

Causality between GDP, Energy and Coal Consumption in India, 1970-2011: A Non-parametric Bootstrap Approach

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ABSTRACT: The aim of this paper is to examine the direction of causality between real GDP on the one hand and final energy and coal consumption on the other in India, for the period from 1970 to 2011. The methodology adopted is the non-parametric bootstrap procedure, which is used to construct the critical values for the hypothesis of causality. The results of the bootstrap tests show that for total energy consumption, there exists no causal relationship in either direction with GDP of India. However, if coal consumption is considered, we find evidence in support of unidirectional causality running from coal consumption to GDP. This clearly has important implications for the Indian economy. The most important implication is that curbing coal consumption in order to reduce carbon emissions would in turn have a limiting effect on economic growth. Our analysis contributes to the literature in three distinct ways. First, this is the first paper to use the bootstrap method to examine the growth-energy connection for the Indian economy. Second, we analyze data for the time period 1970 to 2011, thereby utilizing recently available data that has not been used by others. Finally, in contrast to the recently done studies, we adopt a disaggregated approach for the analysis of the growth-energy nexus by considering not only aggregate energy consumption, but coal consumption as well.

Keywords: Non-parametric Bootstrap Simulations; energy consumption; coal consumption; Granger causality

JEL Classifications: C15; C32; Q43

1. Introduction

The direction of causality between energy demand and economic growth is an issue of immense importance for the Indian economy. If for instance the direction of causality runs from energy consumption to gross domestic product, then any commitment to reduce carbon emissions by controlling energy consumption (through carbon tax for example) would necessarily result in a fall in the GDP of a country. In the other case where the direction of causality goes from gross domestic product to energy consumption, a commonly held view before the nineties, controlling energy demand for improving environmental performance would not hamper economic growth.

The most important source of power generation for India is coal. In 2011-12, 54 per cent of the total installed power generation capacity was coal based. It was used to generate 70 per cent of total power in the country. However, it is also a highly carbon intensive fuel, accounting for nearly 66 per cent of the total carbon emissions of India. According to the Planning Commission, coal would remain the most important contributor in power generation in India in the near future. Therefore, it is imperative to examine the nature of relationship of coal consumption with real GDP growth for the Indian economy. The utilization of coal resources for power generation would have important consequences not only on the economy but also on the environment, with regard to carbon emissions. Since the Kyoto Protocol became operational in 2005, these issues have received added importance, even though India has not accepted binding emission cuts. This paper attempts to investigate whether implementing carbon mitigation policies would have a limiting effect on the economic growth of India in the future.

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The aim of this study is to examine the direction of causality between real GDP on the one hand and final energy and coal consumption on the other for India over the period 1970-2011. The methodology adopted is the non-parametric bootstrap technique, which is used to construct the critical values for the hypothesis of causality. This method has not been used so far to examine the growth-energy connection for the Indian economy. The plan of the paper is as follows: In section 2, a review of the literature pertaining to causality studies is carried out. Section 3 discusses the methodology used in the model, and demonstrates the problems associated with asymptotic tests. Section 4 describes the data used in the model, and performs unit root and lag selection tests. The results of the causality tests along with interpretations are discussed in section 5. Concluding remarks follow in section 6.

2. Review of Literature

The section on literature review is divided into two parts. In the first part, we discuss the methodological aspects of the causality tests used in the literature. The second part is concerned with the findings of these studies on the energy-GDP causality hypothesis.

2.1. Methodological Issues

Since the seventies, the consensus has been that economic growth causally effects energy consumption, as well as its constituents such as electricity and fossil fuels. However, the use of causality tests suggested by Engle and Granger (1987) began to raise doubts on the direction of the link between income and energy consumption. Studies have since shown that causality could run from energy consumption to economic growth, from economic growth to energy consumption or in both directions at once, or in neither direction. Thus, these studies, spanning different regions and periods, have failed in providing a conclusive answer with respect to the direction of causation. In addition, wide varieties of methods have been employed to examine the causality hypothesis, and they have provided divergent results. The most common of these is the Engle-Granger causality test applied to linear VAR models.

The ARDL bounds testing approach suggested by Pesaran, Shin and Smith (2001) has also been a popular choice among researchers. Hsiao's (1982) measure for causality has also been utilized in some studies in this area. The Modified Wald statistic approach developed by Toda and Yamamoto (1995), Toda and Phillips (1993a, 1993b), and Lütkepohl and Dolado (1996) has similarly been applied to examine the energy-GDP nexus. Multiple-country studies based on panel data methods have been widely used as well. Francis et al. (2007) investigate causality between energy and GDP in a multivariate Bayesian VAR modeling framework.

