ENERGY CONSUMPTION AND ECONOMIC GROWTH IN CHINA

Evidence from a Time Series and Vector Autoregressive Model

By Jinxuan Wang

(8757918)

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Supervisor: Professor Nguyen V. Quyen

Ottawa, Ontario

This study investigates the causal relationship between energy consumption and economic growth for China during the period between 1980 and 2015, using a multivariate framework that includes labor and capital as additional variables. A vector auto-regression model (VAR) and causality tests are employed to infer the existence and direction of the causality relationship. Based on the procedure introduced by Toda and Yamamoto (1995) and Dolado and Lutkepohl (1996), unidirectional causality is present between real GDP and energy use with both the ordinary Granger causality test and the modified Wald test (MWALD). The causality tests indicate the presence of short-term causality from energy consumption to economic growth, and the impulse response function supports the long-term causality in the same direction.

1. INTRODUCTION

The relationship between energy consumption and economic growth has been widely discussed since Kraft and Kraft (1978) found evidence of a uni-directional causal relationship running from GNP to energy consumption in the US using data over the 1947–1974 period. The flourishing studies prompted economists to take a critical look at energy and the limited stocks of fossil fuels and minerals, which might play an important role in constraining economic growth. In the applied econometric literature on the linkages between energy and economic growth, the question of whether energy causes economic growth or growth influences energy use has received much attention from investigators who apply time series analysis to discover the causal relationship between energy and economic growth. However, a consensus is yet to come. Even if the same method is employed, the empirical outcomes of these studies have been varied and sometimes found to be conflicting. These results differ due to different countries' characteristics, data sets in different time spans, and different extra variables attached.

The major research questions of this paper are: (i) "does causal relationship between energy consumption and economic growth for China exist?" and (ii) "if the causality exists, what is the direction of this causal relationship?"

There are several reasons why this research question is interesting. Firstly, if the current growth trends in population, industrialization, pollution, and resource depletion continued unchanged, the most probable result will be an uncontrolled decline in both population and industrial capacity in several decades. Therefore, analyzing the causality between energy consumption and economic growth can help economists make better energy policies upon the current situation. Secondly, the rapid growth of Chinese industrialization and urbanization has considerably contributed to the incremental expenditure of energy resources. In an era in which every country pursues a greener economy and energy conservation, an economy that depends on energy – especially nonrenewable and environmentally hazardous resources – may be negatively affected by the energy conservation policy if the causation runs from energy consumption to GDP. But if the reverse direction of the causality is demonstrated, it implies that the energy conservation policy would not harm China's economic growth. Hence, there is a need to understand the interaction between energy use and output growth.

The method been used is the ordinary Granger causality test and the modified Wald test (MWALD) with a vector auto-regression model (VAR) followed the Toda and Yamamoto (1995) and Dolado and Lutkepohl (1996) procedure. The unidirectional causality from energy consumption to economic growth is investigated in this paper, and this result indicates that the energy conservation policy would harm China's economic growth.

The remainder of the paper is organized as follows: Section 2 briefly reviews the relevant literature on the causal relationship between energy consumption and economic growth. Section 3 outlines the model and the method. Data description and unit root tests are given in Section 4. Section 5 presents the results of the estimation. Concluding remarks and policy implications are given in Section 6.

2. LITERATURE REVIEW

The causal relationships between energy use and economic growth has been widely discussed since the pioneer study of Kraft and Kraft (1978). These authors examined the presence or absence of an empirical relationship between energy and economic growth by employing the Sims (1972) methodology on gross energy inputs and gross national product (GNP). Kraft and Kraft found evidence of a unidirectional causal relationship running from GNP to energy consumption in the period of 1950-1974, using data from the U.S. However, the causality running from energy use to GNP was not been found.

However, using the same methodology as Kraft and Kraft, Akarca, and Long (1980) found that there is no causal link between gross energy consumption and GNP with the two-year shortened period of 1950-1968. This was necessary to emphasize because the recessions in both 1970 and 1973-1974 as well as the World War might have changed the structural relation. Thus, the study of Kraft and Kraft was shown to be spurious with the two-year modification.

Erol and Yu (1987) found no evidence of causality for the United Kingdom and France; a unidirectional causality from energy consumption to GDP was found for Canada, while an inverse unidirectional causality from GDP to energy-use was found for Italy and West Germany; and a bi-directional causality was found for Japan by using the Sims and Granger causality tests.

