Revisiting Coal Consumption and Output Nexus in China and India: A Frequency Domain Approach

Xiaoyan Zhang
Business School, Shandong Normal University
Email: 214964208@qq.com; breezezxy@163.com

Hsiao-Ping Chu
Department of Business Administration, Ling-Tung University, Taichung, TAIWAN
Email: clare@teamail.ltu.edu.tw

Tsangyao Chang
Department of Finance, Feng Chia University, Taichung, TAIWAN
Email: tychang@mail.fcu.edu.tw

Roula Inglesi-Lotz[1]
Department of Economics, University of Pretoria, South Africa
Email: roula.inglesi-lotz@up.ac.za

Abstract

Dependency on coal consumption to maintain energy security is common to the majority of developing countries where the coal is found in abundance. China and India are the leaders in coal consumption from the developing countries group so establishing a relationship between the coal consumption and the economic growth for these two will derive useful lessons for policy makers. This paper re-examines the causal relationship between coal consumption and economic growth in China and India for the period 1969-2013, for the first time using a frequency domain – based Granger causality test proposed by Brietung and Candelon (2006). Our empirical results support unidirectional causality running from coal consumption to economic growth for both China and India. Our findings provide important policy implications for energy policies and strategies for these two countries under study.

Keywords: Coal Consumption, Output; Granger Causality Test; Frequency Domain; China and India
JEL: C23; Q43

[1] Corresponding author.

Introduction

Since the start of the 21st century, coal production has been the fastest-growing global energy source. It is the second source of primary energy in the world after oil, and the first source of electricity generation. The total world coal consumption increased by nearly 63% from 2354 million tonnes of oil equivalent (mtoe) in 2000 to an estimated 3827 mtoe in 2013 (BP, 2014). As of March 2012, approximately 40% of the world's electricity needs were provided by coal.

Growth in coal demand varies from country to country: while coal consumption has stagnated among OECD countries since the beginning of this century, the surge in global coal consumption is driven primarily by developing economies, such as China and India (together close to 58% of the world in 2013 (BP, 2014)). Economic growth is likely to be robust in both China and India over the next five years.

Coal is the key fuel in both countries' energy mix (approximately 75% for China and 55% for India on average for the period 1965 to 2013). This paper aims to re-investigate the causal relationship between coal consumption and economic growth in China and India by using the frequency-domain GC test proposed by Brietung and Candelon (2006) for the first time. With these, the current research hopes to fill the existing gap in the literature.

While the vast majority of empirical research already performed has been focused on time domain approach to investigate the causal relationship between coal consumption and economic growth in both developing and developed countries, none has been done using frequency domain approach in this issue. Though traditional approaches to Granger causality (GC, hereafter) have yielded many interesting insights, they generally tacitly ignore the possibility that the strength and/or direction of the GC relationship – if any – could vary over different frequencies (Lemmens et al., 2008). The idea of further disentangling the GC relationship between two time series was first suggested by Granger (1969). In his idea that a spectral-density approach would give a better-off and more complete picture than a one-shot GC measure that is supposed to apply across all periodicities (e.g., in the short run, over the business cycle frequencies, and in the long run).

The paper is structured as follows. The next section discusses briefly past papers that dealt with the same research question. Section 3 first discusses the data and then outlines the GC methodology over the spectrum proposed by Brietung and Candelon (2006) in section 3. Section 4 presents our empirical findings using the frequency domain approach. Section 5 concludes the paper.

Brief literature review

Over the past several decades the relationship between energy consumption and economic growth has been extensively researched (see Payne, 2010; Ozturk, 2010). More specifically, a number of studies have focuses on the coal consumption with the view of testing four different hypotheses: growth hypothesis (coal consumption causes economic growth), conservation hypothesis (economic growth causes coal consumption), feedback hypothesis (bidirectional relationship between economic growth and coal consumption), and neutrality hypothesis (no relationship between the two) (Yang, 2000; Wolde-Rufael, 2010; Lee and Chang, 2005; Yoo, 2006; Apergis and Payne, 2010; Chang et al. (forthcoming)).

