cointegration test. Results of cointegration test are reported in table 2.

It is evident from table 2 that there is no evidence of cointegration among the set of test variables. Therefore, static and dynamic causality analysis should be carried out in the framework of VAR model.

Suppose there are two variables X and Y then Granger causality analysis in the VAR framework will be based on the following equations:

$$\Delta X_t = \alpha_x + \sum_{i=1}^{k} \beta_{x,i} \Delta X_{t-i} + \sum_{i=1}^{k} \gamma_{x,i} \Delta Y_{t-i} + \varepsilon_{x,t} \tag{7}$$

$$\Delta Y_t = \alpha_y + \sum_{i=1}^{k} \beta_{y,i} \Delta Y_{t-i} + \sum_{i=1}^{k} \gamma_{y,i} \Delta X_{t-i} + \varepsilon_{y,t} \tag{8}$$

The null hypothesis (H_0) for the equations (7) is $H_0 : \sum_{i}^{k} \gamma_{x,i} = 0$ suggesting that the lagged terms of ΔY do not belong to the regression i.e., it do not Granger cause ΔX. Conversely, the null hypothesis (H_0) for the equations (8) is $H_0 : \sum_{i}^{k} \gamma_{y,i} = 0$, suggesting that the lagged terms of ΔX do not belong to regression i.e., it do not Granger cause ΔY. The joint test of these null hypotheses has been tested through Wald Chi-square (χ^2) test. This Wald Chi-square (χ^2) test gives us an indication of the 'short-term' causal effects or strict exogenity of the variables.

If the coefficients of $\gamma_{x,i}$ are statistically significant, but $\gamma_{y,i}$ are not statistically significant, then X is said to have been caused by Y (unidirectional). The reverse causality holds if coefficients of $\gamma_{y,i}$ are statistically significant while $\gamma_{x,i}$ are not. But if both $\gamma_{y,i}$ and $\gamma_{x,i}$ are statistically significant, then causality runs both ways (bidirectional). Independence is identified when the $\gamma_{x,i}$ and $\gamma_{y,i}$ coefficients are not statistically significant in both the regressions.

Further, non-significance of any of the 'differenced' variables which reflects only the short-term relationship, does not involve a violation of theory because, the theory typically has nothing to say about short-term relationships. Since in our case lag interval is (1, 1) therefore, Wald Chi-square (χ^2) test is not needed and significance of the variables can be tested through the t-test only. Results of VAR analysis are reported in table 3.

Table 3: VAR Granger causality analysis

Vector Autoregression Estimates					
Included observations: 36 after adjustments					
t-statistics in [ ]					
	LNCO2EMISSIONSPC	LNENERGYUSEPC	LNGDPPCC	LNGFCF	LNPOPULATION GROWTH
LNCO2EMISSIONPC(-1)	0.698369***	-0.002129	-0.041326	0.043202	-0.013439
	[6.48640]	[-0.13342]	[-1.36122]	[0.46091]	[-0.53669]
LNENERGYUSEPC(-1)	0.592581	0.942685***	0.541001 ***	-0.680410	0.062110
	[0.90395]	[9.70447]	[2.92674]	[-1.19223]	[0.40739]
LNGDPPCC(-1)	0.072931	-0.022112	0.336975	0.239768	-0.190850
	[0.12784]	[-0.26158]	[2.09485]	[0.48278]	[-1.43849]
LNGFCF(-1)	0.116454	0.041281**	0.126307 ***	0.933392 ***	0.028392
	[0.77776]	[1.86058]	[2.99163]	[7.16061]	[0.81533]
LNPOPULATION GROWTH(-1)	0.612923	0.037589	-0.408382***	-0.754112	0.817735 ***
	[1.16051]	[0.48030]	[-2.74221]	[-1.64011]	[6.65741]
C	-7.205972**	-0.563644	-2.2052**	4.866350	0.132171
	[-1.95100]	[-1.02986]	[-2.11746]	[1.51343]	[0.15387]
R-squared	0.972149	0.996715	0.996437	0.992906	0.989614
Adj. R-squared	0.967507	0.996167	0.995843	0.991724	0.987883
Sum sq. resids	0.194095	0.004262	0.015432	0.147105	0.010498
S.E. equation	0.080435	0.011919	0.022681	0.070025	0.018707
F-statistic	209.4337	1820.324	1677.884	839.8394	571.7108
Log likelihood	42.93087	111.6666	88.50462	47.92055	95.43935
Akaike AIC	-2.051715	-5.870365	-4.583590	-2.328920	-4.968853
Schwarz SC	-1.787795	-5.606445	-4.319670	-2.065000	-4.704933
Mean depend.	-0.137040	5.910781	5.781331	24.81426	0.647101
S.D. depend.	0.446226	0.192521	0.351774	0.769746	0.169944
Determinant resid covariance (dof adj.)		3.84E-16			
Determinant resid covariance		1.54E-16			
Log likelihood		399.9372			
Akaike information criterion		-20.55207			
Schwarz criterion		-19.23247			
Note: (1)*** and ** denotes significant at 1% and 5% level respectively; (2) (k) denotes lag					
Source: Author's calculation					

It is evident form table 3 that past values of CO_2 emissions, energy consumption capital and population have positive and significant impact on its own current value and energy consumption, capital and population Granger-cause economic growth. Further to test the validity of the VAR results diagnostic checks analysis has been performed to the models used for VAR to test the stochastic properties of the model such as residuals autocorrelation, heteroskedasticity and normality. This was because if the model is stochastic then only further analysis based on the model is possible and inference drawn from the results of VEC modelling will not be biased. For testing the presence of autocorrelation/serial correlation this study has used Lagrange Multiplier (LM) test, which is a multivariate test statistic for autocorrelation in residuals up to the specified lag order. To test the presence of heteroskedasticity, this study has used White heteroskedasticity test with cross products. The null hypothesis of White heteroskedasticity test is that errors are homoskedastic i.e., no heteroskedasticity and independent of the regressors and that there is no problem of misspecification. If any one of the condition is not satisfied White heteroskedasticity test will turn to be significant in most cases. For testing the normality of residuals multivariate extension of Jarque-Bera (JB) normality test has been used, which compares third and fourth moments of the residuals to those from the normal distribution. In the present study, Urzua's (1997) method of residual factorization (orthogonalization) has been preferred for testing the normality of residuals in order to check the specification of the VEC model which provides J-B test statistic. This is because it makes a small sample correction to the transformed residuals before computing JB test as sample elicit size of the present study is small. The null hypothesis in this test is that residuals follow normal distribution. Further, CUSUM and CUSUM square test, ARCH-LM test and multivariate ARCH-LM test also has been performed. Results of diagnostic checks analysis are reported in the following table 4 and figure 1and 2.

