THE CAUSALITY BETWEEN INCOME AND ENERGY CONSUMPTION: A PANEL VECTOR AUTOREGRESSIVE APPROACH

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ABSTRACT

Hubungan sebab-akibat antara pemakaian energi dan pemasukan (produk domestik kotor) telah menjadi isu yang sangat penting di bidang ekonomi. Banyak penelitian yang telah dilakukan dan hasilnya beragam dan berlawanan. Dari hasil penelitian menunjukkan bahwa tidak ada hubungan sebab-akibat yang jelas antara kedua variabel tersebut. Penelitian ini bertujuan untuk melakukan investigasi ulang hubungan sebab-akibat tersebut dengan mengaplikasikan metode panel vector autoregressive kepada data dari enam negara terpadat populasinya di dunia. Selain itu, penelitian ini juga menggunakan impulse response function dan variance decomposition. Hasilnya menunjukkan bahwa adanya hubungan sebab-akibat tidak langsung dari pemakaian energi ke pemasukan. Goncangan pemakaian energi mempunyai efek yang positif dan dapat menjelaskan kira-kira 18,7 persen varian pemasukan.

***Kata kunci** : pemakaian energi, pemasukan, panel vector autoregressive*

INTRODUCTION

Global warming and the production and consumption of energy are major issues affecting our economies. This is evident from the agendas of the United Nations Climate Change Conference 2007 in Bali and the next G-8 meeting to be held in Japan in 2008. Moreover, the commitment period under the Kyoto Protocol will also start in the same year. The energy issue is not only related to the global warming issue, but also encompasses the aspects of energy security and income. Therefore comprehensive understanding of these problems is really essential.

Numerous studies have examined the causal relationship between energy consumption and income. The outcomes of these studies have been contradictory. For example, in the case of Indonesia, Fatai *et al.* (2004) and Asafu-Adjaye (2000) found unidirectional causality running from energy consumption to income. On the other hand, Masih and Masih (1996) found unidirectional causality running from income to energy consumption. However research undertaken by Soytas and Sari (2003) found that there is no causality between energy consumption and income in Indonesia. Conflicting outcomes have also been found in research based on data from Thailand, the Philippines, India, and South Korea (see Appendix 1 for further detail).

The nature of the causal relationship between energy consumption and income has a significant implication for policy decisions (Asafu-Adjaye, 2000; Mozumder and Marathe, 2006). There are four possible outcomes: firstly, that causality flows from energy consumption to income; secondly, that there is reverse causality from income to energy consumption; thirdly, that there is no causality in either direction; finally that there is a possible bi-directional causality between energy consumption and income. Wolde-Rufael (2004) and Sica (2007) argue that if the outcome is unidirectional causality flows from energy consumption to income; it implies that energy conservation policy could cause a negative impact on income. On the other hand, reverse causation implies that energy conservation policy would not disadvantage income.

The following paper contributes to the enrichment of the debate about the causality direction with a new technique, panel vector autoregressive (VAR), using data of the six most highly populated countries world-wide during the period 1965-2005. Panel VAR has never been used before to analyze the causality between energy consumption and income. Most previous studies have used time series data with various methods. A study by Lee (2005) employed panel data but used a different technique, full modified ordinary least square (FMOLS). This is the first study on income-energy consumption causality to use the panel VAR method.

This study also employs Granger causality which is constructed from the panel VAR F-test. Furthermore, impulse response function and variance decomposition are used to study the effect of energy consumption shock on income and vice versa. The impulse response function and variance decomposition analysis will focus on the causality direction that is obtained from the Granger causality test. The results suggest that there is evidence of unidirectional causality running from energy consumption to income.

Subsequent to this introductory section, Section II provides a critical review of some studies which have analyzed the causality between energy consumption and income. In Section III, there is an explanation of the data and the methodology. The results are provided in Section IV. The final section presents concluding remarks.