Stern (1993, 2000) employed a multivariate approach to test the vector auto-regression

(VAR) model, which includes GDP, energy use, capital stock, and labor. He examined the unidirectional relationship between GDP and a quality-adjusted index of energy input for the period of 1947-1990 and an updated period of 1947-1994 in the United States. He also suggested that a quality-adjusted index of energy-input (Divisia aggregation) should be used instead of gross energy-use. Although there is no indication that a Granger causality from gross energy to GDP exists, a Granger causality is found to exist from the Divisia energy aggregate to GDP, which indicates that fluctuations in energy supply will tend to affect output.

Soytas and Sari (2003) conducted a study on the causality between energy consumption and GDP in G-7 countries (excluding China). They found a causal relationship between GDP and energy consumption using the time series properties. They used the co-integration and the Vector Error Correction Model (VECM) to overcome the stationarity problem in the Granger causality test. They found a unidirectional causality running from energy consumption to GDP for Turkey, France, Germany, and Japan; a unidirectional causality running from GDP to energy consumption for Italy and Korea; and bi-directional causality for Argentina. Soytas and Sari (2006) revised their study with multivariate co-integration, error correction models, and generalized variance decompositions to uncover a unidirectional causality from energy use to GDP for the United States and France, from GDP to energy use only for Germany, and a bi-directional causality for Canada, Italy, Japan, and the United Kingdom.

Narayan and Smyth (2008) conducted a study with a panel of G-7 countries using panel co-integration and the Granger causality test in a VECM. The panel co-integration test proposed by Westerlund (2006), which allows for multiple structural breaks, was used. The authors found that energy consumption along with capital information boost real GDP significantly in the long run when multiple structural breaks in the panel co-integration test were allowed.

Among the 11 major industrialized countries, a neutral relationship in the case of the United Kingdom, Germany, and Sweden, and bi-directional causality between energy consumption or energy-use and GDP in the United States were found. Lee (2006) also found a unidirectional causality running from GDP to energy consumption for France, Italy, and Japan, and a reverse causal relationship for the latter 4 countries (Canada, Belgium, the Netherlands, and Switzerland) using the VAR model.

Altınay and Karagöl (2004) used the data from Turkey to conclude that it was inappropriate to indicate the series are I(1) using the conventional unit root tests, and that the endogenous break unit root tests should be used instead. Therefore, when dealing with the time series of energy consumption and real GDP, both series are found to be trend stationary around a structural break. Altınay and Karagöl (2004) investigated the period of 1950-2000 and failed to find causality between energy-consumption and GDP when using a detrended series. The empirical studies using the same country data also failed to achieve unanimous conclusions. Lise and Monfort (2007) used the data for Turkey over the period of 1970-2003, which is notable since an economic policy of opening to the world after 1980 was implemented during that period. While economic growth was the emphasis during this period, a uni-directional relationship from economic growth to energy-consumption was found by Lise and Monfort (2007) using the Ordinary Least Squares (OLS) and the Error Correction Model (ECM) methods. Erdal et al. (2008) reexamined the inter-temporal link between energy-use and GNP for Turkey during 1970-2006; their empirical results indicate that two time series are non-stationary, and they used the first difference of these series to analyze the causality. Their results from this study demonstrate the existence of a bilateral causality between energy consumption and GDP by applying the pair-wise Granger causality and Johansen co-integration tests.

In addition, increasing attention on single-country studies has been paid, especially on China, since China has been the second largest energy consumer. Zhang and Xu (2012) found a causality running from GDP to energy use in all of China by using the data from 1995-2008 in the panel model. However, they highlighted this causal relationship in the different regions because of economic structural change and large regional differences. Shabhaz et al. (2013) applied the ARDL–bounds test and the Granger causality test to investigate the relationship between energy use and economic growth in China over the 1971-2011 period by incorporating financial development, international trade, and capital – as important factors of production function. They found a unidirectional causality running from energy consumption to income (GDP).

From the aforementioned studies, empirical results show little consensus on the direction of the relationship between energy consumption and GDP so far. One possible reason for the inconsistency with the results for individual countries is that they are often impaired with a short data span that lowers the power of the unit root and co-integration tests. As for both the country-specific and multi-countries studies, the conflicting results may arise due to the differences in data sets, econometric methodologies, extra variables, and countries' characteristics.