Table 4: Diagnostic checks analysis

VAR Residual Serial Correlation LM Tests statics with lag 1		P-Value
33.34550		0.1227
VAR Residual Normality Tests-Joint J-B test value (Orthogonalization: Residual Covariance (Urzua)		
115.8851		0.2200
VAR Residual Heteroskedasticity Tests static value: Includes Cross Terms (Joint test of Chi- square)		
317.0502		0.2387
ARCH-LM test with 1 lags		
Variable	Test statistics	p-Value(Chi^2)
u1	0.0201	0.8872
u2	0.1578	0.6912
u3	0.1110	0.7390
u4	0.1967	0.6574
u5	0.0017	0.9676
Multivariate ARCH-LM test statistics with 1 lags		

VARCHLM test statistic: 251.3578	0.1097
Note: *, **and ***denotes significant at 1%, 5%, and 10% level respectively.	
Source: Author's calculation	

It is evident from the table (4) that the specification of VECM is correct as no test is rejecting the null hypothesis. Further, as Hansen (1992) cautions that in time series analysis, estimated parameters may vary over time. Therefore, we should test the parameters stability test since unstable parameters can result in model misspecification and may generate the potential biasness in the results. Therefore, for each equation of VAR we have applied the cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMSQ) tests proposed by Brown et al. (1975) to assess the parameter constancy.[5] The null hypothesis to be tested in these two tests is that the regressions coefficients are constant overtime against the alternative coefficients are not constant. Brown et al. (1975) pointed out that these residuals are not very sensitive to small or gradual parameter changes but it is possible to detect such changes by analyzing recursive residuals. They argue that if the null hypothesis of parameter constancy is correct, then the recursive residuals have an expected value of zero and if the parameters are not constant, then recursive residuals have non-zero expected values following the parameter change. Results of CUSUM and CUSUMSQ plot have been presented in figure 1 and 2 respectively.

Results for CUSUM and CUSUMSQ test are conflicting since CUSUM test indicates that parameters of VAR are stable but CUSUMSQ test did not support the argument as for equation 1 and 3rd of VAR CUSUMSQ plots crosses the 1% boundary limit. Since in all other our VAR model performs well which allows us to analyze the dynamic properties of the VAR system by using forecast error Variance Decompositions (VDs) and Impulse Response Functions (IRFs). IRFs analysis traces out the responsiveness of the dependent variable in VAR to shocks to each of the other explanatory variables over a period of time (10 years in the presented study).[6] A shock to a variable in a VAR not only directly affects that variable, but also transmits its effect to all other endogenous variables in the

[5] The first of these involves a plot of the cumulative sum (CUSUM) of recursive residuals against the order variable and checking for deviations from the expected value of zero. Symmetric confidence lines above and below the zero value allow definition of a confidence band beyond which the CUSUM plot should not pass for a selected significance level. A related test involves plotting the cumulative sum of squared (CUSUMSQ) recursive residuals against the ordering variable. The CUSUMSQs have expected values ranging in a linear fashion from zero at the first-ordered observation to one at the end of the sampling interval if the null hypothesis is correct. Again, symmetric confidence lines above and below the expected value line define a confidence band beyond which the CUSUMSQ plot should not pass for a selected significance level, if the null hypothesis of parameter constancy is true. In both the CUSUM and CUSUMSQ tests, the points at which the plots cross the confidence lines give some in diction of value(s) of the ordering variable associated with parameter change.

[6] To calculate confidence intervals (at 5 percentage level) for IRFs we have used Hall (1992) and Efron and Tibshirani (1993) methods with 500 bootstrap replications and for VDs standard errors have been calculated with Monte Carlo simulations with 500 replications.

system through the dynamic structure of VAR. There are several ways of performing IRFs but generalized approach has been preferred over Choleskey orthogonalization approach or other orthogonalization approaches for the present study because it is invariant of ordering of the variables as results of IRFs are sensitive to the ordering of the variables. Variance decomposition measures the proportions of forecast error variance in a variable that is explained by innovations (impulses) in it and by the other variables in the system. For example it explains what proportions of the changes in a particular variable can be attributed to changes in the other lagged explanatory variables. IRFs have been presented in fig 3.
It is evident from figure 3 that one SD shock/innovation in CO_2 emissions has positive impact on its own value, energy use and capital but negative impact on population. However, for GDP it has negative impact in first 5 years and then its impact is positive. Impact of one SD shock in energy consumption on CO_2 emissions has shows first positive impact and after 8^{th} year negative impact; positive impact on its own value and GDP and negative impact on capital and population.

Impact of one SD shock in GDP has positive impact on all variables except population wherein its impact is negative. One SD shock in capital has positive impact on all variables while on population its impact is first positive but in later period it turns out to be negative. One SD shock in population has positive impact on its own value and has first positive and in later period negative impact on CO_2 emissions and negative impact on rest of the variable i.e., energy use, GDP and capital. One can find similar results from VDs analysis. Results of VDs are presented in annexure 1.

3. Discussion, conclusions, policy implications and future scope

The paper examined the linkage between energy consumption, environmental degradation and economic growth in the framework of production function i.e., by incorporating capital and labour as control variables in the context of India. Stationary property of the study variables indicates that all variables are non stationary at level form and stationary in first difference form i.e., they have autoregressive of order one (AR (1)). Cointegration analysis indicated that linear combinations of these explanatory variables are not cointegrated. Therefore, static Granger-causality among the test variables has been examined through VAR approach test and dynamic Granger-causality has been examined through Impulse Response Functions (IRFs) and Variance Decomposition (VDs) analysis. The result from the application of VAR analysis suggests that energy consumption, capital and population Granger-cause economic growth not the vice versa. Results from dynamic Granger-causality analysis shows that one SD shock/innovation in CO_2 emissions has positive impact on energy use and capital but negative impact on population and GDP. There are a number of studies that suggest environmental degradation, including air and noise pollution, has negative impact on life satisfaction and thus delivers negative impact on population (see Ferrer-i-Carbonell and Gowdy, 2007; Di Tella and MacCulloch, 2008; Van Praag and Baarsma, 2005; Welsch, 2002, 2006; Rehdanz and Maddison, 2008 and Smyth et al., 2008). Addition to it, a persistent decline in environmental quality may generate negative externalities for the economy through reducing health human capital and, hence, productivity and so on GDP in the long-run (Ang, 2008). Impact of one SD shock in energy consumption on CO2 emissions and GDP has shown positive impact but its impact is negative on capital and population. This implies that, in the framework of production function, capital and population/labour has been rapidly substituted by energy use in the production process. Impact of one SD shock in GDP has positive impact on all variables except population wherein its impact is negative. This implies that increase in the growth rate do not encourage the population growth. One SD shock in capital has positive impact on all variables while on population its impact is first positive but in later period it turns out to be negative. This implies that in the initial period both factors of production work as complementary but in later years due to advancement in the technology labour is substituted by capital. Impact of one SD shock in population has positive impact on CO_2 emissions and negative impact on rest of the variable i.e., energy use, GDP and capital. This implies that with the increase in the population growth CO_2 emissions increases and population acts as a substituttary factor of production. In nut shell we find that CO2 emissions increases energy use on one hand and decreases GDP and population on the other hand. Addition to it, energy use increases GDP and CO_2 emissions and substitutes labour and capital in the production process. Here, we have contradictory finding to Tiwari (2011) as he observed that energy consumption do not increase GDP and so he concludes that consumption of energy should be reduced. This may be due to the difference in measurement of the energy variable where Tiwari (2011) has measured energy consumption as electricity consumption while we have measured it in aggregate form. We argue that since energy consumption generates GDP therefore, reduction in the energy consumption will have negative impact on the economic growth. Since energy consumption increases CO_2 emissions to, we are suggesting to the policy makers to take corrective measures to replace fissile fuel by renewable sources of energy for consumption and production purposes.