CRITICAL REVIEW

Studies about the causal relationship between energy consumption and income have used different approaches, countries, periods and proxy variables. A common approach has been to use the standard Granger causality test. Yang (2000) applied the standard Granger causality test on five variables, namely GDP (gross domestic product), energy, oil, gas, and electricity consumption, for Taiwanese data. The test provided mixed results with some apparent conflicts. Yang revealed bi-directional causality between energy consumption and GDP. However, the causality between various kinds of energy consumption and GDP was not the same. Bi-directional causality only applied to the relationship between GDP and coal consumption and GDP and electricity consumption. Moreover, Yang found a different direction of causality where the unidirectional causality moved from GDP to oil consumption and from gas consumption to GDP.

Marimoto and Hope (2004) used the same approach to estimate the causal relationship between electricity supply and GDP in Sri Lanka. Marimoto and Hope found a unidirectional causality running from the electricity supply to GDP. From these two studies it can be concluded that the standard Granger causality test is not reliable enough to estimate the direction of causality. Glasure and Lee (1997) argue that the Granger causality test is inconsistent. Glasure and Lee found that when the sample period was changed, either by being shortened or extended, the result was different. Moreover, the standard Granger causality test may only investigate the short run linkage of the variables because of the differencing procedure which may remove information relating to the longer term (Masih and Masih, 1996). Using the standard Granger causality test, a researcher has the problem of choosing the exact lag length. If the lag length is less than it should be, the outcome could be biased. In contrast, if the lag length chosen is more than it should be, the outcome will be inefficient (Aqeel and Butt, 2001).

In order to improve the result, some researchers have used modified versions of the Granger causality test. Two modifications are known as the Hsiao version and the Toda and Yamamoto (TY) version. Cheng and Lai (1997) and Aqeel and Butt (2001) used the Hsiao version to analyze causality in Taiwan and Pakistan. Using the Hsiao version, these two studies applied a systematic autoregressive method to choose the optimal lag length for each variable. Practically, this method is a combination between Granger causality and Akaike's final prediction error (FPE). Cheng and Lai (1997) found unidirectional causality running from GDP to energy consumption using data from Taiwan. The same direction of causality was also found by Aqeel and Butt (2001) using data from Pakistan.

Wolde and Rufael (2004) employed the TY version of the Granger causality test on data from Shanghai, while Fatai *et al.* (2004) used the same version on data from the following six countries: New Zealand, Australia, India, Indonesia, the Philippines and Thailand. In this version, the modified Wald test was applied to restrict the parameter of the VAR (k) where k is defined as the lag length. The study of Wolde and Rufael (2004) indicated the existence of unidirectional causality running from coal, coke, electricity and total energy consumption to GDP. Moreover, Wolde and Rufael found no causality between oil consumption and GDP. Another study by Fatai *et al.* (2004), using data from Australia and New Zealand, found unidirectional causality running from real GDP to aggregate final energy consumption and from real GDP to industrial and commercial energy consumption. Fatai *et al.* (2004) also drew conclusions about various directions of causality for four developing countries. Their studies revealed a unidirectional link running from energy to income for India and Indonesia and bi-directional causality for Thailand and the Philippines. In this study, the autoregressive distributed lag regression (ADLR) approach was also employed to clarify the results from the TY version. Generally, both methods produced the same outcomes.

Another approach which has been used to test causality is the co-integration and error correction model (ECM). According to this model, it is assumed that as long as the variables are cointegrated, it can be said that those variables have linear combinations without differencing: in other words those variables are stationary (Glasure and Lee, 1997). Therefore, any long range information will be lost. Then, using the error correction model, the direction of causality both in the short and long run can be estimated. Glasure and Lee (1997) used the method to analyze data from South Korea and Singapore. They found no causality in the South Korean data and unidirectional causality running from energy consumption to GDP in the Singaporean data.

Three other studies have followed a similar approach, applying the co-integration and ECM model - the study of Asafu-Adjaye (2000) using data from developing countries in Asia, the study of Jumbe (2004) using data from Malawi and that of Sica (2007) using data from Italia. Again, they found mixed and conflicting outcomes. Asafu-Adjaye (2000) used three variables, energy consumption, income and prices and found bi-directional causality between energy consumption and income for the Philippines and Thailand. Unidirectional causality was found to occur running from energy consumption to income for India and Indonesia. Another study by Jumbe (2004) revealed bi-directional causality between electricity consumption and GDP. Jumbe also found unidirectional causality occurred running from GDP and non-agricultural GDP to electricity consumption. The exact causality between energy consumption and income under co-integration and ECM is still inconclusive if consideration is given to a study by Sica (2007) of Italian data in which no causality in was found.