3. THE MODEL AND THE METHOD

3.1. The Neoclassical Production Technology

To investigate the relationship between energy use and economic growth, we propose a framework based on the conventional neo-classical one-sector aggregate production function where we treat capital, labor, and energy as separate inputs; that is,

$$\boldsymbol{Y_t = f(K_t, L_t, E_t)},$$

where $\boldsymbol{Y, K, L, E}$ denote, respectively, output or real GDP; the capital stock; the labor input; and the total energy consumption, and the subscript t denotes the time period.

A four equation VAR is set up on annual China's real GDP, capital input, labor input, and energy input. The generalized form of the VAR model in this paper is

Let $\mathbf{Y}_t = (y_{1t}, y_{2t}, \ldots, y_{nt})'$ denote an $(n\times1)$ vector of time series variables. The basic p-lag vector autoregressive (VAR(p)) model has the form

$$\mathbf{Y}_t = c + \mathbf{\Pi}_1\mathbf{Y}_{t-1} + \mathbf{\Pi}_2\mathbf{Y}_{t-2} + \cdots + \mathbf{\Pi}_p\mathbf{Y}_{t-p} + \varepsilon_t,\ t=1,\ldots,T$$

where $\mathbf{\Pi}_i$ are $(n \times n)$ coefficient matrices and ε_t is an $(n \times 1)$ unobservable zero mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix $\mathbf{\Sigma}$.

3.2. The Method

This study uses the modified WALD test devised by Toda and Yamamoto (1995) and Dolado and Lutkepohl (1996) (TYDL hereafter) as well as the VAR model to investigate the causal relationship between energy use and GDP for China. The TYDL procedure has been widely used to test for Granger non-causality. The benefit here is that the testing does not require the co-integration properties of the system, and is acceptable when the series are not stationary. Engel and Granger (1987) pointed out that when the variables in the VAR model are co-integrated, but non-stationary, the validity of the standard Granger causality test cannot be guaranteed. The TYDL procedures introduced a modified WALD test (MWALD) to remove these restrictions and uncertainty. TYDL conducted a lag selection procedure on a VAR model, which is believed to be integrated or co-integrated. If $\boldsymbol{p}$ is the appropriate maximum lag length for the series, and $\boldsymbol{d_{max}}$ is the maximal order of integration of the series determined by unit root tests, then a $(\boldsymbol{p}+\boldsymbol{d_{max}})^{\boldsymbol{th}}-\boldsymbol{order}$ VAR model can be estimated. While testing linear or nonlinear restrictions, the $\boldsymbol{d_{max}}-\boldsymbol{lagged}$ vector can be ignored to focus on the first $\boldsymbol{p}$ coefficients matrices using the standard asymptotic theory. The extra $\boldsymbol{d_{max}}$ lags of each variables can be declared to be an “exogenous” variable to sustain its usual asymptotic chi-square distribution.

The VAR model and the VECM are most commonly used to test for the Granger causality between variables. The reason why the VAR model is used here is that the VECM could be used only if the variables were already known to be co-integrated. The prior step of testing for co-integration is indispensable. Only if the hypothesis of "no-co-integration" is rejected, can we then consider estimating a VECM. In this case, the co-integration between variables cannot be guaranteed. Another important piece of information that arises is when we pre-test, the second test (Granger non-causality test and the modified WALD test) may be a random mixture of two tests, and a "size distortion" may occur. Hence, the VAR model is being adopted in this paper. Although the TYDL procedure are not the most powerful among all the available procedures, it is the most appropriate to be performed when it is uncertain that variables are $\boldsymbol{I(0)}, \boldsymbol{I(1)},$ or $\boldsymbol{I(2)}$. The steps for the TYDL procedure are as follows:

1. Test each of the time-series variables to determine its order of integration. Let the maximal order of integration for the group of time-series be $\boldsymbol{d_{max}}$.

2. Set up a VAR model in the levels of the data, regardless of the orders of integration of various time-series variables.

3. Determine the optimum lag length $\boldsymbol{p}$ for the variables in the VAR model, based on the information criteria, such as AIC, SIC, and residual serial correlation LM test. Then take the preferred $\boldsymbol{VAR(p)}$ model, which should be:

   $$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + ... + \alpha_p Y_{t-p} + \beta_1 X_{t-1} + ... + \beta_p X_{t-p} + u_t \qquad (1)$$

   $$X_t = c_0 + c_1 X_{t-1} + ... + c_p X_{t-p} + d_1 Y_{t-1} + ... + d_p Y_{t-p} + v_t \qquad (2)$$

   where u_t and v_t are the stationary error term. α's, β's, c's and d's are coefficients, which need to be derived.