The present study can be extended by analyzing the role of energy consumption at disaggregate level (in component form) in order to get more insights so that appropriate policy decision can be made in face of deregulation of Indian economy. Secondly, possible structural breaks have to be considered while carrying out the analysis; so that methodological improvements can be made which will provide more reliable results. And last but not least direction for future research would be to carry out non linear Granger-causality analysis to check the robustness of the causality results.

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Annexure 1: Results of Variance Decompositions (VDs) analysis

Variance Decomposition of LNCO2EMISSIONSPC:					
Period	LNCO2EMISSIONSPC	LNENERGYUSEPC	LNGDPPCC	LNGFCF	LNPOPULATIONGROWTH
1	100.0000	0.000000	0.000000	0.0000	0.000000
	(0.00000)	(0.00000)	(0.00000)	(0.000)	(0.00000)
2	97.32343	1.105787	0.129319	0.209339	1.232121
	(4.81480)	(2.69909)	(1.44810)	(1.330)	(2.64139)
3	91.95691	3.783211	0.305866	1.07047	2.883533
	(9.41993)	(5.48279)	(2.36516)	(3.117)	(5.17825)
4	85.42452	7.121936	0.601092	2.67298	4.179469
	(12.8939)	(7.88599)	(3.23974)	(5.015)	(6.83101)
5	79.00967	10.21060	1.115642	4.84730	4.816778
	(15.1544)	(9.71765)	(4.25478)	(6.778)	(7.66787)
6	73.26888	12.58480	1.942086	7.345538	4.858695
	(16.5642)	(11.0374)	(5.43119)	(8.2899)	(7.94120)
7	68.24030	14.13760	3.137504	9.92860	4.555994
	(17.4540)	(11.9689)	(6.70334)	(9.477)	(7.91250)
8	63.74927	14.94201	4.706664	12.38841	4.213640
	(18.0396)	(12.6261)	(7.95507)	(10.33)	(7.84551)
9	59.59728	15.13886	6.598243	14.55693	4.108680
	(18.4269)	(13.0909)	(9.08297)	(10.91)	(7.96401)
10	55.64381	14.88346	8.715153	16.3178	4.439721
	(18.6612)	(13.4252)	(10.0474)	(11.30)	(8.34718)
Variance Decomposition of LNENERGYUSEPC					
Peri	LNCO2EMISSIO	LNENERGYUS	LNGDPP	LNGFCF	LNPOPULATION

od	NSPC	EPC	CC		GROWTH
1	0.454792	99.54521	0.000000	0.00000	0.000000
	(4.33379)	(4.33379)	(0.00000)	(0.000)	(0.00000)
2	0.360238	97.94405	0.214650	1.3314	0.149573
	(4.39447)	(5.22731)	(1.56013)	(1.585)	(1.15320)
3	0.368285	94.76532	0.888937	3.7596	0.217780
	(5.20171)	(7.89674)	(3.29116)	(3.854)	(2.13853)
4	0.459725	90.46251	2.117310	6.7846	0.175782
	(6.22688)	(10.9199)	(5.16283)	(6.164)	(2.90794)
5	0.634812	85.25574	3.914893	10.033	0.161458
	(7.22575)	(13.7405)	(7.05659)	(8.176)	(3.61544)
6	0.890262	79.32072	6.221736	13.195	0.371995
	(8.10832)	(16.2153)	(8.91575)	(9.735)	(4.42438)
7	1.212812	72.86904	8.910376	16.020	0.987744
	(8.85933)	(18.2659)	(10.6183)	(10.83)	(5.44489)
8	1.580136	66.16016	11.80814	18.330	2.120926
	(9.47990)	(19.8751)	(12.0731)	(11.55)	(6.71213)
9	1.965521	59.47166	14.73115	20.038	3.793120
	(9.98088)	(21.0808)	(13.2694)	(11.99)	(8.14831)
10	2.343496	53.05524	17.51837	21.140	5.942261
	(10.3928)	(21.9340)	(14.2332)	(12.26)	(9.62000)
Variance Decomposition of LNGDPPCC:					
Peri od	LNCO2EMISSIO NSPC	LNENERGYUS EPC	LNGDPP CC	LNGFCF	LNPOPULATIONGR OWTH
1	0.029148	1.304672	98.66618	0.0000	0.000000
	(4.11121)	(5.79100)	(7.17869)	(0.000)	(0.00000)
2	0.082668	15.79577	72.76753	5.6850	5.668984
	(3.95645)	(10.4665)	(12.8707)	(3.885)	(4.80551)
3	0.074953	22.07769	57.05464	10.051	10.74084
	(4.38505)	(12.4722)	(14.8072)	(6.123)	(8.03084)
4	0.272392	23.58358	48.79105	12.745	14.60772
	(5.17080)	(13.5844)	(15.6316)	(7.795)	(10.5606)
5	0.636799	23.09563	44.17278	14.390	17.70438
	(6.15084)	(14.3659)	(16.1369)	(9.078)	(12.5778)
6	1.072402	21.83872	41.40043	15.378	20.31002
	(7.12046)	(14.9862)	(16.5410)	(10.076)	(14.1803)
7	1.511227	20.34680	39.62772	15.937	22.57655
	(7.97880)	(15.5258)	(16.8858)	(10.849)	(15.4202)
8	1.917303	18.85614	38.42870	16.210	24.58775
	(8.70001)	(16.0327)	(17.1712)	(11.45)	(16.3729)
9	2.275853	17.46879	37.57464	16.289	26.39153
	(9.29170)	(16.5287)	(17.4029)	(11.92)	(17.1138)
10	2.583871	16.22390	36.93622	16.239	28.01670
	(9.77446)	(17.0167)	(17.5904)	(12.30)	(17.6986)
Variance Decomposition of LNGFCF:					
	LNCO2EMISSIO NSPC	LNENERGYUS EPC	LNGDPP CC	LNGFCF	LNPOPULATIONGR OWTH
1	0.535463	22.29586	24.67934	52.489	0.000000