We find that the above mentioned methods have limitations: the Wald statistic used to test for the hypothesis of causality in the conventional Granger test has a non-standard distribution in the presence of integrated variables. The problem is compounded if cointegration exists between the variables, thus making inference unreliable under these situations. We will discuss this in detail in later sections. The modified Wald statistic developed by Lütkepohl and Dolado (1996) addresses this problem by augmenting the VAR by additional lags to account for non-stationary data. The resulting adjusted Wald statistic has a standard chi-squared distribution. Another advantage of this method is that no prior information about cointegration is required. However, this method is inefficient when the lag order is small. For example, each additional lag results in an increase of k^2 new coefficients to be estimated. Therefore, the Dolado-Lütkepohl approach is best suited for systems where the lag order is large, such that the loss in power may not be substantial.

The ARDL bounds testing approach of Pesaran and Shin (1999) also accounts for the integrated and cointegrated properties of the data. They propose two sets of critical values, depending on the deterministic specification and cointegration structure, which serve as upper bounds and lower bounds respectively for the F-test of non-causality of long run and short run parameters. If the realized critical value lies between the upper and lower bound, then the test results are inconclusive and no inference can be made about the direction of causality. The panel data models testing for causality have been the most inconclusive, primarily because of the divergent results. This may be due to the loss in heterogeneity and smallness of cross sections of countries. The most significant problem however is with the dimension of the VAR models considered in the literature. We will see later that several papers in this area have adopted a multivariate modeling approach, as opposed to a bivariate VAR/VEC framework. In order to analyze causality between two variables in higher dimensional systems, we need to impose non-linear restrictions on the coefficients, as mentioned by Lütkepohl

(2005). Additionally, in a bivariate setting, the results of causality based on one-period ahead forecasts also apply to multi-period forecasts. This is not the case with higher dimensional systems: for example in a three-variable VAR constituted by x_t , y_t and z_t , the variable x_t maybe one-step non causal for y_t , but it may be s -step causal, for $s > 1$. Hsiao (1982), Dufour and Renault (1998), Eichler (2006) and Lütkepohl (1982, 2007) have examined issues related to multivariate causality.

Granger and Newbold (1974) and Phillips (1986) showed that for integrated variables, the standard asymptotic theory does not work. Subsequently, contributions to cointegration theory by Engel and Granger (1987) and Johansen (1988) brought forth the use of vector error correction (VEC) models. The VEC models were useful in modeling long-run relationships between cointegrated variables; this could not be possible in the conventional vector autoregressive (VAR) models. Granger also showed that the VEC models could be used to examine causality hypotheses. However, Sims, Stock and Watson (1990) showed that even in the presence of cointegration, asymptotically based causality tests are inapplicable and lead to faulty inference.

Following the seminal paper by Efron (1979), residual based bootstrapping techniques are increasingly being used in time series literature. Shakur and Mantolos (1998, 2000), Davison and Hinkley (1999) and Hacker and Hatemi (2005) have extended the use of bootstrapping to causality analysis. They point out the limitations of the asymptotic-based tests discussed earlier. For example, Mantolos and Shakur (2000) show through Monte-Carlo simulations that in small samples, both the standard and modified Wald approach has poor size properties, and lead to over rejection of the null hypothesis. They show that even in the presence of integrated variables and cointegration, the bootstrap test outperforms all the other tests in terms of size and power. In addition, the bootstrapping technique is much simpler to compute, as no prior information about the cointegration structure is required. We will describe the bootstrap method in detail in section 3. Recently, there have been several applications of bootstrap based causality tests in the literature including those investigating the GDP-energy nexus; some notable examples being Narayan and Prasad (2008), Hatemi and Shakur (1999), Hatemi and Irandoust (2009), Konya (2006), and Yalta (2009).

2.2. Studies on Causality

The issue of the direction of causality between energy consumption and GDP has been studied in great detail since the seventies, starting from the work of Kraft and Kraft (1978) who provide evidence in support of unidirectional causality from GNP to energy consumption for the U.S. Data for all the major countries and regions has been examined by employing different methodologies, covering different time periods. Unfortunately, the evidence from most studies for individual and groups of countries using different methodologies has failed to reach a consensus as to the direction of causation (see Ozturk, 2010 for literature survey). For instance, consider the case of the U.S: as mentioned earlier Kraft and Kraft (1978) found evidence of unidirectional causality running from GNP to energy consumption. However, Akarca and Long (1980), Hwang and Yu (1984), Erol and Yu (1987), and Yu and Choi (1985) using the same methodology did not find any causal relationship between the two variables. Moreover, Stern (1993) found that the direction of causation goes from energy consumption to GDP. Therefore, we can see that for the same country, all the three possible results have been obtained.