In the case of confirmation of the growth hypothesis, excessive energy protection and reduction in energy consumption may lead to negative economic growth while if the conservation hypothesis is confirmed, energy conservation policies designed to reduce energy consumption and waste may not have an adverse impact on real GDP but higher economic growth will drive the coal demand higher. Thus, knowledge of the causal relationship and the direction between energy consumption and economic growth are of particular importance to policy makers to make an appropriate energy strategy.

Jinke et al. (2008) indicate that there is a unidirectional causality running from growth to coal in China but the neutrality hypothesis is confirmed for India. Govindarajau and Tang (2013) showed that for India, a unidirectional causality runs from economic growth to coal consumption for the period 1965 to 2009. Wolde-Rufael (2010) concluded that for China the conservation hypothesis is confirmed while Chang et al. (forthcoming) concluded the opposite by employing a methodology taking into account cross-sectional dependence among the BRICS countries with more recent data than Wolde-Rufael (2010). For India, Wolde-Rufael (2010) and Chang et al. (forthcoming) agreed in favour to the growth hypothesis. More recently, Bildirici and Bakirtas (2014) concluded that there is a bidirectional causality between coal consumption and economic growth for China and India with data ending for the year 2011 while in a panel framework with data from 2000 to 2010 and using coal prices as a third variable, Lei and Pan (2014) have shown that economic growth caused coal consumption in China and the neutrality hypothesis was confirmed for India. Our study although aiming to address the same issue, it does so with more updated information (period from 1969 until 2013) and with a methodology that has not been previously employed in the literature.

Methodology

Following Brietung and Candelon (2006), first of all, let $z_t = [x_t, y_t]'$ be a two-dimensional vector of time series (coal consumption and per capita real GDP, respectively, in our case) observed at $t = 1,...,T$. We assume that z_t has finite-order VAR representation of the following form:

$$\Theta(L)z_t = \epsilon_t \tag{1}$$

In equation (1), $\Theta(L) = I - \Theta_1 L - ... - \Theta_p L$ is a 2x2 lag polynomial with $L^k z_t = z_{t-k}$. Here we assume that the error vector ε_t is white noise with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t{}') = \Sigma$, where Σ is positive definite. For ease of exposition we neglect any deterministic terms in (1) although in empirical applications the model typically includes a constant, trend or dummy variables.

Let G be the lower triangular matrix of the Cholesky decomposition $G'G = \Sigma^{-1}$ such that $E(\eta_t \eta_t') = I$ and $\eta_t = G\varepsilon_t$. If the system is assumed to be stationary, the MA representation of the system is

$$z_t = \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \qquad (2)$$

In equation (2), $\Phi(L) = \Theta(L)^{-1}$ and $\Psi(L) = \Theta(L)G^{-1}$. Using this representation the spectral density of x_t can be expressed as

$$f_x(\omega) = \frac{1}{2\pi}\left\{\left|\Psi_{11}(e^{i\omega})\right|^2 + \left|\Psi_{12}(e^{i\omega})\right|^2\right\} \qquad (3)$$

The measure of causality suggested by Gweke (1983) and Hosoya (1991) is defined as

$$M_{y\to x}(\omega) = \log\left[\frac{2\pi f_x(\omega)}{\left|\Psi_{11}(e^{-i\omega})\right|^2}\right] \qquad (4)$$

$$= \log\left[1 + \frac{\left|\Psi_{12}(e^{-i\omega})\right|^2}{\left|\Psi_{11}(e^{-i\omega})\right|^2}\right] \qquad (5)$$

The measure is zero if $\left|\Psi_{12}(e^{i\omega})\right| = 0$, in which case we say that y does not cause x at frequency ω. If the elements of z_t are $I(1)$ and cointegrated, then the autoregressive polynomial $\Theta(L)$ has a unit root. The remaining roots are outside the unit circle. Subtracting z_{t-1} from both sides of (1) gives us the following form

$$\Delta z_t = (\Theta_1 - I)z_{t-1} + \Theta_2 z_{t-2} + \cdots + \Theta_p z_{t-p} + \varepsilon_t = \tilde{\Theta}(L)z_{t-1} + \varepsilon_t \qquad (6)$$

