INVESTIGATING ECONOMIC GROWTH AND ENERGY CONSUMPTION IN INDONESIA: TIME SERIES ANALYSIS 1971 TO 2007

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ABSTRACT

This paper has two objectives. The first is to re-investigate the relations between economic growth and energy consumption in Indonesia. The second is to analyse the consistency between several econometric techniques in explaining the causality test. This paper is different from previous studies in five ways. First, we expanded the time period of analysis. Second, we applied Bayesian techniques to obtain the third variable for trivariate analysis. Third, we applied bivariate and trivariate causality analysis. Fourth, we conducted the Hodrick-Prescott (HP) filter technique and applied the causality test on the cyclical components. Finally, we conducted variance decomposition analysis. Although the Bayesian analysis showed that energy consumption is a good explanatory variable for economic growth, and vice versa, we did not find any short-run and long-run relations in the cases of bivariate and trivariate analysis. Variance decomposition analysis also supported no causal relation, even after we changed the Cholesky order. By applying the HP filter, the results also supported the neutrality hypothesis between energy consumption and economic growth. The results of our study imply that the Indonesian government needs to implement energy efficiency programs more broadly in all economic sectors.

Keywords: *Economic growth, Energy consumption, Bayesian, Bivariate, Trivariate*

JEL classification: *C110, C220, O100*

I. INTRODUCTION

The relations between economic growth and energy consumption have become interesting research topics in energy economics. Applying new techniques for estimations, using different data definitions and time periods have driven many scholars to re-examine previous studies. In the case of Indonesia, we found no Granger causality between economic growth and energy consumption. Asafu-Adjaye (2000) investigated the relation of energy consumption to economic growth by including the energy prices as intermittent variables. He applied time series analysis and used real income (GDP in constant 1987 prices in the local currency), energy consumption (kilograms of oil equivalent per capita), and prices (consumer price index, 1987=100). Data covered the period from 1973 to 1995. He found two cointegrating relations and applied an error correction model (ECM) and the study supported the neutrality hypothesis. Similarly, Soytas and Sari (2003) used annual energy consumption and GDP per capita data. Energy consumption was measured in million tonnes (metric tons) of coal equivalent and the data were from the United Nation's Statistical yearbook. GDP per capita data were obtained from the Penn world table. In the case of Indonesia, the period of analysis was from 1960 to 1992. Although, the results provide evidence of a cointegrating vector in Indonesia, they did not show a significant relation between energy consumption and GDP. This implies a lack of short-run causality.

Further, Wei, Chen and Zhu (2008) argued that most of the previous studies were limited in scope to the application of linear models but it is possible for there to be structural changes in the pattern of energy consumption because of economic events and regime changes. Thus a non-linear relation has to be taken into account when one investigates relations between energy consumption and economic growth. For Indonesia, Wei et al. used the period 1971 to 2003. Energy consumption was measured in kilo tonnes of oil equivalent and real GDP with the year 2000 as the base year. They found no cointegrating vector for Indonesia and applied a VAR model. The VAR model indicated that energy consumption Granger causes economic growth and this is accepted at the 10% critical level.

Next, to test for non-linearity, Wei et al. (2008) performed the Bayesian discovery sample (BDS) test to check residual indenpendent and indirectly distributed variables i.i.d. assumptions. If the i.i.d. assumption is rejected, non-linearity embedded in series might exist. Then, instead of the standard Granger causality test, the non-linear Granger causality test would appear to be more appropriate. In the case of Indonesia, they found three and four embedding dimensions that are significant for an energy consumption series. The results show that a non-linear causality supports bidirectional relations. Thus, it seems that there is non-linear relation between GDP and energy consumption. Similarly, Lee and Chang (2007) investigated the relations between energy consumption and GDP by applying panel data analysis. Although there is no country-specific information, the results for Indonesia showed that the panel data stationary test with structural breaks showed that Indonesia had three structural breaks in 1976, 1989 and 1997.

The studies showed different results in terms of short-run and long-run relations. However, results by Asafu-Adjaye (2000) and Soytas and Sari (2003) supported no causal relations or neutrality hypothesis. Similarly, Wei et al. (2008) found energy consumption Granger causes economic growth but with a high critical level.

This paper re-investigates the relation of economic growth to energy consumption in Indonesia and examines the consistency of several econometric approaches in investigating causal relations. This paper is organised as follows: section 2 describes the data and methods of the study; section 3 reports and analyses empirical results; section 4 provides the policy implications of the empirical analysis; and section 5 is the conclusion.

II. DATA AND METHODS

2.1 Data Description

The data cover the period of 1971 to 2007. We obtained the data from the World Development Indicators and the International Financial Statistics in the IMF's statistical databases. The measure of economic openness is the authors' calculation based on data from the World Development Indicators. Variables are selected subject to data availability and with previous studies in mind, especially those of Moral-Benito (2009) (see Table 1). Moral-Benito (2009) investigated the growth model by applying Bayesian Model Averaging for panel data model. The data that he used covered 73 countries (one being Indonesia) for the period 1960 to 2000. Variables of interest can be summarised as follows:

2.2 Bayesian Model Averaging

As can be seen in Table 1, we had 13 variables of which 12 became dependent variables. When we have many regressors, Bayesian Model Averaging (BMA) can help us to select the best model. Generally speaking, the BMA technique will use all the variables in the iteration process, but not all the variables will be selected for the best model. Thus, it is better to have several candidate variables in the early stages

Table 1. Variables of Interest

No.	Variables
1	Gross domestic product (GDP) at constant prices (2000 US$)*
2	Domestic credit provided by banking sector (% of GDP)
3	Energy consumption (kilo tonne of oil equivalent)
4	General government final consumption expenditure (% of GDP)*
5	Gross capital formation (% of GDP)*
6	IBRD loans and IDA credits (DOD, current US$)
7	Life expectancy at birth, total (years)*
8	Manufacturing exports (% of merchandise exports)
9	Population aged from 15 to 64 (% of total)
10	Population in urban agglomerations of more than 1 million
11	Urban population
12	Economic openness: (exports + imports)/GDP*
13	Index of crude petroleum production (2005 = 100)

Note: Variables marked with an asterisk (1, 4, 5, 7 and 12) are those chosen by Moral-Benito (2009).

of analysis. Raftery (1995) argued that when there are many candidate independent variables, standard model selection procedures are misleading and tend to suggest that there might be strong evidence for effects that do not exist. On the other hand, Raftery (1995) also argued that BMA enables one to take into account model uncertainty and to avoid the difficulties with standard model selection procedures.