The same can be said for India-based studies. For example, Masih and Masih (1996) find that there is unidirectional causality running from energy consumption to GDP. On the other hand, Cheng (1999) shows that GDP growth precedes energy consumption, so the causation is in the other direction. He employs the Johansen–Hsiao’s version of the Granger causality method on the Indian data for the time period 1952–1995. His analysis shows that energy consumption, economic growth, capital and labor are cointegrated and the direction of causality runs from economic growth to energy consumption both in the short-run and in the long run. No causal relation is found from energy consumption to economic growth. However, Paul and Bhattacharya (2004) find empirical evidence of bidirectional causality between energy and GDP for the Indian economy.

The modeling strategy adopted in Asafu-Adjaye (2000) is based on Engle and Granger (1987). He used three variables – commercial energy use, real income and the consumer price index for the period 1973–1995. He found unidirectional Granger causality running from energy consumption to economic growth both in the short run and in the long run. This discrepancy in results between Cheng (1999) and Asafu-Adjaye (2000) may be due either to the choice of the sample period or to the measure of the variables or to the choice of the methodology or a combination of the factors.

There have been disaggregated approaches as well, looking at the constituents of energy consumption, like electricity, coal, petroleum and natural gas and their respective relationships with economic growth. Ghosh (2002) finds GDP in India causally influencing electricity, with no feedback effects. Mozumdar and Marathe (2006) find that a similar result holds for Bangladesh as well. Oh and Lee show the existence of bidirectional causality between South Korean electricity consumption and GDP in the long run. Other papers investigating the electricity-GDP relation are Yang (2000) Fatai et al. (2002), Squalli (2007), Zamani (2007), and Keppler (2007). Fatai et al. (2002), Zamani (2007), and Keppler (2007) also look at other factors such as oil and coal consumption.

The use of bootstrap methods to examine Granger causality in other areas has been increasing over the past decade: for example, Hatemi and Shakur (1998) examine the Granger causality hypothesis for government spending and government revenue in Finland. Konya (2006) analyses the causal relationship between savings and growth for a panel of eighty-four countries. Bootstrap methods to examine the energy-GDP relationship have been carried out only recently, i.e., after 2005. Narayan and Prasad (2008) examine this relationship for 30 OECD countries using bootstrap simulations. Hatemi and Irandoust (2005) investigate the direction of causality for Sweden using the leveraged bootstrap approach of Davison and Hinkley (1999), and find univariate causality flowing from GDP to final energy consumption. Yalta (2011) uses the method of maximum entropy bootstrap for Turkey to show the non-existence of a causal relationship between energy and GDP, after controlling for oil prices and exchange rate. The method of maximum entropy bootstrap, developed by Vinod (2004, 2006), relaxes the assumption of the independence of draws of the bootstrap sample in order to retain the strong dependence and heterogeneity that might be present in the data. We present a summary of some of the major papers that have examined the hypothesis of causality between energy consumption and GDP in table 1 below.

Table 1. Studies on Energy Consumption-GDP Causality Relations

No.	Author(s)	Period	Countries/ Regions	Methodology	Causality Results
1.	Kraft and Kraft (1978)	1947-74	U.S.	Bivariate Sims Test	GNP → Energy.
2.	Akarca and Long (1980)	1950-70	U.S.	Bivariate Sims Test	No causal relation.
3.	Yu and Hwang (1984)	1947-79	U.S.	Bivariate Sims Test	No causal relation.
4.	Yu and Choi (1985)	1954-76	U.S, South Korea, Philippines, U.K, Poland	Bivariate Granger Test	No causal relation for U.S, U.K, Poland, Energy → GNP for Korea and Philippines.
5.	Erol and Yu (1987)	1974-89	U.S.	Bivariate Granger Test	No causal relation.
6.	Abosedra and Baghestani (1989)	1947-87	U.S.	Bivariate Granger Test	GNP → Energy
7.	Hwang and Gum (1991)	1961-90	Taiwan	Bivariate VCEM Granger Test with Cointegration	GNP ↔ Energy
8.	Yu and Gin (1992)	1974-90	U.S.	Bivariate VCEM Granger Test with Cointegration	No causal relation.
9.	Stern (1993)	1947-90	U.S.	Bivariate Granger Causality	Energy → GDP
10.	Cheng (1995)	1947-90	U.S.	Bivariate VCEM Granger Test with Cointegration	No causal relation.
11.	Masih and Masih (1996)	1955-90	India, Indonesia, Philippines, Malaysia, Pakistan, Singapore	VCEM Granger Test with Cointegration	Energy → GDP for India, No causal relation for Philippines, Malaysia and Singapore, GDP → Energy for Indonesia, GDP ↔ Energy for Pakistan.