	(4.56955)	(12.1210)	(10.9814)	(11.10)	(0.00000)
2	1.333737	17.10453	29.01339	50.689	1.858565
	(5.58618)	(11.3269)	(13.1223)	(11.17)	(2.88674)
3	2.154800	13.01739	32.25448	47.123	5.449377
	(6.92120)	(10.6582)	(14.8268)	(11.61)	(6.30173)
4	2.856499	10.00471	34.38757	42.830	9.920557
	(7.96265)	(10.0745)	(15.8135)	(12.08)	(9.37826)
5	3.395408	7.848298	35.62930	38.511	14.61512
	(8.68856)	(9.64673)	(16.4039)	(12.47)	(11.9770)
6	3.781733	6.313517	36.24056	34.537	19.12634
	(9.20774)	(9.42612)	(16.8068)	(12.75)	(14.0896)
7	4.044980	5.215139	36.44217	31.052	23.24499
	(9.62064)	(9.42762)	(17.1054)	(12.89)	(15.7065)
8	4.216329	4.426337	36.39498	28.075	26.88703
	(9.97852)	(9.64146)	(17.3293)	(12.93)	(16.8844)
9	4.322015	3.867085	36.20692	25.566	30.03776
	(10.2942)	(10.0429)	(17.4976)	(12.91)	(17.7283)
10	4.382038	3.489159	35.94653	23.465	32.71696
	(10.5687)	(10.5914)	(17.6254)	(12.85)	(18.3429)
Variance Decomposition of LNPOPULATIONGROWTH:					
	LNCO2EMISSIONSPC	LNENERGYUSEPC	LNGDPPCC	LNGFCF	LNPOPULATIONGROWTH
1	2.972822	0.353603	3.470769	1.4507	91.75206
	(6.72014)	(4.10697)	(6.85953)	(4.425)	(9.93195)
2	3.790476	0.213077	8.138197	0.8506	87.00756
	(7.20666)	(4.42411)	(9.29099)	(3.978)	(11.6231)
3	4.025586	0.221430	10.98626	0.6366	84.13007
	(7.86116)	(4.89089)	(11.1965)	(4.258)	(13.3438)
4	4.047285	0.620206	12.86342	0.5624	81.90660
	(8.46402)	(5.53094)	(12.4897)	(4.854)	(14.6874)
5	3.992363	1.508014	14.25735	0.61300	79.62927
	(8.97444)	(6.48447)	(13.3763)	(5.601)	(15.8099)
6	3.912020	2.823472	15.40347	0.8146	77.04639
	(9.38323)	(7.67936)	(14.0089)	(6.395)	(16.7718)
7	3.827625	4.426539	16.42211	1.1926	74.13108
	(9.68931)	(8.96569)	(14.4845)	(7.171)	(17.5719)
8	3.749978	6.153095	17.38114	1.7564	70.95932
	(9.90249)	(10.2283)	(14.8680)	(7.888)	(18.2090)
9	3.685634	7.850236	18.32122	2.4952	67.64764
	(10.0447)	(11.4094)	(15.2013)	(8.528)	(18.6945)
10	3.638707	9.397030	19.26562	3.3796	64.31902
	(10.1432)	(12.4888)	(15.5085)	(9.092)	(19.0459)
Cholesky Ordering: LNCO2EMISSIONSPC LNENERGYUSEPC LNGDPPCC LNGFCF LNPOPULATIONGROWTH					
Standard Errors: Monte Carlo (500 repetitions)					

Annex

Table 1: Unit root analysis

Variables	Unit root tests					
	Constant	Constant and trend	DF/ADF (k)	PP (k)	NP	
					(MZa) (k)	(MZt) (k)
LNCO2EMISSIONSPC	----	Yes	-2.808324 (0)	-2.736425 (4)	-7.92952 (0)	-1.98007 (0)
D(LNCO2EMISSIONSPC)	Yes	------	-5.473262*** (0)	-5.549623*** (7)	-18.3048*** (0)	-2.99925*** (0)
LNENERGYUSEPC	------	Yes	-2.122373 (0)	-2.122373 (0)	-3.81155 (0)	-1.08591 (0)
D(LNENERGYUSEPC)	Yes	----	-5.041526*** (0)	-5.034978*** (2)	-15.3885*** (0)	-2.51582** (0)
LNGDPPCC	----	Yes	-0.747216 (0)	-0.600240 (1)	-0.83264 (1)	-0.29197 (1)
D(LNGDPPCC)	Yes	----	-5.311097***(0)	-5.353720***(4)	-7.72508* (1)	-1.78282* (1)
LNPOPULATIONGROWTH	----	Yes	-1.122061 (0)	--1.078959 (2)	-1.16644 (0)	-0.50664 (0)
D(LNPOPULATIONGROWTH)	Yes	----	-5.094291***(0)	-5.192295***(3)	-17.8817***(0)	-2.96369***(0)
LNGFCF	----	Yes	1.166591(0)	1.447811(4)	-7.18997(1)	-1.47747(1)
D(LNGFCF)	Yes	----	-3.650899***(0)	-3.629743**(2)	-15.4239***(0)	-2.70413***(0)
Note: (1) ***, ** and *denotes significant at 1%, 5% and 10% level respectively. (2) "K" Denotes lag length. (3) Selection of lag length in NP test is based on Spectral GLS-detrended AR based on SIC and selection of lag length (Bandwidth) and in PP test it is based on Newey-West using Bartlett kernel.						
Source: Author's calculation						