4. Check the new VAR model with $\boldsymbol{p}$ lags for its robustness using diagnostic tests, such as normality test, AR unit root graph, and heteroscedasticity test. Based on the results in step 1, if the time-series variables have the same order of integration, use the Johansen co-integration test to see if they are co-integrated.

5. Test for Granger non-causality by testing the hypothesis that the coefficients of the first $\boldsymbol{p}$ lagged values of X are zero in the Y equation. Then do the same test for the coefficients of the lagged values of Y in the X equation.

In this paper, the test for Granger causality is employed with the modified $\boldsymbol{VAR}(\boldsymbol{p})$ model. The new VAR model has two equations, one from X to Y, and one from Y to X. Test the null hypothesis that the effects of X are not significant in the Y equation, and do the same test in the X equation. The common Granger causality test and the MWALD test, which was introduced by Toda and Yamamoto (1995) and Dolado and Lutkepohl (1996), are employed in this model to guarantee accountability. Rejection of the null hypothesis implies a presence of the Granger causality.

4. DATA AND UNIT ROOT TESTS

4.1. *Data*

Data on the Chinese economy constitute yearly observations over the period of 1980-2015, which are:

- Gross domestic product in billions of local currency (YUAN) in constant 1980 prices
- Total energy consumption in million tons standard coal equivalent
- Gross fixed capital stock
- Total employment.

All the data were obtained from the National Statistics Bureau of China. Since energy consumption is directly related to domestic goods and services, real GDP for this analysis was used. All variables are transformed into natural logs denoted as LNRGDP, LNEC, LNK and LNL. In most studies undertaken in the survey, empirical studies on this subject investigated the causality between energy use and economic growth in either a bivariate or a multivariate test. The results are often contradictory or economically implausible with bi-variate causality tests on small samples. Although the sample size is not too large here, the validity of the results can be supported by using the multivariate model.

4.2. *Unit Root Tests*

The TYDL procedure requires the knowledge of the maximal order of integration for the time series involved. In order to test for the stationarity properties of the variables, 3 different unit root tests are used, namely the augmented Dickey and Fuller (1979) (ADF) test, the Dickey-Fuller GLS detrended (DF-GLS) test, and the Kwiatkowski-Phillips-Schmidt-Shin (1992) (KPSS) test. The null hypothesis for the ADF and DF-GLS test is non-stationarity, while the KPSS test is a test for which the null hypothesis is stationary. Here the KPSS test can work as a cross check. The results of unit root tests are reported in Table 1. The results of the ADF test and the DF-GLS test show slightly contradictory results, and the KPSS test show that all variables are stationary in the second difference. Hence, we can assume that the results to be robust and that the maximal order of integration is 2, we identify $\boldsymbol{d_{max} = 2}$.

Table 1

Unit root test results

		ADF	DFGLS	KPSS
Levels				
Intercept	RGDP	-0.973949 (0.7509)	-0.861137 (0.3956)	0.651795*** (0.0000)
	EU	0.286534 (0.9732)	-0.698861* (0.0873)	0.652240*** (0.0000)
	K	1.259815 (0.9979)	-1.096688 (0.2815)	0.704181*** (0.0000)
	L	-3.174534** (0.0302)	-0.249392 (0.8048)	0.641590*** (0.0000)
Intercept and trend	RGDP	-3.041079 (0.1369)	-1.883541* (0.0687)	0.188342*** (0.0000)
	EU	-2.347250 (0.3986)	-1.767556 (0.4900)	0.179323*** (0.0000)
	K	-2.633124 (0.2691)	-1.144448 (0.2615)	0.213144*** (0.0000)
	L	-1.167317 (0.9019)	-0.883254 (0.3833)	0.182744*** (0.0000)
First differences				
Intercept	RGDP	-3.247633** (0.0257)	0.384967 (0.7027)	0.632670*** (0.0000)
	EU	-2.474947	-1.571760	0.455979***