12.	Masih and Masih (1997)	1955-91	Taiwan and South Korea	Three Variable VCEM Granger Test with Cointegration	GDP <=> Energy
13.	Masih and Masih (1998)	1955-91	Thailand and Sri Lanka	Three Variable VCEM Granger Test with Cointegration	Energy -> GDP
14.	Cheng (1999)	1952-95	India	Johansen-Hsiao VCEM, Cointegration	GDP -> Energy
15.	Asafu-Adjaye (2000)	1973-95	India, Thailand, Indonesia, Philippines	Three Variable VCEM Granger Test with Cointegration	Energy -> GDP for India and Indonesia, GDP <=> Energy for Thailand and Philippines.
16.	Yang (2000)	1954-97	Taiwan	Bivariate Granger test	Electricity -> GDP
17.	Chang and Wong (2001)	1975-95	Singapore	Bivariate VCEM with Cointegration	GDP -> Energy.
18.	Ghosh (2002)	1950-97	India	Bivariate Engle-Granger test	GDP -> Electricity (per capita).
19.	Fatai et al. (2002)	1960-99	New Zealand	Multivariate Granger VCEM, Toda Yamamoto, Pesaran ARDL approach.	No causal relation between Total Energy and GDP, GDP->Oil and GDP-> Electricity.
20.	Sotyas and Sari (2003)	1950-92	France, U.K, U.S., Germany, Argentina, Turkey, Japan, South Korea, Italy.	Bivariate VCEM with cointegration	Mixed results.
21.	Paul and Bhattacharya (2004)	1950-96	India	VCEM with cointegration	GDP <=> Energy
22.	Oh and Lee (2004)	1970-99	South Korea	Bivariate VCEM with cointegration	Short-run; Electricity -> GDP, Long-run; Electricity <=> GDP
23.	Wolde-Rufael (2004)	1952-99	Shanghai	Toda and Yamamoto	Energy -> GDP
24.	Yoo (2005)	1970-02	South Korea	Bivariate VCEM with cointegration	Energy -> GDP
25.	Altinay and Karagol (2005)	1950-00	Turkey	Lütkepohl and Dolado modified Wald approach.	Energy -> GDP
26.	Narayan and Smyth (2005)	1966-99	Australia	Bivariate VCEM with cointegration	GDP <=> Energy
27.	Hatemi and Irandoust (2005)	1965-00	Sweden	Leveraged Bootstrap Test Approach	GDP -> Energy
28.	Yoo (2006)	1971-01	Indonesia, Thailand, Malaysia and Singapore.	Johansen's Multivariate Cointegration, Hsiao Trivariate Causality Approach.	Mixed Results.
29.	Mahadevan and Asafu-Adjaye (2006)	1971-02	20 developing and developed countries.	Panel VCEM and cointegration	GDP <=> Energy for energy exporting developed countries, Energy -> GDP (short-run) for energy exporting developing countries.
30.	Mozumder and Marathe (2006)	1971-99	Bangladesh	Bivariate VCEM with cointegration.	GDP -> Electricity
31.	Al-Iriani (2006)	1970-02	6 Gulf Countries	Panel VCEM and cointegration	Long-run; Energy -> GDP

32.	Zachariadis (2007)	1960-04	G-7 countries	Toda-Yamamoto Modified Wald Approach.	Mixed results.
33.	Squalli (2007)	1980-03	OPEC countries	Toda-Yamamoto Modified Wald Approach, ARDL bounds testing approach.	Electricity GDP, No consensus.
34.	Zamani (2007)	1967-03	Iran	VECM and cointegration	Long-run; GDP → Energy, coal, electricity, petrol.
35.	Lise and Montfort (2007)	1970-03	Turkey	Bivariate VCEM with cointegration.	Energy → GDP
36.	Yuan et al. (2007)	1978-04	China	Bivariate VCEM with cointegration.	Energy → GDP
37.	Francis et al. (2007)	1971-02	Caribbean Group	Bayesian VAR.	GDP ↔ Energy
38.	Narayan and Prasad (2008)	1971-04	30 OECD Countries	Bootstrap Causality Test	Mixed
39.	Keppler (2007)	1971-02	India, Brazil, China, Argentina, Egypt, Indonesia, Kenya, South Africa, Thailand	Bivariate VCEM with Cointegration	Long-run: per capita GDP → per capita oil and electricity for India.
40.	Narayan and Singh (2007)	1971-02	Fiji	ARDL Bounds Testing Approach	Electricity Consumption → GDP
41.	Ghosh (2009)	1970-06	India	ARDL Bounds Testing Approach	GDP, Electricity Supply → Employment
42.	Lee et al. (2008)	1960-01	22 OECD Countries	Trivariate Panel VCEM	Long-run; GDP ↔ Energy
43.	Yalta (2011)	1950-06	Turkey	Maximum Entropy Bootstrap Testing approach (Bivariate and Multivariate)	No causal relation between energy and GDP.
44.	Ozturk and Uddin (2012)	1971-07	India	Multivariate Johansen Juselius maximum likelihood procedure	GDP ↔ Energy
45.	Ocal et al. (2013)	1980-06	Turkey	Asymmetric causality test	No causal relation between coal consumption and growth.