Raftery (1995) said that the 'Bayesian model selection does not remove the need to check whether the models chosen fit the data. Even if many models are considered initially, they could all be bad! Thus, diagnostic checking, residual analysis, graphical displays, and so on, all remain essential'. Thus, we attempted to re-examine stationary conditions for every variable.

Technically, a posterior probability is assigned to each model based on the BIC (Bayesian Information Criterion, sometimes known as Schwarz Information Criterion or SIC). The estimate of each model is weighted according to the posterior probability and final estimates are a weighted average. The posterior probabilities are calculated as:

$$\Pr(M_i) = \frac{\exp(BIC_i)}{\sum_{i=1}^{n} \exp(BIC_i)} \qquad (1)$$

where i indicates the index of the model (M). Final estimate of the weighted average can be written as follows:

$$\hat{\theta}_1 \Pr(M_1) + \hat{\theta}_2 \Pr(M_2) + \hat{\theta}_3 \Pr(M_3) + ... + \hat{\theta}_n \Pr(M_n) \qquad (2)$$

where $\hat{\theta}_i$ is the estimated parameter of each model.

In this exercise, we have 12 regressors and 2^{12} or 4096 possible models. When the number of models is too large, the Markov Chain Monte Carlo Model Composition (MC^3) is one popular computational technique that we can apply. We applied the MC^3 technique to obtain the posterior probability of inclusion of each regressor and its posterior mean.

2.3 Stationarity, Cointegration, Error Correction Model And Vector Autoregression

An important issue in time series analysis is whether a time series process is stationary or non-stationary. Stationary means the distribution of the variable of interest does not depend upon time. We applied several tests to measure the presence of unit root. However, according to Engle and Granger in 1987, (cited in Yuan, Zhao, Yu and Hu, 2007), it is possible that two or more non-stationary series (with the same order of integration) may be stationary and we said the series are cointegrated or that a long-run equilibrium relation exists. We applied the Johansen Maximum likelihood to test for the presence of cointegration. We applied vector autoregressive (VAR) at first difference for the Granger causality test if there was no evidence for cointegration among the variables. However, if there is evidence for cointegration, we need to add a term for a lagged period of error correction in the Granger causality model. The bivariate model for the error correction model (ECM) is specified as follows:

$$\Delta \ln Y_t = \upsilon_1 + \sum_{i=1}^{p} \nu_i \Delta \ln Y_{t-i} + \sum_{i=1}^{p} \kappa_i \Delta \ln EU_{t-i} + \pi_1 ECT_{t-i} + \varepsilon_{1t} \quad (3)$$

$$\Delta \ln EU_t = \upsilon_2 + \sum_{i=1}^{p} \kappa_i \Delta \ln EU_{t-i} + \sum_{i=1}^{p} \nu_i \Delta \ln Y_{t-i} + \pi_2 ECT_{t-i} + \varepsilon_{2t} \quad (4)$$

Then, trivariate ECM is written as follows:

$$\Delta \ln Y_t = \upsilon_3 + \sum_{i=1}^{p} \nu_i \Delta \ln Y_{t-i} + \sum_{i=1}^{p} \kappa_i \Delta \ln EU_{t-i} + \sum_{i=1}^{p} \phi_i \Delta \ln X_{t-i} + \pi_1 ECT_{t-i} + \varepsilon_{1t} \quad (5)$$

$$\Delta \ln EC_t = \upsilon_4 + \sum_{i=1}^{p} \kappa_i \Delta \ln EU_{t-i} + \sum_{i=1}^{p} \phi_i \Delta \ln X_{t-i} + \sum_{i=1}^{p} \nu_i \Delta \ln Y_{t-i} + \pi_2 ECT_{t-i} + \varepsilon_{2t} \quad (6)$$

$$\Delta \ln X_t = \upsilon_5 + \sum_{i=1}^{p} \phi_i \Delta \ln X_{t-i} + \sum_{i=1}^{p} \nu_i \Delta \ln EU_{t-i} + \sum_{i=1}^{p} \kappa_i \Delta \ln Y_{t-i} + \pi_3 ECT_{t-i} + \varepsilon_{3t} \quad (7)$$

Y is real gross domestic product (GDP), EU is energy consumption and X is the third variable that will be obtained from the BMA. ECT is the lagged error-correction term, and p is the optimal lag length. Letting $M_1=(\nu_1=\ldots=\nu_p)$, $M_2=(\kappa_1=\ldots=\kappa_p)$ and $M_3=(\phi_1=\ldots=\phi_p)$. The causality test is carried out by generatingχ^2 statistics to establish whether the null hypotheses can be accepted. In the bivariate case, we set the null hypothesis as follows:

1. Equation 3: H_0: $M_2 = 0$, this indicates no causality from energy consumption to economic growth.
2. Equation 4: H_0: $M_1 = 0$, this indicates no causality from economic growth to energy consumption.

In the case of the trivariate model, hypothesis testing summaries are as follows:

1. Equation 5: H_0: $M_2 = 0$, this indicates no causality from energy consumption to economic growth; similarly H_0: $M_3 = 0$, this indicates no causality from the third variable to economic growth.
2. Equation 6: H_0: $M_1 = 0$, this indicates no causality from economic growth to energy consumption; similarly H_0: $M_3 = 0$, this indicates no causality from the third variable to economic growth.
3. Equation 7: H_0: $M_1 = 0$, this indicates no causality from energy consumption to the third variable; similarly H_0: $M_2 = 0$, this indicates no causality from economic growth to the third variable.