		(0.1302)	(0.1255)	(0.0000)
Intercept and trend	RGDP	-3.348500* (0.0756)	-1.345189 (0.1890)	0.167802*** (0.0000)
	EU	-1.499922 (0.8063)	-1.740237* (0.0911)	0.087211*** (0.0001)
	K	-2.616445 (0.0996)	-1.948556* (0.0618)	0.140543*** (0.0000)
	L	-6.176462*** (0.0001)	-6.319124*** (0.0000)	0.078286*** (0.0001)
Second differences				
Intercept	RGDP	-4.862259*** (0.0004)	-5.739293*** (0.0000)	0.314031 (0.9049)
	EU	-4.692452*** (0.0006)	-4.541640*** (0.0001)	0.148687 (0.8756)
	K	-3.321033** (0.0219)	-3.329319*** (0.0022)	0.415493 (0.2356)
	L	-10.04613*** (0.0000)	-2.664860*** (0.0018)	0.500000 (0.9095)
Intercept and trend	RGDP	-4.787282*** (0.0027)	-5.822697*** (0.0000)	0.079758 (0.4909)
	EU	-4.625901*** (0.0041)	-4.713494*** (0.0000)	0.086733 (0.3154)
	K	-3.593064** (0.0459)	-3.714192*** (0.0008)	0.085110 (0.2067)
	L	-9.882692*** (0.0000)	-10.19177*** (0.0000)	0.500000 (0.9679)

Note: Probability values are in brackets.

* denotes the rejection of the null hypothesis in the 10% significance level.

** and *** denotes the rejection of the null hypothesis in the 5% and 1% significance level, respectively.

5. RESULTS

The principal question addressed in this paper is the existence of causality between the variables EU and RGDP with the help of K and L. If there is support for the existence of this causality, a direction is required by using the Granger causality test. The first step to test for the Granger causality in the TYDL procedure is to employ a VAR in the levels without differencing the data, ensuring there is no loss of information. Next, various information criteria including the Akaike information criteria (AIC), final prediction error (FPE), and Hannan-Quinn (HQ) information criterion suggest that a maximum lag length of 3 for four variables. The Schwarz information criteria (SIC) and the likelihood ratio test (LR), on the other hand, suggest a lag length of 2. Since the Granger causality test is very sensitive to the lag length, and to ensure the robustness of the results, the LM test for serial correlation is employed to double check. However, when the residuals are examined and the LM test applied for the null hypothesis of serial independence, the result is slightly contradictory where it shows the serial correlation is eliminated at least at 5% significance level if the maximal lag length is increased to $p = 4$. The result from the LM test was chosen since the serial correlation suggests model misspecification, which is not acceptable.

Various diagnostic tests were conducted as well to ensure the robustness of this modified VAR. According to the test results, there are no violations of normality or heteroscedasticity of concern. Figure 1, which is an AR root graph, suggests the estimated model is dynamically stable since all AR roots lie inside the unit circle.