3. Methodology

3.1. Introduction

According to Granger (1969), the notion of causality is based on the assumption that the future cannot cause the past, i.e., causality can only exist with the past causing the present or the future. Consider a bivariate VAR model with two variables, x_t and y_t . In such a framework, x_t is said to Granger cause y_t if we are able to make better forecasts of y_t with all the information available than if the information independent of x_t had been used. For a formal description of Granger causality used in Lütkepohl (2005), let us define Ω_t to be the information set containing all the information relevant to the model till time t , and let $x_t(s|\Omega_t)$ and $y_t(s|\Omega_t)$ be the optimal s -period ahead forecasts of x_t and y_t respectively. Further, let $\theta_x(s|\Omega_t)$ and $\theta_y(s|\Omega_t)$ be the corresponding forecast minimum squared errors (MSE). Then x_t Granger causes y_t if the following holds:

$$\theta_y(s|\Omega_t) < \theta_y(s|\Omega_t \setminus (x_q | q \leq t)) \quad \text{for at least one } s = 1, 2, 3, \dots \quad (1)$$

Here the set $\Omega_t \setminus (x_q | q \leq t)$ contains all information available apart from information on the past and present values of x_t . According to (1), if by incorporating all the information including that of the past and present values of variable x_t , we are able to make more efficient forecasts of y_t (due to the

lower MSE) than by excluding the past and present values of variable x_t , then x_t is Granger-causal for y_t . We can write the bivariate VAR (p) process as the following:

$$\begin{aligned} x_t &= \mathbf{e}_{1t} + \mathbf{A}_{11,1}x_{t-1} + \mathbf{A}_{12,1}y_{t-1} + \dots + \mathbf{A}_{11,p}x_{t-p} + \mathbf{A}_{12,p}y_{t-p} + \mathbf{u}_{1t} \\ y_t &= \mathbf{e}_{2t} + \mathbf{A}_{21,1}x_{t-1} + \mathbf{A}_{22,1}y_{t-1} + \dots + \mathbf{A}_{21,p}x_{t-p} + \mathbf{A}_{22,p}y_{t-p} + \mathbf{u}_{2t} \\ \Leftrightarrow z_t &= \mathbf{e}_t + \mathbf{A}_1 z_{t-1} + \dots + \mathbf{A}_p z_{t-p} + \mathbf{u}_t \end{aligned} \tag{2}$$

$$z_t = (x_t \ y_t)'$$

Since the null hypothesis in causality tests is always set up under the assumption of Granger-causality, we can say that in the system (2), x_t does not Granger cause y_t if and only if $\mathbf{A}_{21,i} = 0$, for all $i = 1, 2, \dots, p$. If the variables are non-stationary, then (2) can be expressed in the VEC model form in the following manner:

$$\begin{aligned} \Delta x_t &= \mathbf{e}_{1t} + \Gamma_{11,1} \Delta x_{t-1} + \Gamma_{12,1} \Delta y_{t-1} + \dots + \Gamma_{11,p-1} \Delta x_{t-p+1} + \Gamma_{12,p-1} \Delta y_{t-p+1} + \mathbf{A}_{11,1} x_{t-1} + \mathbf{A}_{12,1} y_{t-1} + \mathbf{u}_{1t} \\ \Delta y_t &= \mathbf{e}_{2t} + \Gamma_{21,1} \Delta x_{t-1} + \Gamma_{22,1} \Delta y_{t-1} + \dots + \Gamma_{21,p-1} \Delta x_{t-p+1} + \Gamma_{22,p-1} \Delta y_{t-p+1} + \mathbf{A}_{21,1} x_{t-1} + \mathbf{A}_{22,1} y_{t-1} + \mathbf{u}_{2t} \end{aligned} \tag{3}$$

The hypothesis of non causality of x_t for y_t is tested with the linear restrictions $\mathbf{A}_{21,i} = 0$ and $\Gamma_{21,i} = 0$ for $i = 1, 2, \dots, p$. However, we mentioned before that the asymptotic distribution of the test for (3) would be non-standard, particularly if cointegration is present. To derive the Wald statistic for (1), we make use of the following notation (the same notation will be used for describing the bootstrap method):

$$\begin{aligned} W &= (x_t \ y_t)' && (2 \times T) \\ A &= (\mathbf{e} \ \mathbf{A}_1 \ \mathbf{A}_2 \ \dots \ \mathbf{A}_p) && (2 \times (2p+1)) \\ Z_t &= (1 \ z_t \ z_{t-1} \ \dots \ z_{t-p+1}) && ((2p+1) \times 1) \\ Z &= (Z_0 \ Z_1 \ \dots \ Z_{T-1}) && ((2p+1) \times T) \\ U &= (u_1 \ u_2 \ \dots \ u_T) && (2 \times T) \\ a &= \text{vec}(A') && ((2^2 p + 2) \times 1) \end{aligned}$$

Then (1) can be written in the following form:

$$W = AZ + U \tag{4}$$

We now describe the null hypothesis and the corresponding Wald statistic:

$$H_0: C\alpha = 0$$

$$\lambda_{WALD} = (C\hat{\alpha})' [C((ZZ')^{-1} \otimes \Sigma_{\hat{u}})C']^{-1} (C\hat{\alpha}) \tag{5}$$

Where C is a restriction matrix of dimension $(N \times (2^2 p + 2))$, and rank equal to N (N is the number of restrictions to be tested). The problem, as mentioned before is that under the case of $I(1)$ variables and cointegration, (5) will not converge to the chi-squared distribution with N degrees of freedom.