A vector error correction model (VECM) has also been widely used in the following studies of causality which have taken an econometric approach: Masih and Masih (1996; 1997; 1998), Glasure (2002), Hondroyiannis *et al.* (2002), Soytas and Sari (2003), Ghali and El-Sakka (2004), Oh and Lee (2004), Zamani (2006), and Mozumder and Marathe (2007). Some modifications and differences to previous studies have been developed. Masih and Masih (1996) completed their analysis using constructed variance decomposition technique. In their next two studies, Masih and Masih used prices as an additional variable in the VECM model. An analysis with only two variables could be biased because of the problem of an omitted variable (Glasure, 2002). Glasure (2002) extended the model by using five variables instead of two. The new variables are real money and real government expenditure. The multivariable analysis approach was also applied by Ghali and El-Sakka (2004) who used four variables in the model, namely real GDP, energy consumption, capital stock and total employment. Ghali and El-Sakka constructed the model based on neoclassical one-sector aggregate production technology.

Some new studies have adopted new approaches or modified those taken in earlier studies. Hondroyiannis *et al.* (2002) analyze the causality in more specific types of energy. In this model, Hondroyiannis divides energy consumption into three categories: total energy consumption, residential energy consumption and industrial energy consumption. In the study of Zamani (2006) a more specific series of variables is defined. Income is represented by three variables: real GDP, industrial value added and agricultural value added. Energy consumption is represented by total energy consumption, total petroleum consumption, total gas consumption, industrial energy consumption, industrial petroleum consumption, industrial gas consumption, industrial electricity consumption, agricultural energy consumption, agricultural petroleum consumption and agricultural electricity consumption. The results are still inconclusive. All possibilities, namely unidirectional causality running from energy consumption to income, reverse causality and bi-directional causality were found in these studies.

Various types of methods have already been applied to analyze causality between energy consumption and income. Unfortunately, it is still not possible to resolve the question of the exact direction of causality. All methods, namely standard and modified Granger causality tests, ECM, and VECM have found various and sometimes conflicting directions of causality. This could happen because the studies analyzed the causality in individual countries. Moreover, most studies used data provided over the short time period of about 20-30 years, an approach which lowers the power of the unit root and co-integration test (Lee, 2005).

Lee (2005) tried to cope with this short data span by using panel data. He pooled the data obtained from eighteen developing countries. Lee employed a panel data co-integration test which is more powerful and has higher degrees of freedom. Then full modified ordinary least square (FMOLS) technique was employed to estimate the co-integration vector for heterogeneous cointegrated panels. An error correction model for heterogeneous panels was then applied to analyze the short-run and long-run causality between three variables, namely energy consumption, income (GDP), and capital stock. However, in the panel based error correction model, capital stock was dropped because it was not relevant. The result indicated the existence of long-run and short-run unidirectional causality running from energy consumption to income. This high energy consumption leads to high income (GDP).

DATA AND METHODOLOGY

Data

The data sets are obtained from two sources. Firstly, GDP of the six most populous countries, namely China, India, United States, Indonesia, Brazil and Pakistan, is obtained from the World Development Indicator, the World Bank. The GDP is defined as real GDP in constant US dollars (base year = 2000). Secondly, the energy consumption data is taken from the British Petroleum (BP) Statistical Review of World Energy 2007. In this paper, energy consumption is defined as total primary energy consumption which is the sum of consumption of oil, natural gas, coal, nuclear energy and hydro electricity.

The summary of the data is shown in Table 1. All the data is measured in natural logarithm.

Table 1. Summary Statistics of Data

Variables	Obs	Mean	Std. Dev	Min	Max
GDP	246	26,34	1,75	23,23	30,03
EC	246	4,94	1,70	1,93	7,76

Methodology

The causality between energy consumption and income is analyzed using the panel vector autoregressive (VAR) method. VAR is frequently used in time series analysis with a long period data. Unfortunately, we cannot easily gather long period data in our studies. Sometimes the data used only covers a short period of time and this will cause a problem if we still regress it with a time series method. Therefore, Eakin *et al.* (1988) and Lee (2005) suggest using panel data to deal with the short span of data.