Figure 1: CUSUM test

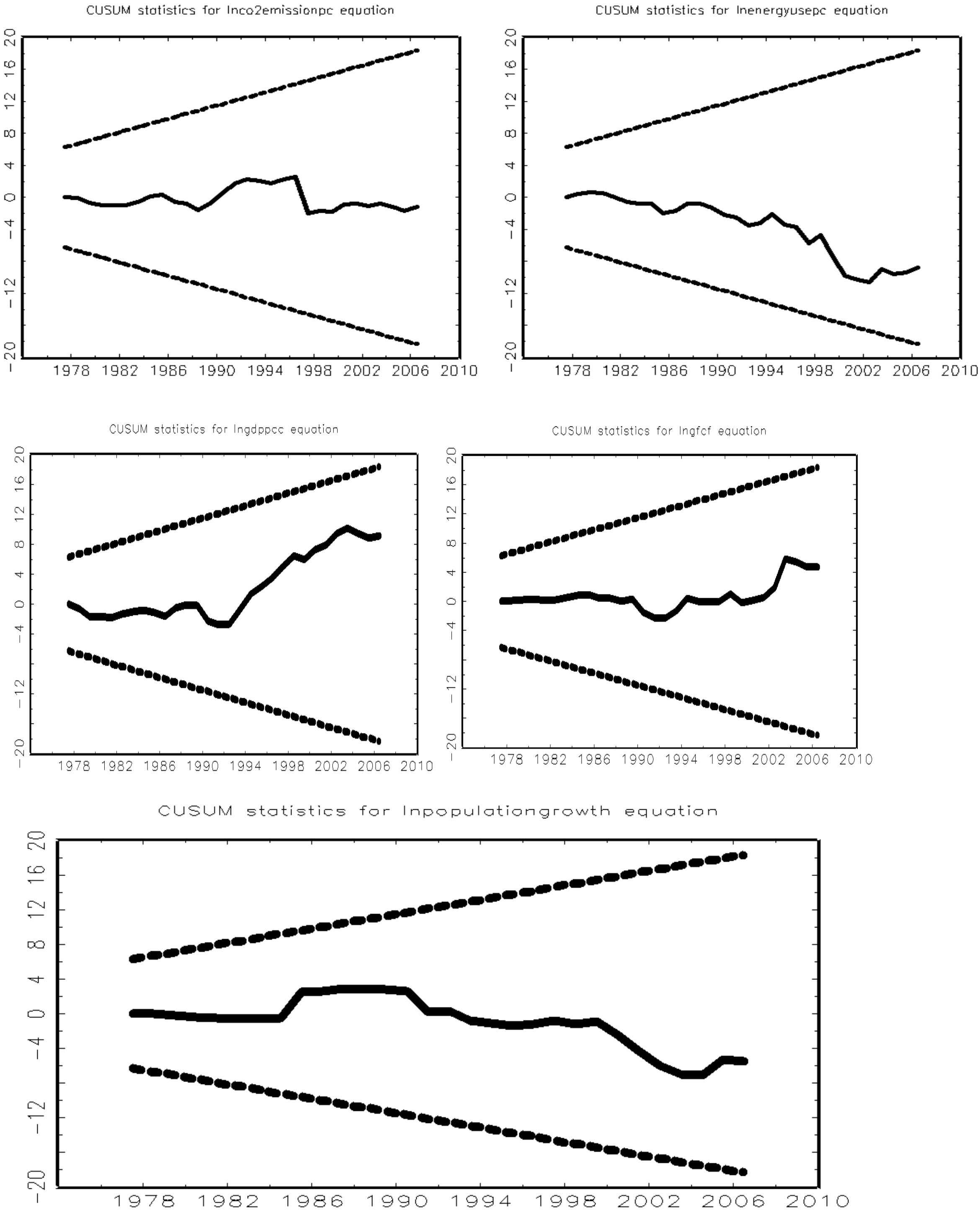


Figure 2: CUSUM square test

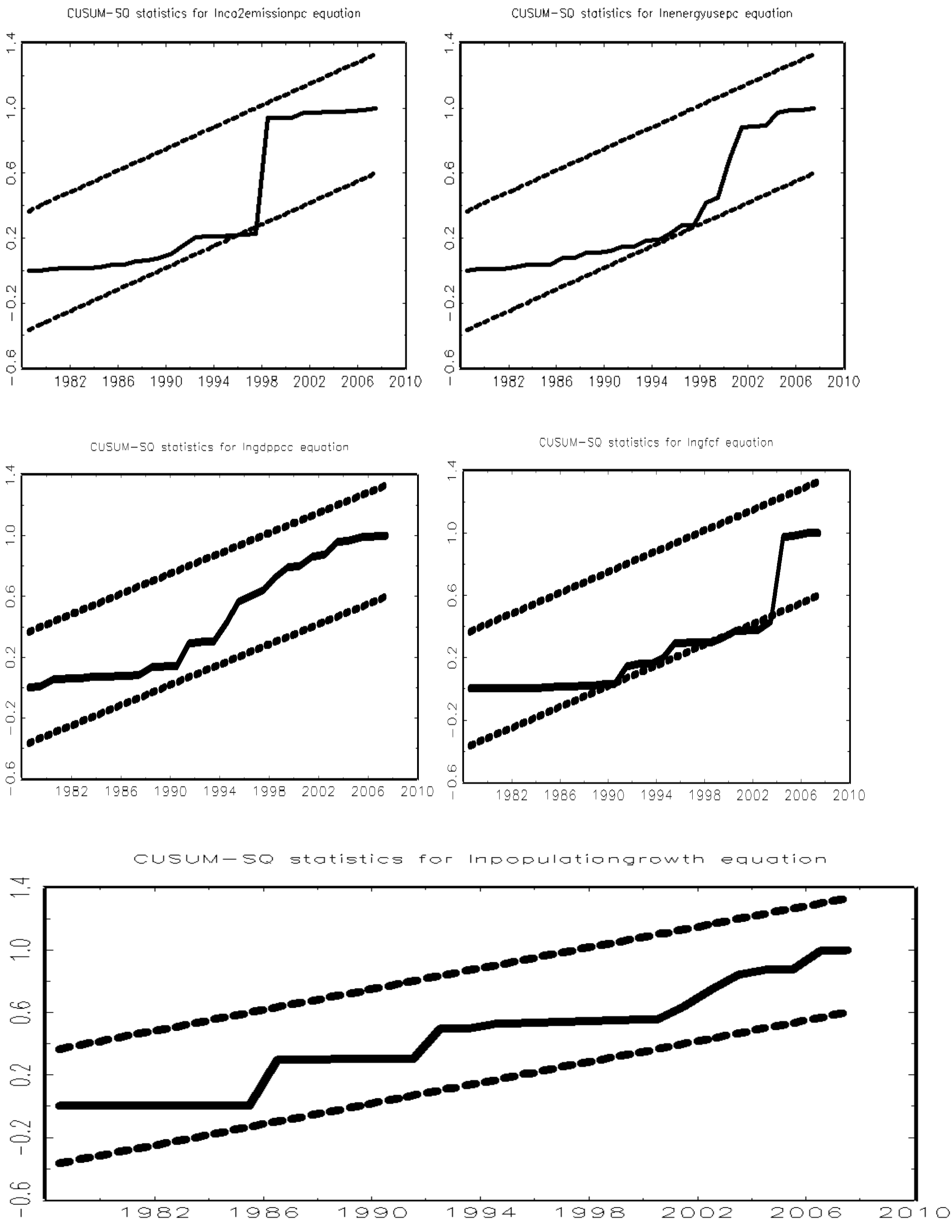
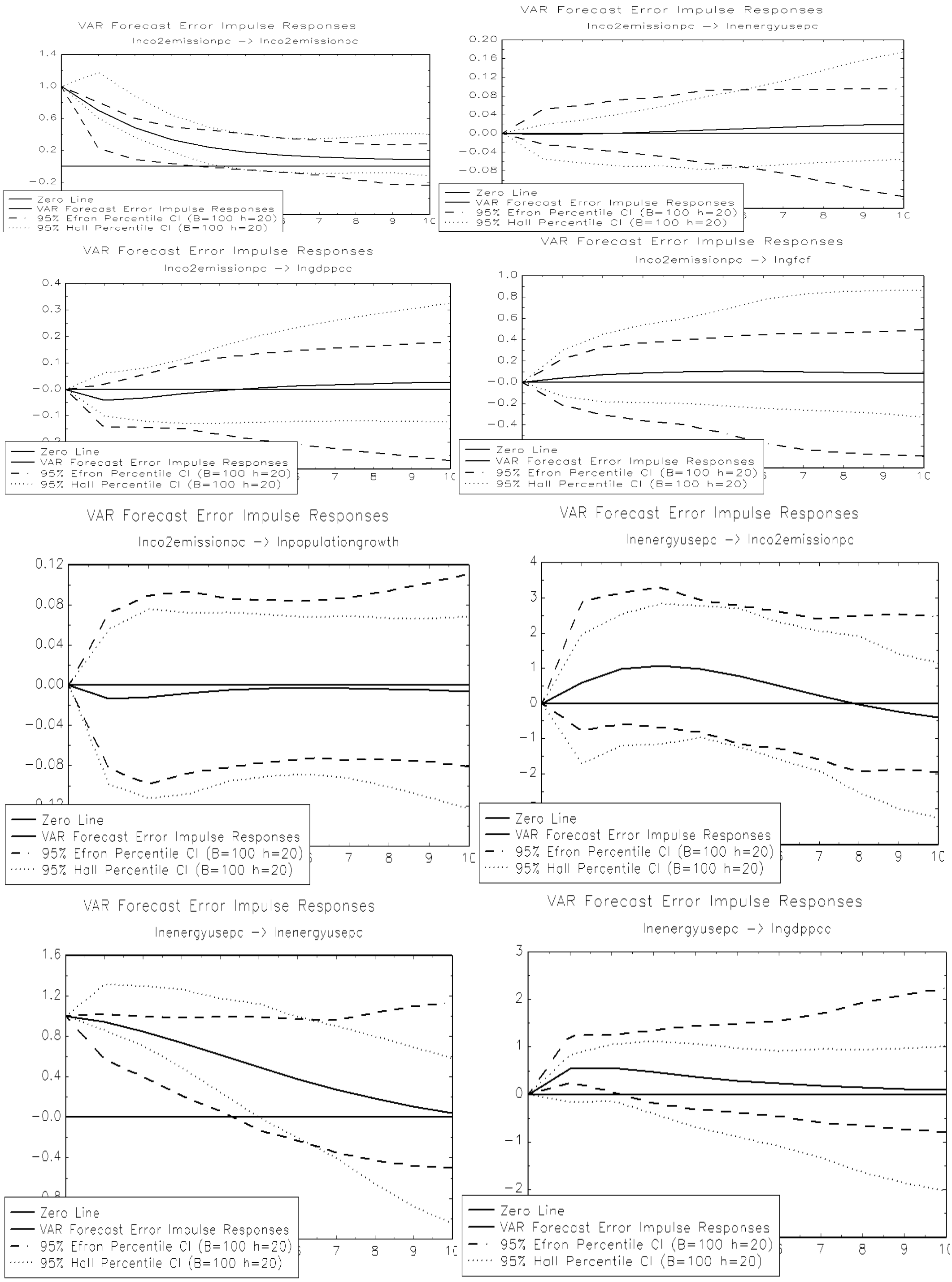
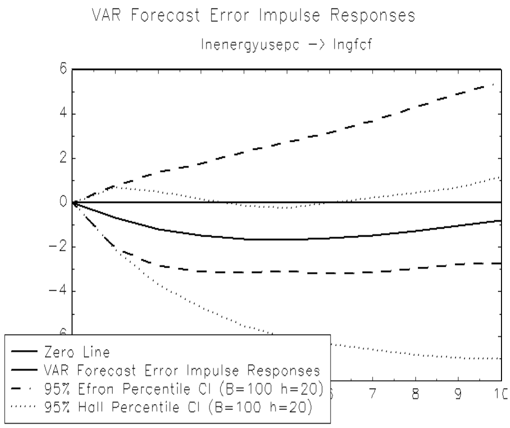
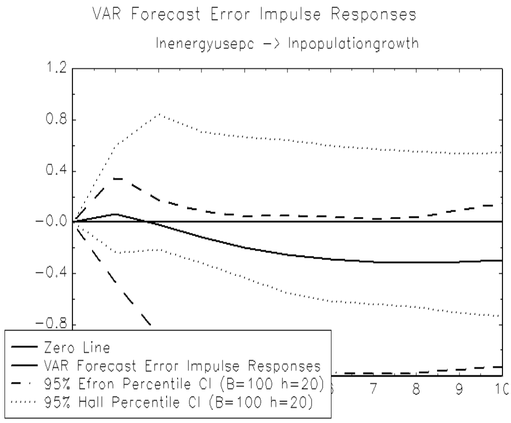
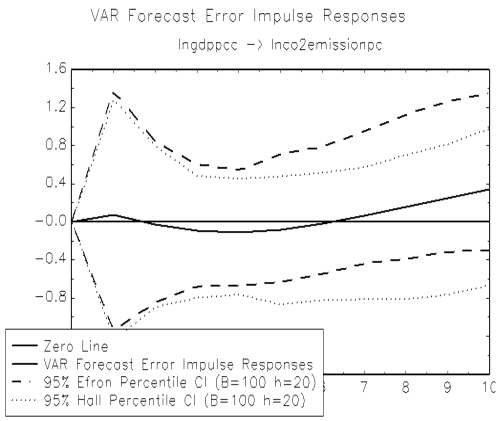