3.2. Bootstrapping

The bootstrap simulation method based on Efron (1979) provides a useful alternative to the large-sample asymptotically based causality tests discussed earlier. The procedure involves estimating (2) by OLS (under the restricted model), which gives us estimates of the parameters $\mathbf{A}_1, \mathbf{A}_2, \dots, \mathbf{A}_p$ and d . This yields the following bootstrap data generating process (DGP):

$$z_t^* = \hat{\mathbf{e}}_t + \hat{\mathbf{A}}_1 z_{t-1}^* + \dots + \hat{\mathbf{A}}_p z_{t-p}^* + \mathbf{u}_t^* \tag{6}$$

In (6), the stars indicate that the data has been simulated. Now the residuals obtained from the OLS estimation of (2) provide consistent estimates of u_t , for all T . We now use these residuals to draw a random sample of size T (for each of the two variables), with replacement, with each draw having the probability $1/T$. This process is replicated K number of times, and in our case, $K = 10,000$. Once we have drawn a sample, we then obtain the bootstrapped values of z_t^* by substituting the parameters estimated earlier and the sampled residuals in (6). Since there are p lags in the VAR model, the bootstrap samples must be constructed recursively. This means that each sample is conditional on the first p values of the VAR.

Since we make no assumptions about the nature of the distribution of the residuals, the cumulative density function (CDF) is unknown. To estimate the CDF of the errors, the Fundamental Theorem of Statistics is used, which states that the CDF of a random variable is consistently estimated by its empirical distribution function (EDF). The empirical distribution of a random variable X , with CDF equal to $G(x)$, can be defined for a sample of T observations as a discrete distribution that assigns a weight of $1/T$ to each $x_t, t = 1, 2, \dots, T$. The EDF can be expressed as the following:

$$\hat{G}(x) = 1/T \sum_t I[x_t \leq x] \tag{7}$$

Where the function $I[.]$ is the indicator function, assuming the value of unity when its argument is true, and equaling zero in other cases. In the next step of the process, for each of the K bootstrapped

samples of z_t^* , we compute the Wald statistic λ_{WALD}^* given below, and then construct the EDF of λ_{WALD}^* analogous to (7):

$$\lambda_{WALD}^* = (\hat{C}\hat{a})'[C((Z^*Z^*)^{-1} \otimes \Sigma_{u^*})C']^{-1}(\hat{C}\hat{a}) \quad (8)$$

$$\hat{G}(x) = 1/K \sum_K I[\lambda_{WALD, K}^* \leq \lambda_{WALD}^*] \quad (9)$$

Finally, in the last step we compute the p-value of the null hypothesis by using (8) and (9):

$$p^*(\lambda_{WALD}^*) = 1 - 1/K \sum_K I[\lambda_{WALD, K}^* \leq \lambda_{WALD}^*] \quad (10)$$

The principal reason why this method is called non-parametric bootstrapping is that it is not based on the assumption of normality of the error terms. In other words, we make no distributional assumptions about the errors. These methods of bootstrapping are also popularly known as resampling methods. Resampling methods can be distinguished from parametric bootstrap techniques, where the bootstrap samples are drawn from a normal distribution. Not surprisingly, resampling or non-parametric bootstrap methods have been more popularly used in the literature than parametric methods, because of the non-requirement of the assumption of normality.

4. Data

4.1. The Dataset

The paper utilizes annual data on three variables for the period 1970-2011. The variables are real GDP (gdp_t) (in billions U.S dollars at 2005 prices), total primary energy consumption (ec_t), measured in gigawatt-hours, and coal consumption (cc_t), measured in million metric tons. The source of data on real GDP is the United Nations Statistics Division Database. Data on energy and coal consumption has been sourced from the Energy Statistics Report 2013. All variables are expressed in natural logarithms. Note that coal is one of the primary sources of energy. The total primary energy consumption is the sum of four sources of energy: coal, natural gas, petroleum and non-thermal electricity, which comprises of nuclear, hydroelectric, and renewable resources. We consider two bivariate VAR models: the first is a VAR model of real GDP and energy consumption, and the second is a VAR model with two variables, namely, real GDP and coal consumption.