2.4 Variance Decomposition Analysis

As has been discussed in Enders (2010), impulse analysis and variance decompositions (together called innovation accounting) can be useful tools to examine the relations among economic variables. Variance decomposition analysis (VDA) can be interpreted as out of sample causality test. Further, by investigating the effect of shock on variances for several periods, researchers can have better idea of how to determine the most important variable. The key analysis of VDA is Cholesky ordering because ordering indicates prior causality. However, previous studies, such as that by Yuan et al. (2007) did not discuss the Cholesky ordering. Mathematically, variance decomposition analysis (VDA) techniques, and how the Cholesky ordering works, can be seen in the Appendix.

2.5 The Hodrick-Prescott filter

Generally speaking, series can be decomposed into two parts; trend and cycle components. The Hodrick-Prescott (HP) filter decomposes observed series (x_t) into a smooth trend (m_t) that captures the long-term growth of the series and into a residual (c_t) or cyclical component that represent deviation from that growth (Kaiser and Maravall, 2001). In the decomposition:

$$x_t = m_t + c_t \qquad (8)$$

The HP filter provides the estimator of c_t and m_t such that the following expression (Kaiser and Maravall, 2001) is minimised.

$$\min \sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=3}^{T} (\nabla^2 m_t)^2,$$

$$\text{where } \nabla m_t = m_t - m_{t-1} \qquad (9)$$

The filter depends on one parameter, which needs to be determined a priori. With the decomposed components, we analysed the causality among trends and among cyclical components of the original series. Further, Enders (2010) argued that because the HP filter is a function that smoothens the trend, it has been shown to introduce spurious fluctuations into irregular components of a series. Further, he also said that the filter forces the stochastic trend to be a smoothened version of $\nabla^2 m_t = \nabla(m_t - m_{t-1})$. Then he argued that the filter works best if the series is I(2), so that smoothening the second difference of the stochastic trend is appropriate. Following Yuan et al. (2007), if the original series are cointegrated and the cyclical components are also cointegrated, we can say that the series are cointegrated and co-featured. This implies that the causality relation may be correlated with the business cycle. One of the drawbacks of the HP filter is in deriving. According to Kaiser and Maravall (2001), the lack of a proper foundation for derivation can induce arbitrariness into the measurement of the cycle.

III. RESULTS

3.1 Bayesian Model Averaging Analysis

As can be seen in Table 2, many variables are not stationary at level and they become stationary after first and second difference. Thus we need to conduct Bayesian Model Averaging (BMA) on stationary data. Table 3 shows that under BMA I, there are nine variables that are important in explaining economic growth. BMA I selected 18 models with cumulative

Table 2. Stationary Results by Applying the Augmented Dickey Fuller Test

No.	Variables	Stationary test
1	Gross domestic product (GDP) at constant price 2000 US$	First difference
2	Domestic credit provided by banking sector (% of GDP)	First difference
3	Energy consumption (kilo tonne of oil equivalent)	First difference
4	General government final consumption expenditure (% of GDP)	First difference
5	Gross capital formation (% of GDP)	First difference
6	IBRD loans and IDA credits (DOD, current US$)	At level
7	Life expectancy at birth, total (years)	At level
8	Manufacturing exports (% of merchandise exports)	First difference
9	Population aged 15 to 64 years (% of total)	At level
10	Population of more than 1 million in urban agglomerations	At level
11	Urban population	Second difference
12	Economic openness: (exports + imports)/GDP	At level
13	Index of crude petroleum production (2005 = 100)	First difference

Table 3. Result of BMA for Period 1971 to 2007 (GDP as Dependent Variable)

No.	Variables	BMA I	BMA II
1	Domestic credit provided by banking sector (% of GDP)	100*	0.80692*
2	Energy consumption (kilo tonne of oil equivalent)	100*	0.87625*
3	General government final consumption expenditure (% of GDP)	58*	0.15409
4	Gross capital formation (% of GDP)	100*	0.97756*
5	IBRD loans and IDA credits (DOD, current US$)	83.8*	0.09099
6	Life expectancy at birth, total (years)	83.8*	0.12320
7	Manufacturing exports (% of merchandise exports)	20.9	0.10727
8	Population aged 15 to 64 years (% of total)	83.8*	0.12756
9	Population of more than 1 million in urban agglomerations	83.8*	0.10952
10	Urban population	15.3	0.06975
11	Economic openness	100*	0.99894*
12	Index of crude petroleum production (2005 = 100)	22	0.08395
	Number of variables selected at first best model	9	4
	R^2	0.886	
	BIC	-44.11	
	Posterior probability	0.256	0.31710
	BMA I: Cumulative posterior probability (best 5 of 18 models selected) is 0.6225 BMA II: Cumulative posterior probability (best 5 of 409 models selected) is 0.5033		

Note: *variables selected according the first best model. To calculate the BMA, we used R program. BMA I was run under the command: bicreg(y,x,strict=FALSE,OR=20) and BMA II run under the command MC3.REG(y,x,num.its=2000,rep(TRUE,12), outliers=FALSE), where MC3 stands for Markov Chain Monte Carlo Model Composition.

posterior probability of 62.25%. However, BMA II considered more models compared to BMA I. BMA II also has lower cumulative posterior probability than BMA I. According to BMA II, four variables are important in explaining economic growth; economic openness, gross capital formation, energy consumption and domestic credit. However, capital formation and economic openness had the highest posterior probability. Further, we also investigated variables that are important in explaining energy consumption. As seen from Table 4, domestic credit and GDP have the highest posterior probability under BMA I and BMA II.

In conclusion, BMA analysis shows that energy consumption is not the only variable that is important in explaining economic growth. But economic growth is important in explaining energy consumption. Further, we also can argue that the domestic credit provided by the banking sector is important in explaining economic growth and energy consumption. Thus, domestic credit can be used as a candidate variable for trivariate analysis. However, is there a causal relation between economic growth and energy consumption? Time series analysis is applied to answer this question.