In equation (6), $\tilde{\Theta}(L) = \Theta_1 - I + \Theta_2 L + \ldots + \Theta_p L^p$, If y is not a cause of x in the usual Granger sense, then (1,2)-element of $\Theta(L)$ (or $\tilde{\Theta}(L)$) is zero. In the frequency domain, the measure of causality can be defined by using the orthogonalized MA representation

$$\Delta z_t = \tilde{\Phi}(L)\varepsilon_t = \tilde{\Psi}(L)\eta_t \qquad (7)$$

In equation (7), $\tilde{\Psi}(L) = \tilde{\Phi}(L)G^{-1}$, $\eta_t = G\varepsilon_t$, and G is a lower triangular matrix such that $E(\eta_t \eta_t{}') = I$. Under a bivarite cointegrated system $\beta'\tilde{\Psi}(1) = 0$, where β is a cointegrating vector such that $\beta' z_t$ is stationary (Engle and Granger, 1987).[2] As in the stationary case, the resulting causality measure is defined as the follows

$$M_{y\to x}(\omega) = \log\left[1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right] \qquad (8)$$

In order to test the hypothesis that y does not cause x at frequency ω we consider the null hypothesis as the follows

$$M_{y\to x}(\omega) = 0 \qquad (9)$$

From (5) if follows that $M_{y\to x}(\omega) = 0$ if $\left|\Psi_{12}(e^{i\omega})\right| = 0$. Using $\Psi(L) = \Phi(L)^{-1}G^{-1}$ and

$$\Psi_{12}(L) = -\frac{g^{22}\Theta_{12}(L)}{|\Theta(L)|} \qquad (10)$$

Where g^{22} is the lower diagonal element of G^{-1} and $|\Theta(L)|$ is the determinant of $\Theta(L)$.

If follows that y does not cause x at frequency ω if

$$\left|\Theta_{12}(e^{i\omega})\right| = \left|\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega) - \sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)i\right| = 0 \qquad (11)$$

Where $\theta_{12,k}$ is the (1,2)-element of Θ_k. Thus a necessary and sufficient sets of conditions for $\left|\Psi_{12}(e^{i\omega})\right| = 0$ is

$$\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega) = 0 \qquad (12)$$

$$\sum_{k=1}^{p}\theta_{12,k}\sin(k\omega) = 0 \qquad (13)$$

Since $\sin(k\omega) = 0$ for $\omega = 0$ and $\omega = \pi$, restriction (13) can be dropped in these cases.

[2] Of course, this model can also be extended to higher-dimensional systems. Details see Hosoya (2001) and Brietung and Candelon (2006).

Following Brietung and Candelon (2006), our approach is also based on the linear restrictions (12) and (13). To simplify the notation, we let $\alpha_j = \theta_{11,j}$ and $\beta_j = \theta_{12,j}$, so that our VAR equation for x_t is written as

$$x_t = \alpha_1 x_{t-1} + \cdots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_{1t} \quad (14)$$

The null hypothesis $M_{y \to x}(\omega) = 0$ is equivalent to the linear restriction

$$H_0: R(\omega)\beta = 0 \quad (15)$$

Where $\beta = [\beta_1, \ldots \beta_p]'$ and

$$R(\omega) = \begin{bmatrix} \cos(\omega)\cos(2\omega)\ldots\cos(p\omega) \\ \sin(\omega)\ \sin(2\omega)\ldots\sin(p\omega) \end{bmatrix} \quad (16)$$

According to Brietung and Candelon (2006), the ordinary F statistic for (15) is approximately distributed as $F(2, T-2p)$ for $\omega \in [0, \pi]$.

Data

This study uses annual data cover the period from 1969 to 2013 for both China and India. The variables in this study include total coal consumption (*COC*) and real GDP (*RGDP*). Coal consumption is expressed in terms of millions of tonnes and data is from the BP Statistical Review of World Energy, 2014. Real GDP measured in constant 2005 U.S. dollars and comes from the World Development Indicators (WDI, 2014). Table 1 and Table 2 show the summary statistics of real GDP and total coal consumption, respectively. Based on Tables 1 and 2, we find that China and India have the mean real GDP of US$1860.22 and US$684.30 millions, respectively. Regarding the coal consumption, China and India have the mean coal consumption of 669.82 and 120.91 millions of tons, respectively. Based on Jarque-Bera results from Tables 1 and 2, we also find all data series are approximately non-normal for both real GDP and coal consumption.