In this paper, VAR in panel data is used to analyze the causality between two variables, GDP and energy consumption. The basic model of VAR with the individual fixed effects and time fixed effects is:

$$y_{it} = a_t + a_i + \Gamma_1 y_{it-1} + u_{it} \text{ ....(1)}$$

where is two variables vector (GDP and energy consumption), is the time specific effect, is the country specific effect, is matrix polynomial in the lag operator, and is idiosyncratic error.

In order to run the regression in panel VAR, we have to transform the model to eliminate time specific effect and country specific effect. Suppose if we take an average on this equation over time, hence

$$\bar{y}_{it} = \bar{a}_t + \bar{a}_i + \Gamma_1 \bar{y}_{it-1} + \bar{u}_{it} \text{ ....(2)}$$

Because is constant over time, so , therefore we can eliminate the time specific effect by time-demeaned transformation. We cannot do the same for country specific effects, because the country specific effects are correlated with the regressors due to lags of the dependent variables. If we employ the same method to eliminate country specific effects, the coefficient will be biased (Love and Zicchino, 2006). To deal with this problem, Arellano and Bover (1995) suggest Helmert procedure to remove only the forward mean.

Now, suppose $\bar{y}_{it}, \bar{y}_{it-1}, \bar{u}_{it}$ denote the means of y_{it}, y_{it-1}, u_{it} that are calculated from the future value. Hence, our new model after transformation is

$$\tilde{y}_{it} = \Gamma_1 \tilde{y}_{it-1} + \tilde{u}_{it} \quad \text{..(3)}$$

where : $\tilde{y}_{it} = \theta_{it}\left(y_{it} - \bar{y}_{it}\right)$

$$\tilde{y}_{it-1} = \theta_{it}\left(y_{it-1} - \bar{y}_{it-1}\right)$$

$$\tilde{u}_{it} = \theta_{it}\left(u_{it} - \bar{u}_{it}\right)$$

$$\theta_{it} = \sqrt{(T_i - t)/(T_i - t + 1)}$$

In this transformation procedure, we will lose the observation for the last year (Amuedo-Dorantes *et al.*, 2007). Next, we estimate the impulse response function and the variance decomposition. The impulse response function gives information about the path and time that the variable returns to equilibrium as an impact of the one time shock to the model . Finally, variance decomposition is calculated to measure the percent of variation in a variable that is explained by the shock of another variable .

The Unit Root Test

In this paper three types of unit root tests used on panel data. These are the Levin, Lin and Chu unit root test (LLC), the Im, Pesaran and Shin unit root test (IPS) and the Hadri test LLC (Levin et al, 2002) proposed the use of the Augmented Dickey-Fuller (ADF) test on panel data by the following procedures. First, we implement ADF regression for each individual country, thus

$$\Delta y_{it} = \alpha_i + \delta_i y_{it-1} + \sum_{j=1}^{k} \theta_j \Delta y_{it-1} + e_{it} \quad \text{....................(4)}$$

The lag order, k, could be different across countries. However, it is preferable to use the maximum lag order. Subsequently, we can check whether the smaller lag order is better by using t-statistic of .

Next, we run two regressions and save the errors, hence

$$\Delta y_{it} = \alpha_i + \sum_{j=1}^{k} b_{ij} \Delta y_{it-j} + e_{it} \quad \text{..............................(5)}$$

$$y_{it-1} = \alpha_i + \sum_{j=1}^{k} b_{ij} \Delta y_{it-j} + v_{it-1} \quad \text{..............................(6)}$$

Then, we normalize the two errors by the regression standard error from equation (4), thus

$$\tilde{e}_{it} = \frac{\hat{e}_{it}}{\sigma_{\varepsilon i}} \text{ and } \tilde{v}_{it-1} = \frac{\hat{v}_{it-1}}{\sigma_{\varepsilon i}}$$

Finally, we run the regression, hence

$$\hat{e}_{it} = \rho v_{it-1} + \hat{\varepsilon}_{it} \quad \text{..............................(7)}$$

And test the null hypothesis .