Table 4. Result of BMA for the Period 1971 to 2007 (Energy Consumption as Dependent Variable)

No.	Variables	BMA I	BMA II
1	Domestic credit provided by banking sector (% of GDP)	94.6*	0.66707*
2	Gross domestic product (GDP) at constant price 2000 US$	100*	0.92988*
3	General government final consumption expenditure (% of GDP)	25.3	0.10807
4	Gross capital formation (% of GDP)	55.7	0.25438
5	IBRD loans and IDA credits (DOD, current US$)	9.5	0.10985
6	Life expectancy at birth, total (years)	9.5	0.10684
7	Manufacturing exports (% of merchandise exports)	20.1	0.15953
8	Population aged 15 to 64 years (% of total)	9.3	0.09703
9	Population of more than 1 million in urban agglomerations	9.3	0.11983
10	Urban population	5.7	0.05561
11	Economic openness	5.4	0.16232
12	Index of crude petroleum production (2005 = 100)	4.0	0.05115
	Number of variables	2	2
	R^2	0.443	
	BIC	-13.347	
	Posterior probability	0.117	0.19108
	BMA I: Cumulative posterior probability (best 5 of 39 models selected) is 0.3528 BMA II: Cumulative posterior probability (best 5 of 541 models selected) is 0.3989		

Note: *variables selected according the first best model. To calculate the BMA, we used R program. BMA I was run under the command: bicreg(y,x,strict=FALSE,OR=20) and BMA II run under the command MC^3.REG(y,x,num.its=2000,rep(TRUE,12), outliers=FALSE), where MC^3 stand for Markov Chain Monte Carlo Model Composition.

3.2 Bivariate Analysis

Table 5 shows that GDP and energy consumption are stationary at first difference. Thus we can conclude that the two series have the same order of integration or I(1). Before conducting the Granger causality test, we applied Johansen cointegration. Following the Schwarz Information Criterion, we selected lag 1 as the optimal lag length. As seen from Table 6, the cointegration test indicated that we do not reject the null hypothesis, that is, there is no long-run relation between economic growth and energy consumption. Thus, the causality test runs with the VAR model. Although economic growth has a positive effect on energy consumption, as seen from Table 7, the result is not significant. Similarly with energy consumption, no significant effect is shown. In conclusion, bivariate analysis shows that there is no causal relation between economic growth and energy consumption or bivariate analysis supports a neutral hypothesis between economic growth and energy consumption.

Bayesian Model Averaging (BMA) analysis might provide intuitive support for a neutral hypothesis, where gross capital formation and economic openness are more important in explaining economic growth. We also expect that there are other variables that are more important than economic growth in explaining energy consumption.

Table 5. Unit Root Test Results of GDP and Energy Consumption in Logarithmic Series

Variables	ADF test		PP test		KPSS test	
	Level	First difference	Level	First difference	Level	First difference
Y*	-2.275	-4.13	-2.275	-4.134	0.723	0.322
5% critical value		-2.945				0.463
EU**	-1.362	-6.25	-1.362	-6.25	0.131	0.088
5% critical value			-3.54			0.119

Notes: *include intercept in test equation; **include trend and intercept in ADF and PP test.

Table 6. Bivariate Johansen Cointegration Estimation Results (Trace Test)

Number of cointegration	Eigenvalue	Trace-statistic	5% Critical value
None	0.228	11.712	15.495
At most 1	0.073	2.657	3.841

Table 7. Estimation Result of VAR bivariate Model

Variables	ΔY	ΔUC
ΔY_{t-1}	-	-0.07015(0.2039)
ΔUC_{t-1}	0.0664(0.2077)	-

Note: figure in parenthesis indicates standard error; we checked for autocorrelation problem by applying residual portmanteau test.

Next, we conducted variance decomposition analysis (VDC) to investigate the variance of forecast error from real GDP and energy consumption with the Cholesky ordering of GDP and energy consumption (Figure 1). This indicates that energy consumption is causally prior to economic growth. The results show that after 10 years about 99.7% of variance in real GDP comes from its own innovation. However, if we analysed variance on energy consumption, almost 40% came from economic growth. We also changed the order of Cholesky decomposition with ordering energy consumption and GDP. This indicates that economic growth is causally prior to energy consumption. We can conclude that 59% of GDP decomposition comes from its own shock, but almost 100% of energy consumption decomposition came from its own shock (Figure 2). Thus, by changing the order of Cholesky, variance decomposition has changed moderately. This might indicate that the order really does matter. However, VDC provided information that variance of its own shock is more dominant in explaining the variance. Thus, we can conclude that we did not find strong evidence of a causal relation between GDP and energy consumption, even after we considered future periods.

3.3 Trivariate Analysis

Before we conducted cointegration analysis to investigate long-term relations between GDP, energy consumption and domestic credit, we applied the Schwarz Information Criterion, and we selected lag 1 as the optimal lag length. Cointegration results can be seen from Table 8 and the test shows that we reject long-run relations among

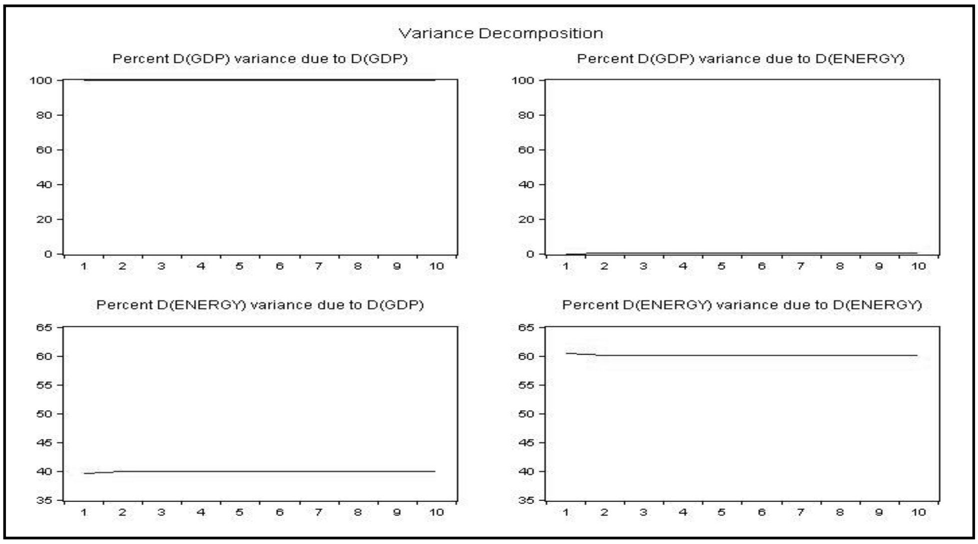

Figure 1. Variance Decomposition of GDP and Energy (With Cholesky Order GDP, Energy)