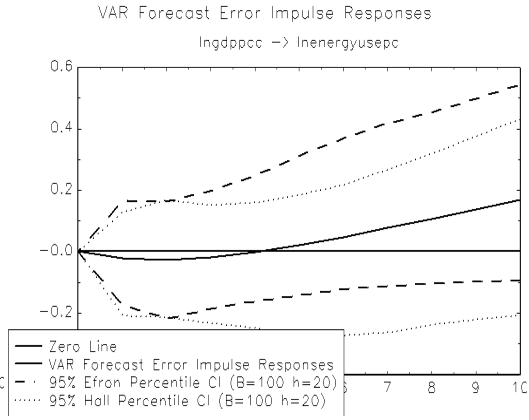
Fig3: Impulse response functions. IRFs analysis

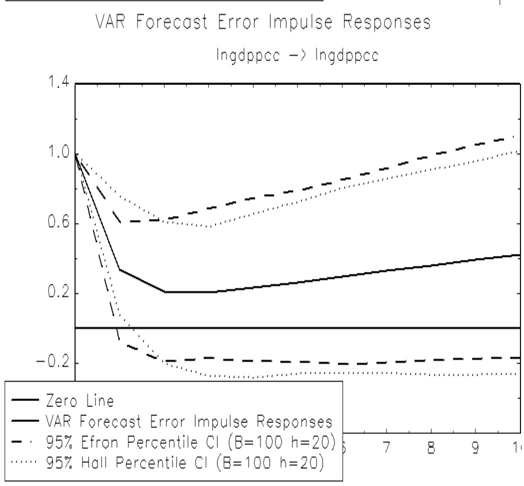


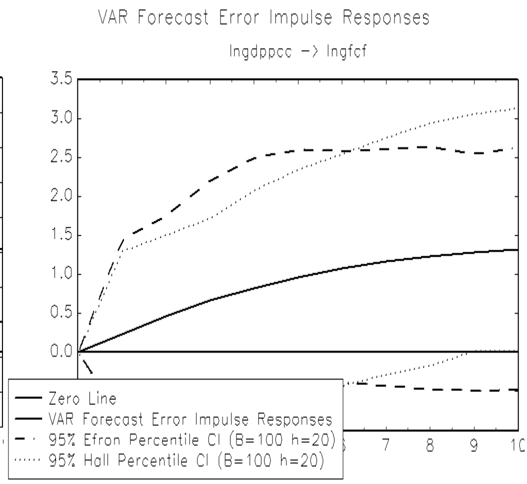

VAR Forecast Error Impulse Responses
lnenergyusepc -> lngfcf
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

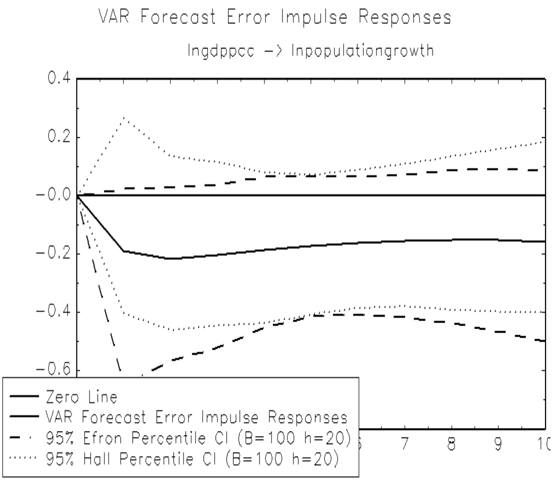

VAR Forecast Error Impulse Responses
lnenergyusepc -> lnpopulationgrowth
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