Table 1. Summary Statistics of GDP

country	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
China	1860.12	7513.69	142.02	2057.86	1.35	3.72	14.64***
India	684.30	1988.89	196.71	512.49	1.14	3.19	9.82***

Note: 1. The sample period is from 1969 to 2013.

Table 2. Summary Statistics of Coal

	Mean	**Max.**	**Min.**	**Std. Dev.**	**Skew.**	**Kurt.**	**J.-B.**
China	669.82	1925.29	130.41	487.97	1.18	3.38	10.63***
India	120.91	324.30	37.56	76.46	0.99	3.17	7.49**

Note: 1. The sample period is from 1969 to 2013.

Empirical Results and Policy Implications

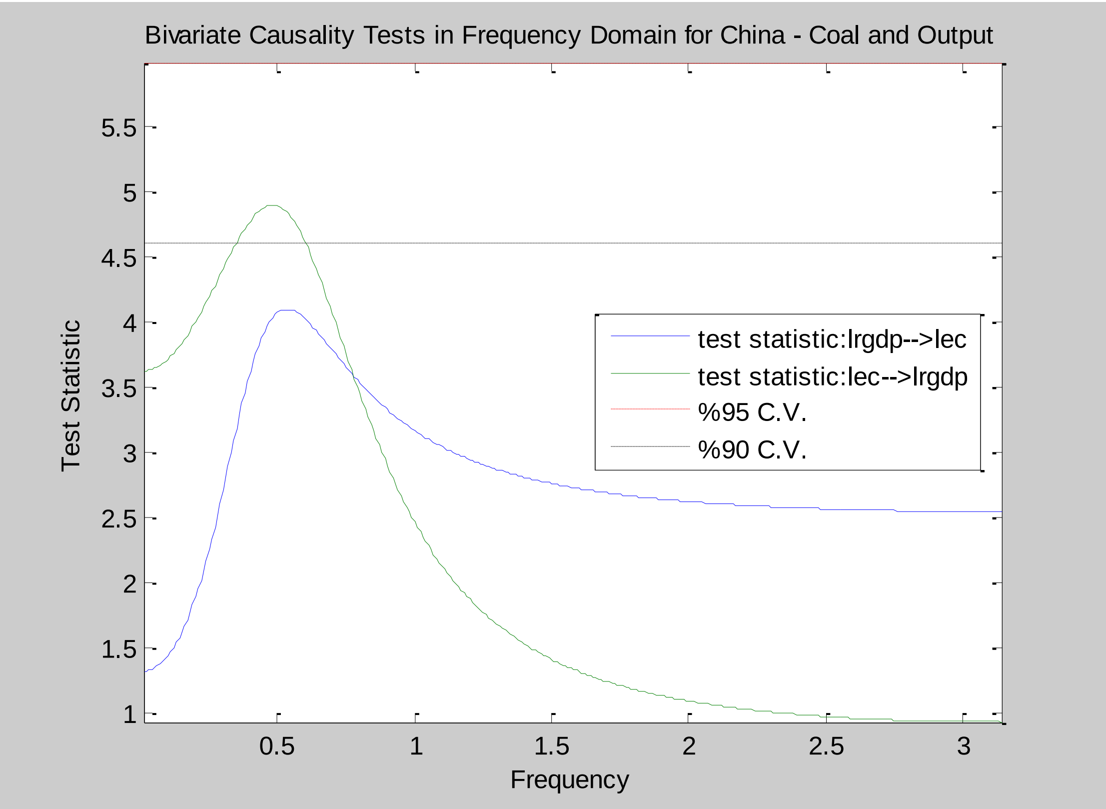
First of all, we need to specify a bivariate system for GC test. Since we find coal consumption and per capital real GDP in China and India are both I(1) process and two data series are also cointegrated.[3] Following Toda and Yamamto (1995), our VAR model is augmented with a redundant lag, that is, instead of using the VAR(p) model, the restriction are tested by using a VAR(p+1) model.[4] According to SBC criterion, a VAR (4) model was selected for both two countries. The results of the GC tests in the frequency domain are presented in Figures 1-2. The figures report the test statistics along with their 10% and 5%