Next, we apply the IPS unit root test. Al-Rabbaie and Hunt (2004) argue that the IPS has more benefit than the LLC because it allows for the heterogeneity in the value under the alternative hypothesis. The Z-statistic in this method is

$$\bar{Z} = \sqrt{N}\left(\bar{t} - E\left(\bar{t}\right)\right) / \sqrt{Var\left(\bar{t}\right)} \quad \text{.........................(8)}$$

Where ; represents the mean of each statistic; and represents the variance of each statistic. Then we test the null hypothesis, for all i against the alternative for all i.

After that, we employ the Hadri test. The difference between the Hadri test and the other two tests above is the null hypothesis. The Hadri test uses a reverse null hypothesis (Lee, 2005) and the panel test statistic is

$$\bar{Z} = \sqrt{N}\left(LMi - \xi\right)/\zeta \rightarrow N(0,1), \text{ for } i = 1 \text{ and } 2 \quad \text{......(9)}$$

where ; and for the only-constant model, otherwise and ; is the average of the individual estimators of the residual spectrum.

RESULTS

Three types of panel unit root tests, the LLC test, the IPS test and the Hadri test are employed to test the stationary of the panel data. The results of these three panel unit roots test are shown in Table 2. In the level, the LLC test rejects the hypothesis of the presence of unit root in the two series. Meanwhile, the other panel unit root tests (IPS, Hadri (Ho) and Hadri (He)) suggest that the two variables have a panel unit root at a 5 persen significance level. Thus, we can conclude that GDP (income) and EC (energy consumption) are not stationary in the level. As a result, we use the first differenced data in our panel VAR model .

All the data is measured in natural logarithm. ** significant at the 5 persen level. Δ refer to first differences

Table 2. Panel Unit Root Test

Variables	LLC	IPS	Hadri (Ho)	Hadri (He)
GDP	-2,62**	-1,21	40,10**	32,53**
ΔGDP	-4,28**	-2,63**	1,38	0,99
EC	-2,28**	-1,95	34,25**	24,29**
ΔEC	-4,36**	-2,53**	1,67**	3,45**

The step before the panel var regression is to determine the number of lags that we will use in the model. In this paper, we obtain Akaike Information Criteria (AIC) for every possible lag option. We start by using one lag and follow by using two lags and continue this calculation until we find the smallest AIC which is found in the three lags model. We use the AIC formula from Akaike (1978), hence

AIC = (-2) log (maximum likelihood) + 2 (number of parameter) ....(10)

Granger Causality test

When the dependent variable : ΔGDPt

F-test : 6,816

ΔEC Granger-cause ΔGDP

When the dependent variable : ΔECt

F-test : 0,026

ΔGDP does not Granger-cause ΔEC

Table 3 shows the results of panel VAR in bivariate model with three lags. The interpretation of the panel VAR results is growth, because the series that we used is in first differenced of its natural logarithm. In order to test the causality between GDP and energy consumption, we calculate the F-test by using sum of square residual (RSS) of each unrestricted and restricted model. This method is adopted from Arellano (2003) and Blancard (2006), by which we test whether energy consumption granger-cause income by imposing the restrictions of ΔECt-i = 0 in the first equation. On the contrary, we can conclude that income granger-cause energy consumption if the restriction of ΔGDPt-i = 0 in the second equation is valid. Based on the result on Table 3, we can conclude that the energy consumption growth granger-cause GDP (income) growth but not vice versa. This means that there is a unidirectional causality running from energy consumption to income.