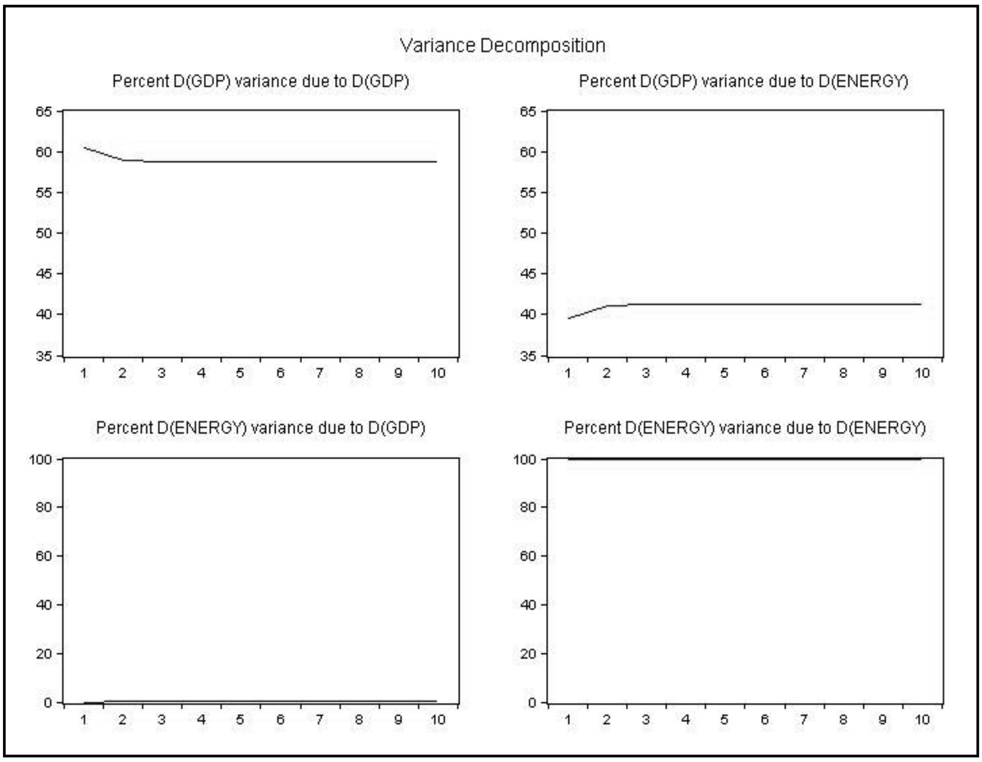

Figure 2. Variance Decomposition of GDP and Energy (With Cholesky Order Energy, GDP)

the variables at 5% critical level. Thus, we applied a VAR model to investigate causal relations. As seen from Table 9, we can conclude that there is no causal relation between economic growth and energy consumption. Although we obtain negative parameters, they are not significant. Thus trivariate analysis supports a neutral hypothesis.

It is important to compare the results with variance decomposition analysis. Figure 3 shows variance in energy consumption had more than 40% explanatory variance in GDP. Further, as seen from Figure 4, about 50% of variance in GDP is driven by energy consumption. Thus, variance decomposition from trivariate analysis supports the evidence that we did not find a strong relation between economic growth and energy consumption. We need further study to explain the relation between energy consumption and economic growth. Thus, we disaggregate trend and cyclical components by applying HP filtering. As seen in Figure 5, after we applied the HP filter, the trend components are much smoother than without filtering. Smoothing caused the economic crisis of 1997–98 not to appear clearly. Further, as Figure 5 shows, the cyclical component from GDP and energy consumption can be seen more clearly.

Table 8. Bivariate Johansen Cointegration Estimation Results (Trace Test)

Number of cointegration	Eigenvalue	Trace-statistic	5% Critical value
None	0.4128	24.6707	29.7971
At most 1	0.1269	6.03704	15.4947
At most 2	0.0361	1.2864	3.8415

Table 9. Estimation Results of VAR Bivariate Model

Variables	ΔY	ΔUC	ΔCredit
ΔY_{t-1}	-	-0.047267(0.21182)	16.649(20.664)
ΔUC_{t-1}	0.16134	-	-21.941(23.2279)
ΔCredit	-0.00177(0.00188)	0.000934(0.00194)	-

Note: figure in parenthesis indicates standard error, we checked for autocorrelation problems by applying residual portmanteau test.