[3] To save space, results about unit root and cointegration tests are not reported here but available upon request.
[4] According to Brietung and Candelon (2006), this approach can also be used to establish standard inference for the frequency domain GC test.

critical values (broken lines parallel to the frequency axis) for all frequencies in the interval $(0, \pi)$. We briefly describe our empirical results for both China and India, respectively, as the follow:

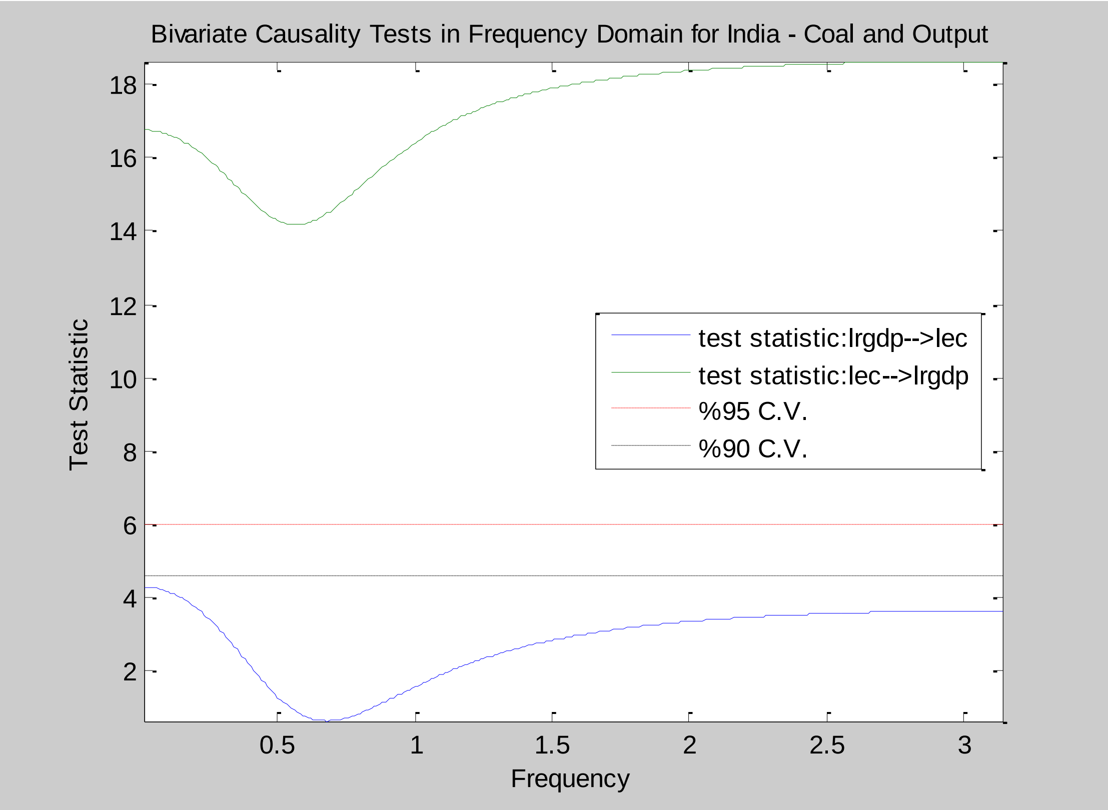
Based on the results from Figure 1, we can see that coal consumption provides significant predictive power for future output movements in the range $\omega \in [0.4, 0.6]$. This result also indicates that coal consumption is a powerful predictor for economic activity. If we further look at Figure 1, we can see that output provides no predictive power for future coal consumption movements for all frequencies in the interval $(0, \pi)$. Our results support growth hypothesis in China.