Figure 1 shows the graphs of impulse response functions that are generated by Monte Carlo simulation with 500 repetitions and 5 persen error bands. The main interest in this paper is the response of income (GDP) to energy consumption (EC) shock. In response to energy consumption shock, income moves positively and reaches the maximum effect in the first period. After that period, the effect is diminishing and returns to the initial level approximately in the third period. Interestingly, income increases again until the

Table 3. Panel VAR Results

Dependent variables	Independent variables					
	ΔGDP_{t-1}	ΔGDP_{t-2}	ΔGDP_{t-3}	ΔEC_{t-1}	ΔEC_{t-2}	ΔEC_{t-3}
ΔGDP_t	0,160 (0,071)**	-0,023 (0,081)	0,078 (0,069)	0,219 (0,056)**	0,018 (0,052)**	-0,077 (0,050)
ΔEC_t	0,040 (0,128)	-0,269 (0,102)**	-0,051 (0,081)	0,283 (0,078)**	0,224 (0,084)**	0,110 (0,056)
Granger Causality test						
When the dependent variable : ΔGDP_t F-test : 6.816 ΔEC Granger-cause ΔGDP						
When the dependent variable : ΔEC_t F-test : 0.026 ΔGDP does not Granger-cause ΔEC						

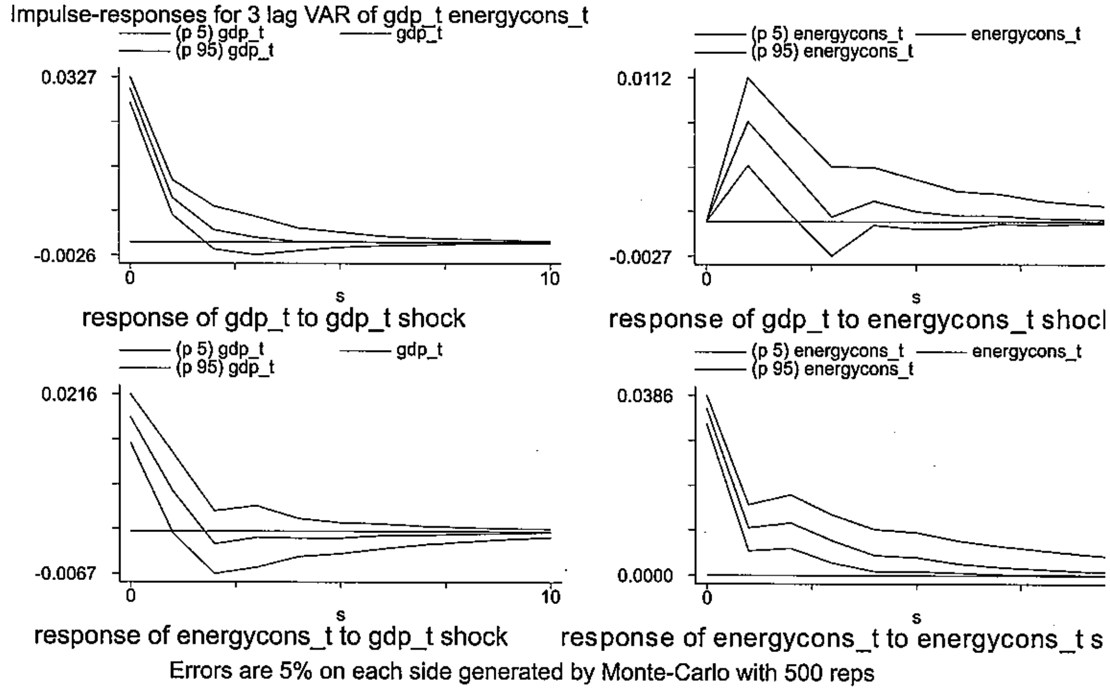

Figure 1. Impulse Response Function

Table 4. Variance Decomposition

	Period	ΔGDP_t	ΔEC_t
ΔGDP_t	10	92,471722	7,5282780
ΔEC_t	10	18,703930	81,296070
ΔGDP_t	20	92,468196	7,5318040
ΔEC_t	20	18,699811	81,300189
ΔGDP_t	30	92,468191	7,5318090
ΔEC_t	30	18,699805	81,300195

fourth period, then slowly decreases and returns to the initial level around periods 7 to 8. The positive effect in the impulse responses supports the result of panel VAR regression which is shown in Table 3.

Finally, to complete the analysis, variance decompositions are constructed. Table 4 reports variance decompositions for periods 10, 20 and 30. In period 10, energy consumption shock explains 18.7 persen variation of income. The effects slightly decrease over the next 10 and 20 periods. However, the differences of variance decomposition between the three periods are very small in magnitude.