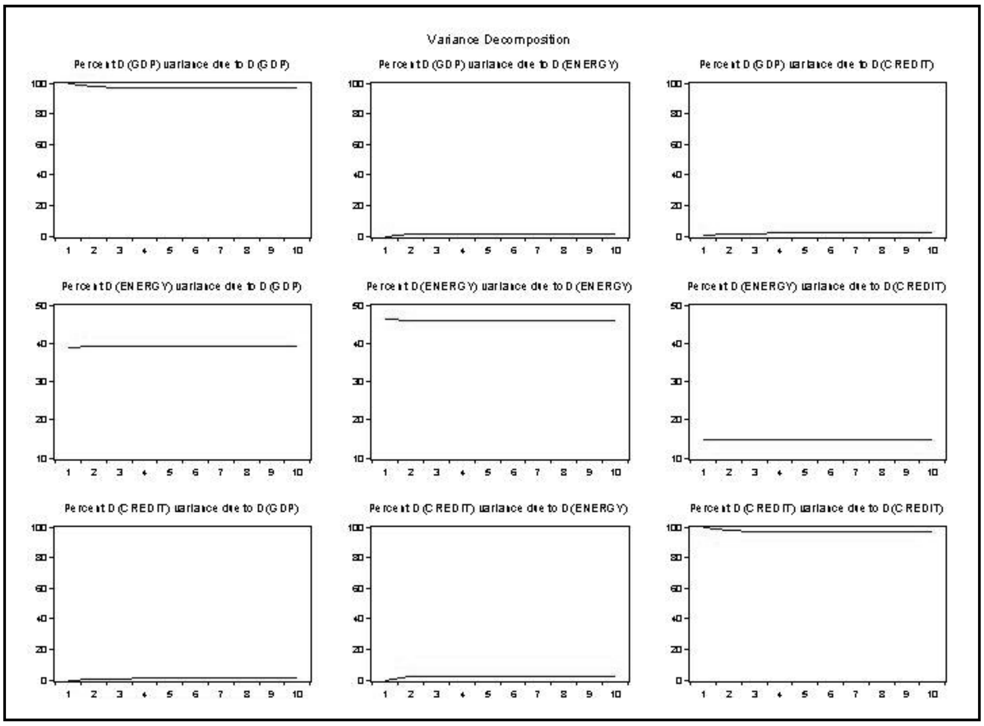

Figure 3. Variance Decomposition of GDP, Energy and Credit (With Cholesky Order Credit, GDP, Energy)

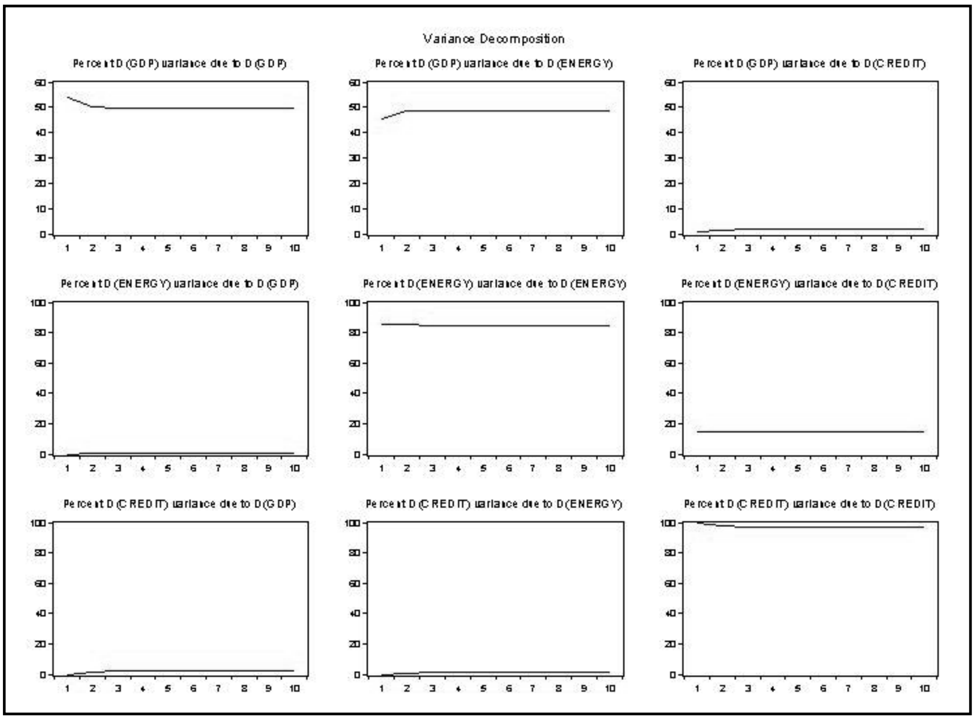

Figure 4. Variance Decomposition of GDP, Energy and Credit (With Cholesky Order Credit, Energy, GDP)

3.4 Bivariate Case after Data Filtering

Stationarity tests on trend and cyclical component showed that the trend component is stationary at second difference, while cyclical component is stationary at level. Further, we applied a cointegration test to investigate the long-run relations between economic growth and energy consumption and there is no cointegration. Then, we investigated the direction of causality between the cyclical components of energy consumption and economic growth. We did not find a significant relation between economic growth and energy consumption (see Table 10). This indicates that energy consumption correlated weakly with economic growth. Similarly, investigating the data in Figure 5 also showed that we had a different pattern of cyclical components between GDP and energy consumption.

We also checked for variance decomposition analysis (VDA) of cyclical components. Figure 6 shows that up to period ten, more than 90% innovation of GDP is explained by itself. Similarly, innovation of energy consumption after 10 years can be explained 70% by itself. Further, Figure 7 also shows that by changing the Cholesky order, around 50% of an innovation in GDP is explained by energy consumption; but less than 5% of an innovation in energy consumption is explained by GDP. Thus, VDA

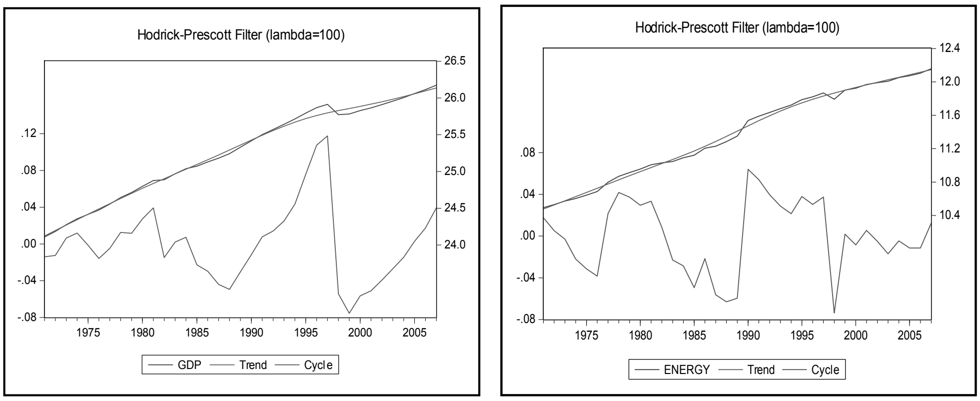

Figure 5. HP Filtering

Table 10. Estimation Result of VAR Bivariate Model after HP Filtering (Cyclical Component)

Variables	Y	UC
Y_{t-1}	0.551011 (0.15289)*	-0.133383 (0.15151)
UC_{t-1}	0.263733 (0.18153)	0.577527 (0.17989)*

Notes: figure in parenthesis indicates standard error, *significant at 5% critical level; we checked for autocorrelation problem by applying residual portmanteau test.