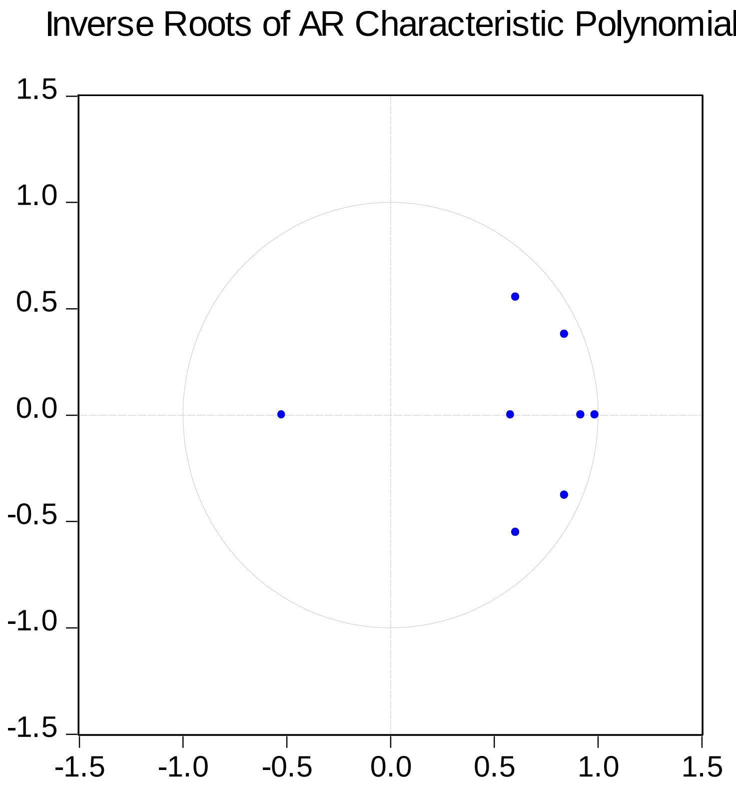

Figure 1. Graph of AR Inverse Root

Rather than declare the lag interval for the four endogenous variables to be $\boldsymbol{p + d_{max} = 6}$, it is better to leave the interval to be 4, and declare the two extra lags of each variable to be an exogenous variable. Hence, the re-estimated VAR (6) system used to conduct the subsequent causality tests is as follows:

$$V_t = \alpha_0 + \beta_1 V_{t-1} + \beta_2 V_{t-2} + \beta_3 V_{t-3} + \beta_4 V_{t-4} + \beta_5 V_{t-5} + \beta_6 V_{t-6} + e_{vt}$$

where $V_t = (LNRGDP_t, LNEU_t, LNK_t, LNL_t)'$; α_0 is a (4×1) vector of intercepts; β_1, β_2, β_3, β_4, β_5, β_6 are (4×4) matrices of coefficient; and e_{vt} is white noise residuals.

For comparison purpose, the Granger non-causality tests can be employed first, and then the MWALD test is used to see if the result from Granger non-causality test can be confirmed. The upper panel of Table 3 shows that the null hypothesis of no causality from LNEU to LNRGDP at the 1% significance level can be rejected. However, there is no evidence that the null of non-causality from LNRGDP to LNEU can be rejected. Therefore, there is sufficient evidence of a unidirectional causality from energy-consumption to the GDP, but not vice versa.

Table 2

Results for the Granger non-causality test

Null hypothesis	Lag	F-statistic	Probability	Result
LNEU does not Granger Cause LNRGDP	4	6.10780***	0.0017	Reject
LNRGDP does not Granger Cause LNEU	4	0.58498	0.6767	Not reject

Note: The lag is 4 here since the extra 5^{th} and 6^{th} lags have not been included in the test.
*** denotes the rejection of the null hypothesis in the 1% significance level.

Now, the MWALD test is conducted with the integration properties of the series and the established length of the VAR. Results of the causality tests with optimal lag length $p = 4$ are presented in Table 4. The results agree with the rejection of the non-causality from energy-consumption to economic growth in the standard Granger causality test, both at 1% significance level. However, there is only a unidirectional Granger causality since the causality running from real GDP to energy use has not been detected, which is consistent with the results from standard Granger causality test.

Table 3

Results of the Modified WALD causality test

Direction of causality		Estimated coefficients	Significance of the p-value
From	To		
LNEU	LNRGDP	1.606795***	0.0000
LNRGDP	LNEU	0.708246	0.3828

Note: *** denotes the rejection of the null hypothesis in the 5% significance level. The MWALD test statistic has an asymptotic chi-square distribution.

The TYDL procedure allows for the examination of the long-term Granger causality relationship between these two variables through generalized impulse response analysis. However, this does not provide information on how these variables will react to any unexpected shock, such as innovation in other variables, and whether this shock is temporary or permanent. Figure 2 (a) and Figure 2(b) show the response of variables to an one-standard deviation shocks to each other in the VAR.