In order to proceed with the analysis, we first carry out unit root tests to establish the non-stationary nature of the variables, and the optimal lag order of the two VAR models. For the unit root test, we use the Augmented Dickey-Fuller and Phillips-Perron tests. Additionally, we make use of the Bayesian Schwartz information criterion (SBC) and the Hannan-Quinn information criterion (HQ) for determining the optimal lag structure of the two models.

4.2. Unit Root Tests

In this section, the variables in the model are tested for the presence of unit roots. To test for the presence of non-stationarity in the data, the Augmented Dickey Fuller test and the Phillips-Perron test are used. The tests are similar in two respects. First, both are set up under the null hypothesis of a unit root. Second, the tests are designed to take account of serial correlation in the data. However, they differ in the method in which they deal with serial correlation. The Augmented Dickey-Fuller test does this by adding lags (in differences) of the concerned variable. In contrast, Phillips and Perron (1988) follow a nonparametric approach to account for autocorrelation in the data, i.e. rather than using additional lags (which consequently results in loss of effective data observations) a correction is made to the standard OLS estimated coefficient and the corresponding standard error to adjust for both autocorrelation and heteroskedasticity. A variant of the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator provided by Newey and West (1987) is used for correcting the test statistics. In both the unit root tests, a deterministic drift term and an intercept term are included in the regression since the levels of all the variables (in logarithms) appear to be trending with non-zero means. The equation for the Augmented Dickey-Fuller test is as follows:

$$\Delta x_t = \gamma_0 + \gamma_1 t + (\lambda - 1)x_{t-1} + \sum_j \beta_j \Delta x_{t-j} + \varepsilon_t \quad (11)$$

$$H_0: \lambda = 1 \quad \text{vs.} \quad H_A: \lambda < 1 \quad (12)$$

The equation for the Phillips-Perron unit root test is identical. However, the terms of lagged changes are excluded and the expression based on the Newey-West estimator of the standard error for accounting for autocorrelation is used.

The asymptotic distribution of the test statistic under the null hypothesis is different from the conventional t-statistic, because x_t follows a random walk if H_0 is true. As a consequence, critical values provided by Dickey and Fuller are used for both versions of the test. The following table

presents the unit root results for the variables, in both levels and first differences. The statistics obtained can be directly compared to the critical values at the one per cent, five per cent and ten per cent significance level for each test. We can clearly see from the results below that all the variables in the levels are non-stationary, and additionally are stationary in first differences.

Table 2. Unit Root Results

Variable	ADF Test Statistic		PP Test Statistic	
	Levels	First Difference	Levels	First Difference
Real GDP (gdp)	-1.462	-5.106**	-1.612	-7.334**
Energy Consumption (ec)	-2.166	-4.360**	-2.599	-7.585**
Coal Consumption (cc)	-2.214	-3.775*	-2.187	-5.542**

Critical Values

Critical Value	ADF Test	PP Test
1% Level of Significance**	-4.202	-4.196
5% Level of Significance*	-3.525	-3.522

4.3. Specification of Lag

Table 3 and 4 display the result of the HQ and SBC lag determination tests for the two VAR models. We specify the maximum lag order of 5 for both the models. The star in the term indicates the optimal lag order, given by the maximum of the log-likelihood function. The results show that for the first VAR model, which includes gdp_t and ec_t , the optimal lag order is 1, and for the second VAR model, it is 2.

Table 3. Hannan-Quinn Information Criterion (HQIC) Lag Specification Test

Lags	Model 1: gdp_t-ec_t	Model 2: gdp_t-cc_t
0	336.55	315.89
1	-306.69*	-315.19
2	-303.70	-320.25*
3	-295.36	-313.70
4	-286.31	-310.88
5	-287.29	-311.61

Table 4. Schwartz Bayesian Information Criterion (SBC) Lag Specification Test

Lags	Model 1: $gdpt-ect$	Model 2: $gdpt-cct$
0	336.54	315.89
1	-302.51*	-311.02
2	-295.36	-311.91*
3	-282.10	-301.18
4	-269.62	-293.99
5	-266.44	-290.74

5. Tests for Granger Causality

After determining the specification of both the bivariate VAR models, we can now proceed with the results of the causality tests. For both models, we test the causality by using the non-parametric bootstrap technique. There are four sets of hypotheses to be tested:

H1₀: GDP does not Granger-cause total energy consumption.

H2₀: Total energy consumption does not Granger-cause GDP.

H3₀: GDP does not Granger cause coal consumption.

H4₀: Coal consumption does not Granger-Cause GDP.

H1₀ and H2₀ belong to model 1 (gdp_t and ec_t), whereas H3₀ and H4₀ are tested in model 2 (gdp_t and cc_t). The corresponding p-values of the bootstrap test for all the four hypotheses are presented below.