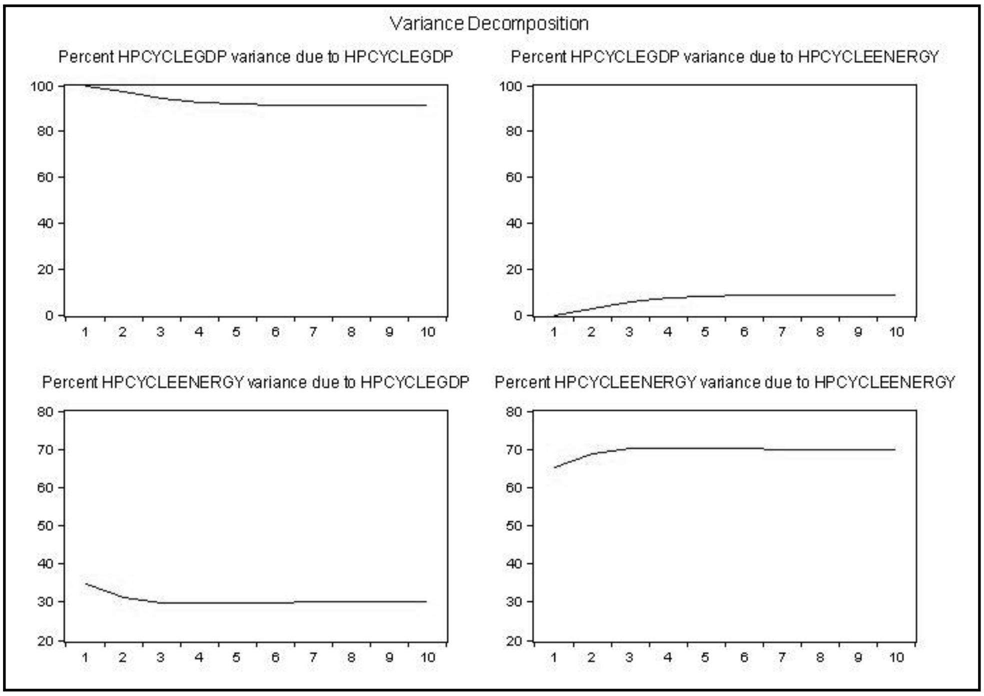

Figure 6. Variance Decomposition of Cyclical GDP and Energy (With Cholesky Order GDP, Energy)

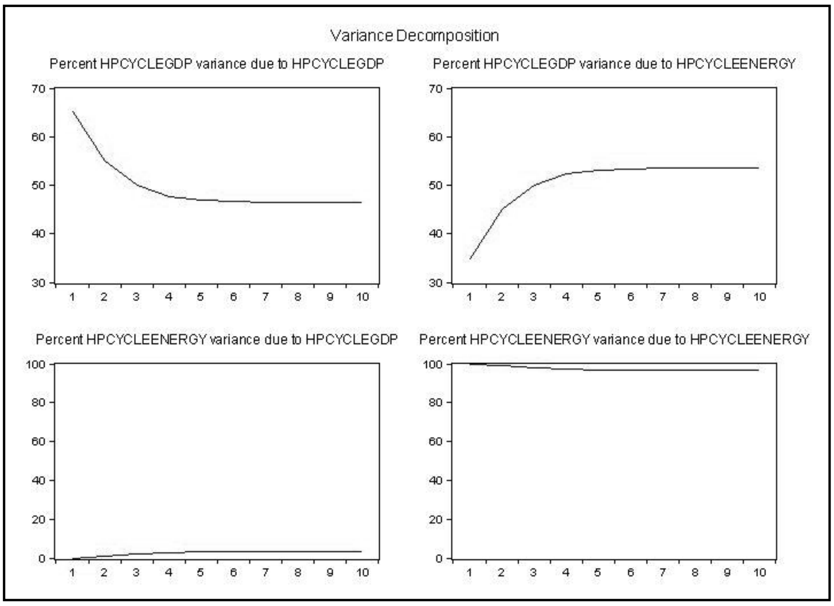

Figure 7. Variance Decomposition of Cyclical GDP and Energy (With Cholesky Order Energy, GDP)

of the cyclical component showed that fluctuations in economic growth and energy consumption are not bilaterally Granger caused. Thus we can infer that causality relations do not correlate with business cycles.

IV. POLICY IMPLICATIONS

By applying three types of analysis, bivariate, trivariate and VDA, we accepted the neutrality hypothesis. This implies that neither conservative nor expansive policies in relation to energy consumption have any effect on economic growth. Thus Indonesia still has huge opportunities to implement more progressive approaches to improve energy conservation policy in all the economic sectors.

Table 11 provides basic information on energy consumption from several sectors; in 1995 and 2009 the household sector consumed the highest amount of energy compared with other sectors. About 80% of primary energy consumption in the household sector is dominated by biomass and share of modern energy such as gas, electricity and other fuels need to be enhanced in the future. The industrial sector is the second largest energy consumer and its share increased from 30% to 31%. The increasing share of the industrial sector was mostly driven by rapid energy consumption from coal and gas, the share of petroleum decreased from 36 to 17%. Further, the share of energy consumption for the transport sector increased from 18.6% to 29.9% and almost all the energy consumption from this sector is of petroleum products.