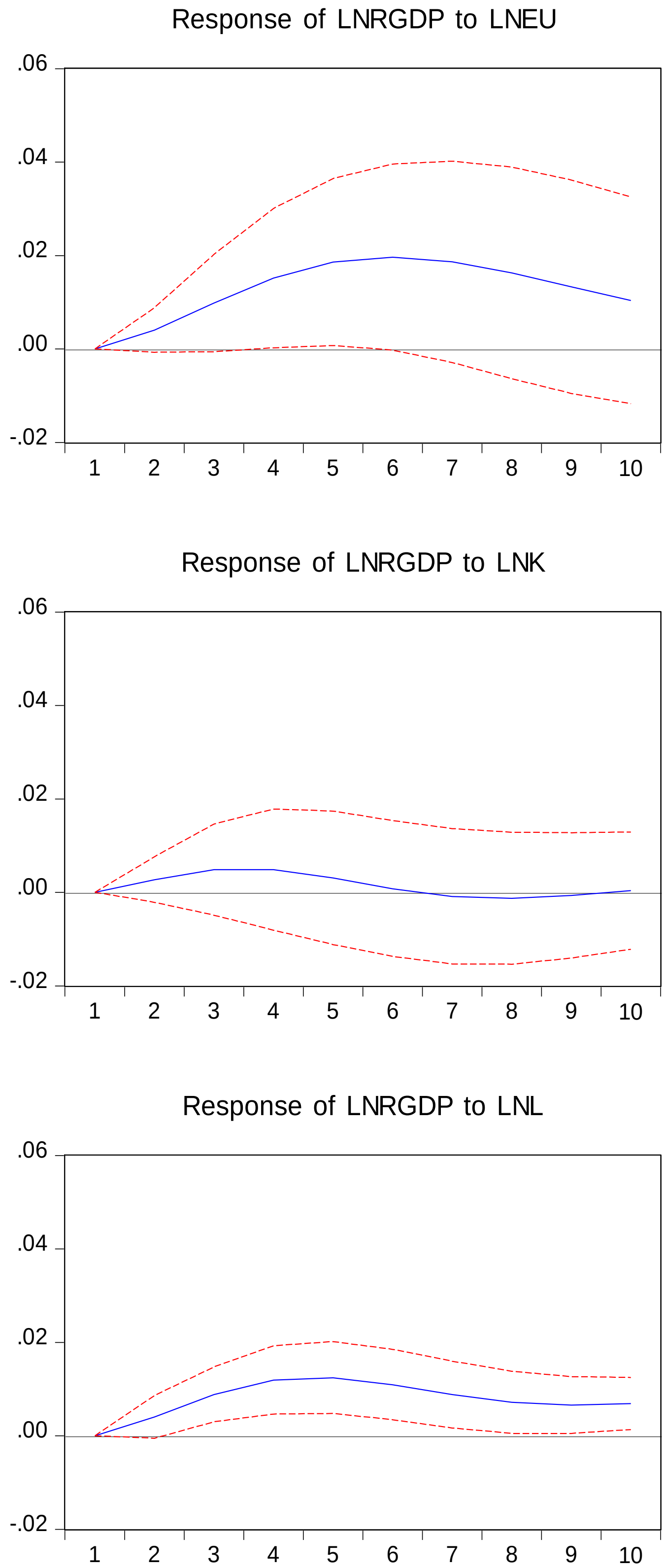

Figure 2(a). Generalized impulse responses of real GDP to other variables

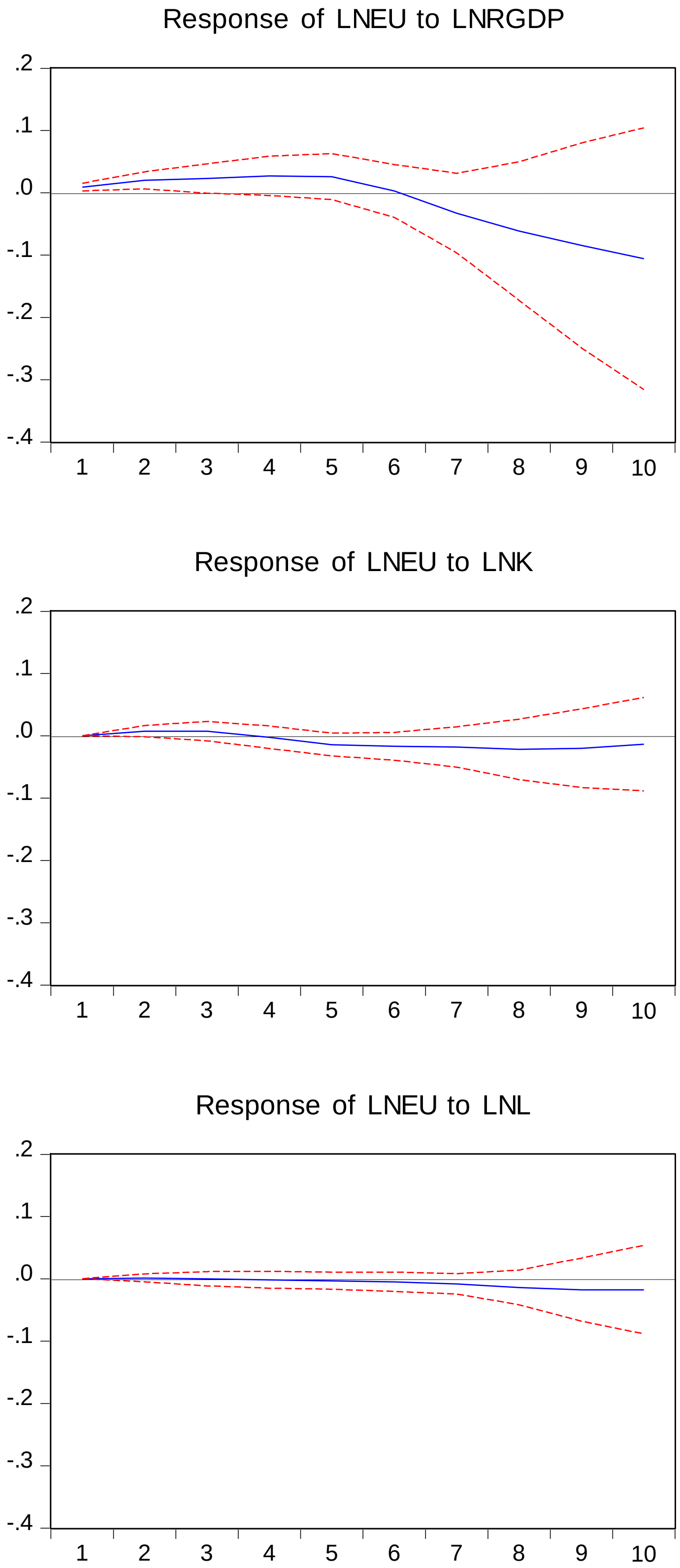

Figure 2(b). Generalized impulse responses of energy use to other variables

The impulse response graphs show two aspects of important information. First, the initial impact of a one-standard deviation shock to the energy use on real GDP can be observed. Second, the persistence of the effect can be assessed. Furthermore, a one-standard deviation shock to energy-use causes real GDP to increase, with the effect becomeing statistically significant 3 periods after the shock. This effect lasts about 5 to 6 periods, and tends to mitigate about 9 periods after the shock. It can be plausibly explained in a case where, for example, the effect of a newly discovered natural gas well can be sustained for some time, and boost real GDP. Shocks in gross fixed capital and labor have temporary impacts on economic growth, but become insignificant after a few periods. When we look at the response of energy-use to the real GDP, it does have some effect but this effect is not very notable which is in line with the previous analysis.

6. CONCLUDING REMARKS

A serious consideration of environmental protection and climate change necessitates the need to analyze the link between energy consumption and GDP. This paper undertakes a TYDL procedure using both the standard Granger non-causality test and the MWALD causality test as well as the generalized impulse response to analyze the energy-economy nexus in a multivariate framework, controlling for gross fixed capital investment and labor for China during the period 1980-2015. A causality investigation was conducted, and it reveals the existence of an interaction between the two. It can be concluded that in China energy consumption contains considerable information to predict real GDP. In