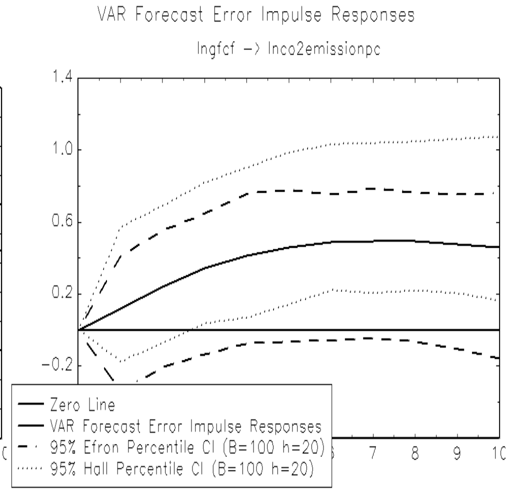

VAR Forecast Error Impulse Responses
lngdppcc -> lnco2emissionpc
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

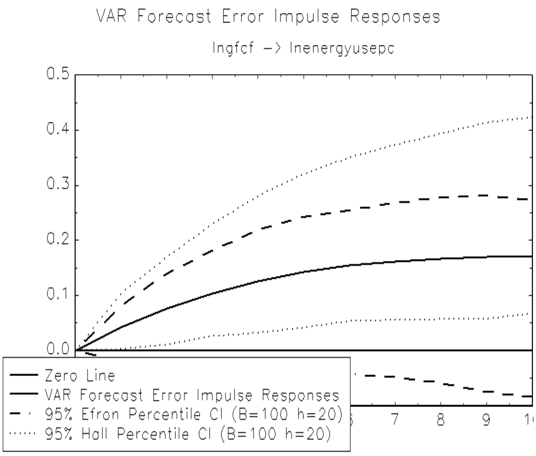

VAR Forecast Error Impulse Responses
lngdppcc -> lnenergyusepc
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

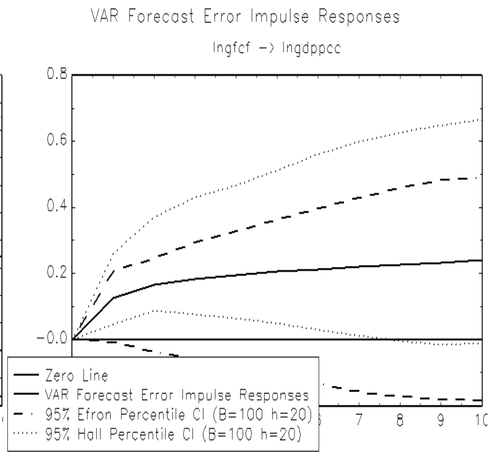

VAR Forecast Error Impulse Responses
lngdppcc -> lngdppcc
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

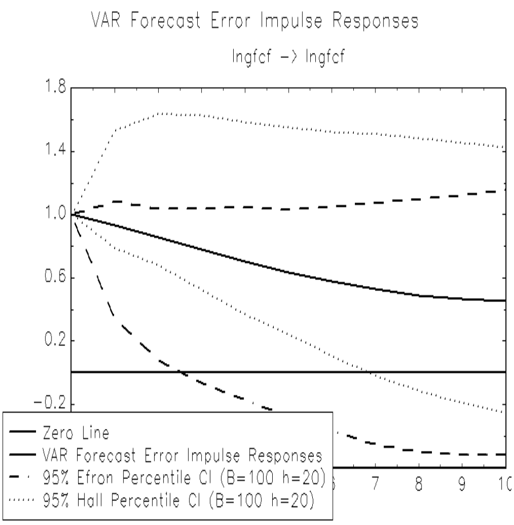

VAR Forecast Error Impulse Responses
lngdppcc -> lngfcf
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

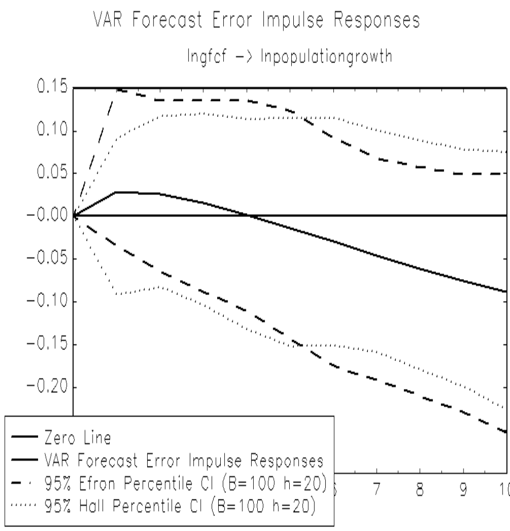

VAR Forecast Error Impulse Responses
lngdppcc -> lnpopulationgrowth
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

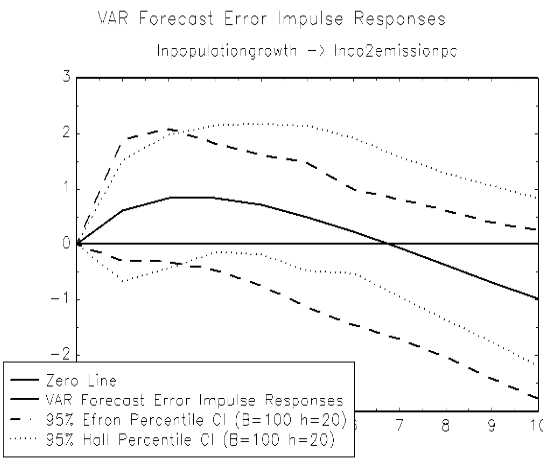

VAR Forecast Error Impulse Responses
lngfcf -> lnco2emissionpc
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

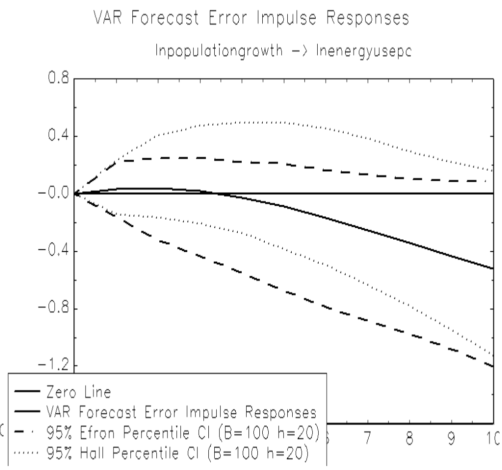

VAR Forecast Error Impulse Responses
lngfcf -> lnenergyusepc
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