The outcomes from the panel vector autoregressive impulse response function and variance decomposition give reasonable evidence to support the argument that energy conservation policy could harm economic performance. The economic performance of the six most populous countries is threatened by an energy conservation policy. If these countries implement energy conservation policy by reducing energy consumption, there would be a fall in their income. This result is supported by Lee (2005). Even using a different method of panel data analysis, Lee found unidirectional causality running from energy consumption to income for data from 18 developing countries. This means, those developing countries are also threatened by an energy conservation policy.

CONCLUSION

I have analyzed the causality between energy consumption and income. Until now, there has been no exact direction of causality between those two variables. All four possibilities, unidirectional causality either running from energy consumption to income or from income to energy consumption, bi-directional causality and no causality are found in previous studies. Most of those studies use time series data with various methods, time periods and case studies. Lee (2005) develops a panel data analysis to analyze the causality between energy consumption and income. Lee argues that panel data could solve the short span of data period and small sample distortion which are the common problems in the time series studies. The outcomes show the presence of unidirectional causality running from energy consumption to income.

A panel vector autoregressive (VAR) method is used in this study to find exact direction causality of two variables, namely energy consumption and income. Then, Granger causality is developed by using the F-test. There is an evidence of unidirectional causality running from energy consumption to income. This result confirms those of Lee (2005). Furthermore, impulse response function and variance decomposition are also employed in this study. The outcome of impulse response function shows the positive effect of the energy consumption shock on income. According to variance decomposition, 18,7 persen variation in income can be explained by the shock of energy consumption. The magnitude slightly decreases after 10 and 20 periods.

Within a policy analysis framework, the outcomes of this paper support the arguments that oppose the energy conservation policy. My results suggest that energy conservation policy which is implemented by reducing energy consumption would have a negative effect on income. Furthermore, my results also suggest that the reduction or the elimination of government subsidies on energy will harm economic performance. Subsidies elimination will push domestic price in line with market price. As a result, people will consume less energy which will lead to lower incomes.

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Appendix 1. Several Conflicting Results on the Energy Consumption-Income Causality Studies Sims' Technique, co-integration, Granger Causality.

Country	Study	Time period	Method	Result
Indonesia	Fatai et al (2004)	1960-1999	Granger causality, Toda and Yamamoto lag technique	Energy consumption cause income
	Asafu-Adjaye (2000)	1973-1995	Co-integration and Granger causality based on ECM	Energy consumption cause income
	Masih and Masih (1996)	1960-1990	Sims' technique, co-integration, Granger Causality and vector decomposition	Income cause energy consumption
	Soytas and Sari (2003)	1950-1992	Co-integration and Granger Causality	No causality
Thailand	Fatai et al (2004)	1960-1999	Granger causality, Toda and Yamamoto lag technique	bi-directional causality
	Asafu-Adjaye (2000)	1971-1995	Co-integration and Granger causality based on ECM	bi-directional causality
	Masih and Masih (1998)	1955-1991	Johansen's multivariate co-integration test, VECM, dynamic VD	Energy consumption cause income
the Philippines	Fatai et al (2004)	1960-1999	Granger causality, Toda and Yamamoto lag technique	bi-directional causality
	Asafu-Adjaye (2000)	1971-1995	Co-integration and Granger causality based on ECM	bi-directional causality
	Masih and Masih (1996)	1960-1990	Sims' technique, co-integration, Granger Causality and vector decomposition	No causality
India	Fatai et al (2004)	1960-1999	Granger causality, Toda and Yamamoto lag technique	Energy consumption cause income
	Masih and Masih (1996)	1955-1990	Sims' technique, co-integration, Granger Causality and vector decomposition	Energy consumption cause income
	Asafu-Adjaye (2000)	1973-1995	Co-integration and Granger causality based on ECM	Energy consumption cause income
	Paul and Bhattacharya (2004)	1950-1999	Combination of Engle-Granger causality approach and standard Granger	bi-directional causality
South Korea	Glasure and Lee (1997)	1961-1990	Co-integration and ECM	bi-directional causality
	Oh and Lee (2004)	1970-1999	VECM	bi-directional causality
	Soytas and Sari (2003)	1950-1992	Co-integration and Granger Causality	Income cause energy consumption