other words, energy appears as an essential factor of economic growth, but not vice versa. This result suggests that China should be cautious when formulating policies. A policy aimed at reducing waste and emissions may be more effective. Further research can be carried out if more economic data are available.

A long-recognized viewpoint is that instead of reducing energy use, increasing the efficiency of energy use is more pragmatic. It is beneficial to promote innovation and research regarding new energy technologies in addition to carrying out an adjustment of the industrial structure in order to abide by the recommendations of the Kyoto Protocol. This is the action that the Chinese government has implemented since 2006. Moreover, the consumption of coal still accounts for about 63.7% of total primary energy use, even when the production of energy increases substantially. China should commit itself to low-carbon and sustainable energy development by shifting away from the use of fossil fuels toward clean and renewable energy. It is not realistic to completely restrict the industrial use of energy. An alternative policy is to put more efforts in reducing the use of outdated capacity and curbing the projects in industries with overcapacity. Hence, a policy to reduce energy consumption aimed at reducing emissions is likely to have a greater impact on the GDP. Not only the industrial sectors, but the private usage of energy also requires some transformation. Government can create some movement aiming at raising awareness of sustainable mode of transport, such as subway, bicycle and electric cars. At last, saving nonrenewable energy and making full use of wind energy, solar energy and other natural energy sources to maintain economic growth is the most sustainable and urgent way to achieve a win-win situation.

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