Figure 1. Bivariate Causality tests in Frequency domain for China - Coal and output



Based on the results from Figure 2, we can see that coal consumption also provides significant predictive power for future output movements at all frequencies in the interval $(0, \pi)$. This result indicates that coal consumption is a powerful predictor for economic activity in India. If we further look at Figure 2, we can see that output also provides no predictive power for future coal consumption movements for all frequencies in the interval $(0, \pi)$. Our results also support growth hypothesis in India.

Figure 2. Bivariate Causality tests in Frequency domain for India - Coal and output.



Conclusions

Coal as a fuel has attracted increasing attraction in the international literature for numerous reasons: firstly, coal is the most "popular" fossil fuel especially in developing economies due to its abundance in nature and hence, cost-effectiveness. At the same time, coal-burning power generation is infamous for its emissions and hence, negative consequences to the environment and climatic conditions.

Although, the causal relationship of coal consumption and economic growth is not a new topic in the literature, this paper is first one to re-examine it for China and India for the period 1970-2011, using a frequency domain – based GC test proposed by Brietung and Candelon (2006). The two countries were chosen because of their dominance in coal consumption internationally.

Our results support the growth hypothesis for both China and India, therefore, economic growth is dependent on coal consumption, which are in agreement with Chang et al. (forthcoming). These findings imply that negative energy shocks and energy conservation policies may depress economic growth in both China and India. The future economic potential of these two countries might be unfolded if the energy policy makers achieve to reduce their dependence to coal and explore more actively other types of fuels.

Funding

Dr. Xiaoyan Zhang acknowledges the “Fund Project: Youth Project from Ministry of Education, Influence of Financial Resources Aggregation on Substantial Economy: Three Economic Zones as an Example (2013YJC790207). Outstanding Young Scientists of Shandong Province, Study on development evaluation and economic performance of Inclusive Finance in Shandong Province (BS2015SF018).

References

Brietung, J., and Candelon, B. (2006) Testing for short- and long-run causality: A frequency-domain approach, *Journal of Econometrics*, 132, 363-378.

Bildirici, M.E., Bakirtas, T., (2014). The relationship among oil, natural gas and coal consumption and economic growth in BRICTS (Brazil, Russia, India, China, Turkey and South Africa) countries. Energy 65, 134-144.

Engle, R.F., and Granger, C.W.J. (1987) Co-integration and error correction: representation, estimation, and testing. *Econometrica*, 55, 251–276.

Geweke, J. (1982) Measurement of linear dependence and feedback between multiple time series, *Journal of the American Statistical Association*, 77, 304–324.

Govindaraju, V.G.R., Tang, C.F., (2013). The dynamic links between CO2 emissions, economic growth and coal consumption in China and India. Applied Energy 104, 310-318.

Granger, C. W. J., (1969) Investigating causal relations by econometric models and cross-spectral methods, *Econometrica*, 37, 424-438.

Hosoya, Y. (1991) The decomposition and measurement of the interdependence between second-order stationary process. *Probability Theory and Related Fields,* 88, 429–444.

Hosoya, Y. (2001) Elimination of third-series effect and defining partial measures of causality, *Journal of Time Series Analysis,* 22, 537–554.

IEA *Medium-Term Coal Market Report 2011*.

Jinke, L., Hualing, S., Dianming, G. (2008). Causality relationship between coal consumption and GDP. Difference of major OECD and non-OECD countries. Applied Energy 85(6), 421-429.

Lei, Y., Li, L., Pan, D. (2014). Study on relationships between coal consumption and economic growth of the six biggest coal consumption countries: with coal price as a third variable. Energy Procedia 61, 624-634.

Lemmens, A., Croux, C., and Dekimpe, M.G. (2008) Measuring and Testing Granger Causality over the Spectrum: An Application to European Production Expectation Surveys, *International Journal of Forecasting*, 24, 414-431.

Ozturk, I. (2010), “A literature survey on energy–growth nexus”, *Energy Policy*, 38, 340–349.

Payne, J. E. (2010). “Survey of the international evidence on the causal relationship between energy consumption and growth”, *Journal of Economic Studies*,37(1), 53-95.

Toda, H.Y., and Yamamoto, T., (1995) Statistical inference in vector autoregressions with possibly integrated processes, *Journal of Econometrics,* 66, 225.

World Development Indicators: World Development Report (2014).World Bank, Washington, DC.