Table 5 indicates that there exists no causality, in either direction between energy consumption and GDP for India over the period 1970-2011, since $H1_0$ and $H2_0$ cannot be rejected. With regard to the relationship between coal and GDP, the results of the bootstrap test confirm that there is unidirectional causality running from coal to GDP. This is a significant result as it shows that coal is a causal factor of GDP growth in India. It may seem surprising that even though aggregate energy consumption does not causally effect real GDP and coal consumption, which is the major component of aggregate energy consumption influences real GDP. There can be two plausible explanations for this. First, coal is an important raw material for industries other than the power sector, such as steel, railways (before 1995), cement paper, and jute, cotton and others. Therefore, it not only contributes to the electricity sector as a primary input of fuel, but also is linked to real GDP by contributing to the production of the above-mentioned industries. Second, it is plausible that while aggregation of all sources of energy is likely to obscure causality, disaggregation of sources of energy may show causality.

Table 5. P-Values of the Bootstrap Causality Test

Hypothesis	p-value: Bootstrap Test
$H1_0$	0.4530
$H2_0$	0.1112
$H3_0$	0.4706
$H4_0$	0.0068**

Previous studies have shown the non-existence of causality, in either direction, when aggregate energy consumption is considered, but the existence of causality between components of energy consumption and GDP. A case in point is the paper by Fatai et al., (2002), which is based on the New Zealand economy. The authors show that there exists no causal relationship between total energy consumption and GDP. However, they find evidence in support of unidirectional causality running from GDP to both oil consumption and electricity consumption. Another example is a study by Keppler (2007), which finds no causal relation between per capita energy consumption and per capita GDP, in either direction for China. However, causality is running from per capita oil and electricity consumption to per capita GDP. We believe that in order to examine the causality between energy and GDP, a disaggregated approach is more desirable.

Increased usage of coal will put a strain on the environment by way of increased emissions of gases that contribute to global warming. This is particularly true for several varieties of coal that are used throughout the rural parts of the country. Growing concerns for the environment and the increasing importance of international forums like the United Nations Framework Convention on Climate Change (UNFCCC) will exert pressure on Indian policymakers to curb the consumption of coal, as well as to switch to cleaner technologies. In such a scenario, restricting carbon emissions and consumption of coal will most likely have adverse effect on economic growth. Therefore, it is imperative that India continues to invest in renewable sources of energy generation, such that the limiting effect of curbing emissions on economic growth is mitigated to some extent.

6. Conclusion

Coal is the most important source of energy for India, the largest contributor in power generation, and additionally used as an input of production in several industries. India is endowed with large reserves of coal. Coal deposits are mainly confined to eastern and south central parts of the country. Jharkhand, Orissa, Chhattisgarh, West Bengal, Andhra Pradesh, Maharashtra and Madhya Pradesh account for more than 99% of the total coal reserves in the country. The total estimated reserves in 2011-12 were estimated to be around 294 billion tons, production for the same year stood at 540 million tons. Coal will continue to be the dominant fuel until 2032, with a projected requirement of 1440 million tons.

However, coal also has the single largest share of nearly 69 percent in aggregate carbon emissions for the Indian economy. As a consequence, there are serious environmental concerns associated with its increased use in the future. The exhaustibility of coal resources is also a major concern, as noted by the report of the Planning Commissions' Integrated Energy Policy. Further, a

large section of India's population still has no access to electricity. Of the 1.4 billion people of the world who have no access to electricity in the world, India accounts for over 300 million. Increasing energy access to rural areas would exert substantial pressure on the existing coal resources. According to the report, given the current levels of production, coal reserves could be exhausted in less than 40 years, and this obviously has serious energy security ramifications.

Therefore, it is imperative that the dependency of future energy requirements of India on coal be reduced. This can be achieved in several ways: undertaking measures to improve the fuel conversion efficiency of power plants (considered low by international standards), expanding the exploration base, controlling excessive and illegal mining, encouraging fuel substitution in the non-power sector (for example in the railways and steel sectors). Besides, efficient demand-side management needs to be undertaken. Most importantly, investing in alternative technologies of power generation can reduce this dependence. This would also lead to a diversification of the energy sector, and of the power sector in particular, making the country less dependent on any one fuel.

We find that the use of bootstrap methods of testing for the presence/ absence of Granger causality has advantages over the conventionally used asymptotic tests. The bootstrap test does not require the strong assumption of normality; it works well for non-stationary data and additionally has better small sample properties than the asymptotic tests. Our analysis shows that according to the non-parametric bootstrap approach, there exists no causal relationship, in either direction, between GDP and total energy consumption for India, for the period under study. However, if coal consumption is considered, we find evidence in support of unidirectional causality running from coal consumption to GDP. This clearly has important implications for the future of the Indian economy. The most important implication is that restricting coal consumption in order to reduce carbon emissions would in turn have a limiting effect on economic growth.

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