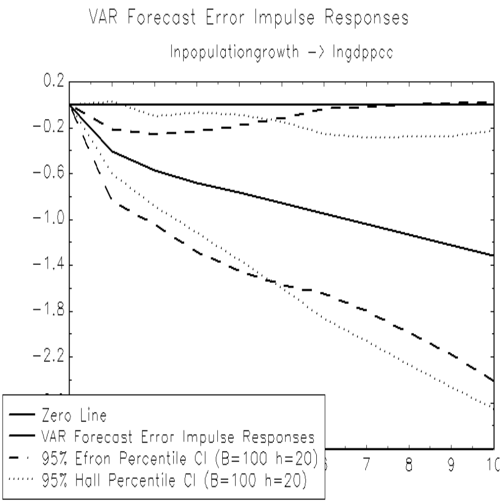

VAR Forecast Error Impulse Responses
lngfcf -> lngdppcc
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

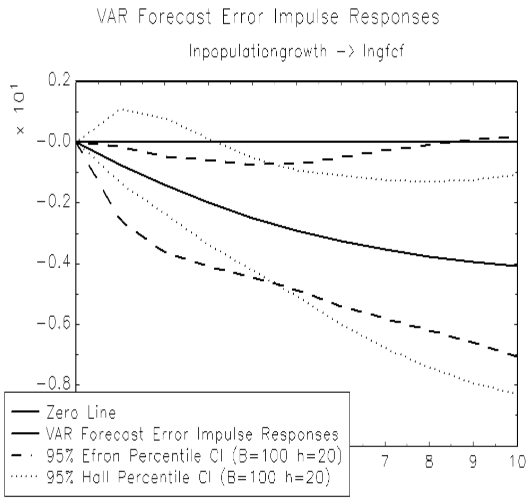

VAR Forecast Error Impulse Responses
lngfcf -> lngfcf
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

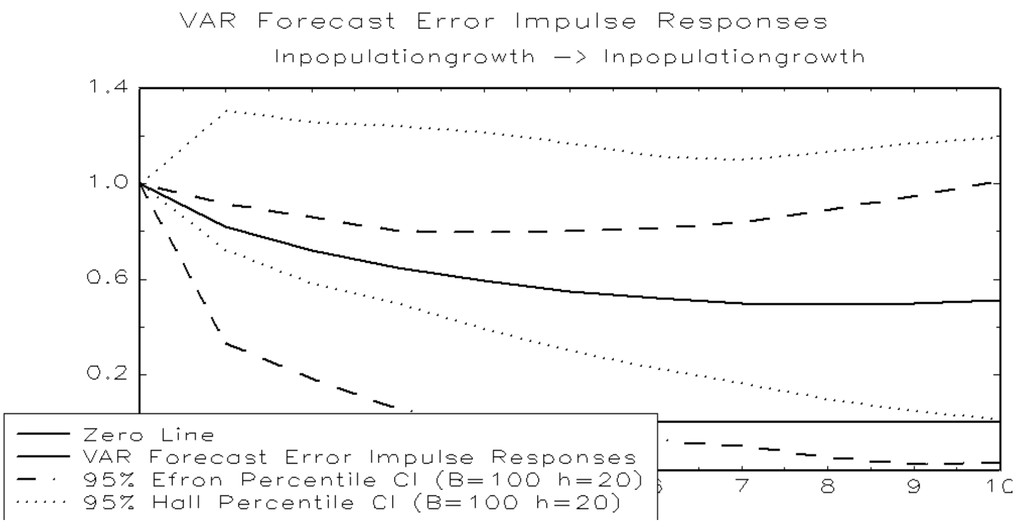

VAR Forecast Error Impulse Responses
lngfcf -> lnpopulationgrowth
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)


VAR Forecast Error Impulse Responses
lnpopulationgrowth -> lnco2emissionpc
3
2
1
0
−1
−2
7 8 9 10
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)


VAR Forecast Error Impulse Responses
lnpopulationgrowth -> lnenergyusepc
0.8
0.4
−0.0
−0.4
−0.8
−1.2
7 8 9 10
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)


VAR Forecast Error Impulse Responses
lnpopulationgrowth -> lngdppcc
0.2
−0.2
−0.6
−1.0
−1.4
−1.8
−2.2
7 8 9 10
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)


VAR Forecast Error Impulse Responses
lnpopulationgrowth -> lngfcf
× 10¹
0.2
−0.0
−0.2
−0.4
−0.6
−0.8
7 8 9 10
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)


VAR Forecast Error Impulse Responses
lnpopulationgrowth -> lnpopulationgrowth
1.4
1.0
0.6
0.2
7 8 9 10
Zero Line
VAR Forecast Error Impulse Responses
95% Efron Percentile CI (B=100 h=20)
95% Hall Percentile CI (B=100 h=20)

year	lngfcf	Lnpopulation growth	$lnco_2$ emissionspc	lngdppcc	Lnenergy usepc
1971	23.75193	0.829681	-1.12261	5.359332	5.630465
1972	23.82094	0.819694	-1.04021	5.331128	5.630829
1973	23.79475	0.814587	-0.93804	5.341194	5.635097
1974	23.77945	0.817093	-0.91875	5.330333	5.653529
1975	23.87465	0.823276	-0.89021	5.395082	5.667049
1976	23.99662	0.825982	-0.77699	5.388659	5.684512
1977	24.07152	0.826006	-0.5113	5.435891	5.688998
1978	24.10446	0.824049	-0.40266	5.46861	5.683769
1979	24.10073	0.819596	-0.41205	5.392117	5.705852
1980	24.17606	0.812176	-0.4368	5.43485	5.709819
1981	24.22092	0.801334	-0.40285	5.470828	5.738853
1982	24.2462	0.786619	-0.37272	5.482937	5.754969
1983	24.29875	0.767555	-0.39755	5.531844	5.765768
1984	24.35245	0.743618	-0.35098	5.548328	5.786358
1985	24.41833	0.714204	-0.29274	5.57892	5.815934
1986	24.47316	0.772417	-0.3075	5.603851	5.827863
1987	24.54141	0.753417	-0.31244	5.62142	5.84579
1988	24.62737	0.739621	-0.26131	5.692476	5.877205
1989	24.69325	0.720932	-0.28755	5.729717	5.903448
1990	24.80458	0.702619	-0.1714	5.763342	5.925654
1991	24.75641	0.684668	-0.00383	5.754091	5.94509
1992	24.82148	0.621959	0.100159	5.788819	5.966036
1993	24.85621	0.616615	0.16104	5.816867	5.969098
1994	24.96425	0.589818	0.158924	5.863252	5.988279
1995	25.11581	0.578881	0.160125	5.918376	6.024257
1996	25.13746	0.566945	0.264502	5.9736	6.039331
1997	25.19581	0.554865	0.345897	5.995928	6.060723
1998	25.26715	0.542637	0.050177	6.038815	6.065289
1999	25.3734	0.530258	0.158949	6.093094	6.10667
2000	25.37332	0.517724	0.22823	6.115825	6.109721
2001	25.44442	0.479938	0.327993	6.150519	6.107651
2002	25.5088	0.440669	0.363399	6.171957	6.11836
2003	25.63682	0.399795	0.358618	6.237431	6.129349
2004	26.08681	0.357178	0.432328	6.302672	6.170483

2005	26.27724	0.312664	0.441306	6.377952	6.190204
2006	26.45568	0.323271	0.433941	6.454302	6.225469
2007	26.64665	0.292955	0.568848	6.532876	6.270821