The government of Indonesia has implemented some policies on energy efficiency and conservation (EE&C) activities such as the Presidential

Table 11. Energy Consumption Based on Economic Sector

Sector	1995		2009	
	('000 BOE)	Share (%)	('000 BOE)	Share (%)
Industry	170,412	29.96	295,634	31.18
Transport	105,867	18.61	226,578	23.90
Household	249,550	43.88	314,759	33.20
Commercial	13,589	2.39	30,473	3.21
Other sectors	29,310	5.15	26,311	2.78
Total	568,728	100.00	948,112	100.00

Source: Ministry of Energy and Mineral Resources, Republic of Indonesia (MEMR), 2006 and 2010.
Note: BOE = barrel of oil equivalent

Instruction No. 10/2005, the Ministry of Energy and Mineral Regulation No. 31/2005 on the Procedure for EE&C Implementation, and the Energy Law No. 30/2007, Article 25, focuses on Energy Conservation and Indonesia's 2003-2020 National Energy Policy. According to the Indonesia's Energy Law No 30/2007, there are two objectives of energy conservation: sustainability of energy resources and improving energy efficiency. Government will give incentives and disincentives to consumers or producers that can implement energy saving or develop energy saving technology.

According to government regulation 70 of 2009, energy conservation can be implemented in several ways, such as efficient processes or procedures, and efficient technology. Further, for any energy utilisation that is equal to or larger than 6,000 tonnes of oil equivalent per year, it is a must to conserve energy by implementing energy management strategies. Thus, internal energy auditors need to be prepared and accredited external auditors will evaluate the program. Some incentives such as tax, tariff, interest rate, and cost sharing subsidies will be provided by government. On the other hand, disincentives such as warnings, public notices in the media, penalties, and reductions in energy supply might be applied. Policies along these lines need to be implemented seriously by the government because energy efficiency has become one of the elements to improve industrial competitiveness, especially for high energy-intensive industries.

However, it is still unclear how effective those polices have been implemented. Further, energy conservation policy also needs to be addressed on the broad perspective rather than sector approach. For example, the transport sector has some serious problems. Thee Kian Wie and Negara (2010) argued that traffic congestion in Jakarta has caused tremendous and wasteful costs. Lack of transport infrastructure development, low capacity of public transport and poor management of metropolitan road drainage systems are the main factors leading to inefficiency in the transport sector.

Further, energy pricing policies lead to inefficiency in energy use. According to IEA (2008), setting the right energy price is important to improve energy efficiency. Energy subsidies become disincentives to improving efficiency. We suggest that, instead of providing fuel and electricity subsidies, the government needs to reallocate those funds for the development of infrastructure, such as public transport systems, that can minimise energy use intensity, and to ensure that the household sector has access to supplies of gas for domestic used.

In terms of institutional settings, IEA (2008) also suggested that it is important to integrate and to synergise many agencies that are involved in energy efficiency and conservation. Further, it is also important to obtain and to develop energy efficiency indicators for policy assessment (IEA, 2008).

V. CONCLUSIONS

Several studies have addressed the relation between economic growth and energy consumption in Indonesia but have not reached an agreement. This paper aims at re-investigating economic growth and energy consumption relations in Indonesia by applying several econometric techniques and to investigate the consistency of the results in several ways.

Bayesian analysis suggests that although economic growth has the highest probability in explaining energy consumption, economic openness and gross capital formation have the highest probability in explaining economic growth. Thus we need to apply time series analysis to investigate causality. Further, Bayesian analysis also suggests that domestic credit can be used as a good candidate for the trivariate analysis.

We did not find any short-run and long-run relations between economic growth and energy consumption with bivariate and trivariate analysis. Similarly, variance decomposition analysis, in bivariate and trivariate cases, did not show any significant indication that innovations from GDP or energy consumption can explain the situation. By applying an HP filter, in terms of cyclical components, we obtained no causal relation from energy consumption to economic growth and vice versa. This finding is also consistent with the variance decomposition analysis.

Because we found no causal relation or neutral hypothesis between economic growth and energy consumption, we advise the Indonesian government to implement energy conservation policies: such as energy consumption conversion from biomass to modern energy sources in the household sector; to improve energy efficiency in industrial sectors; to develop more efficient public transport infrastructures; and to be more flexible in setting domestic energy prices.

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REFERENCES

Asafu-Adjaye, John. (2000). The relation between energy consumption, energy prices, and economic growth: time series evidence from Asian developing countries. *Energy economics*, 22(6): 615–625.

Enders, W. (2010). *Applied econometric time series* (3rd edn). New York: John Wiley & Sons.

IEA. (2008). *Energy policy review of Indonesia.* International Energy Agency: Paris.

Kaiser, R. and A. Maravall. (2000). *Measuring business cycles in economic time series*. New York: Springer

Lee, C-C and CP Chang. (2007). Energy consumption and GDP revisited: a panel analysis of developed and developing countries. *Energy economics*, 29: 1206–1223.

MEMR. (2006). *Handbook of energy and economic statistics of Indonesia 2006*. Jakarta: Ministry of Energy and Mineral Resources, Republic of Indonesia.

MEMR. (2010). *Handbook of energy and economic statistics of Indonesia 2010*. Jakarta: Ministry of Energy and Mineral Resources, Republic of Indonesia.

Moral-Benito, E. (2009). Dynamic panels with predetermined regressors: likelihood-based estimation and Bayesian averaging with an application to cross country growth. Retrieved 16 October 2010 from http://www.moralbenito.com/papers/balimle.pdf.

Raftery, AE. (1995). Bayesian model selection in social research. *Sociological methodology*, 25: 111–163.

Soytas, U and M Sari. (2003). Energy consumption and GDP : causality relation in G-7 countries and emerging markets. *Energy economics*. 25: 33–37.

Thee Kian Wie and SD Negara. (2010). Survey of recent developments. *Bulletin of Indonesian economic studies*. 46(3): 279–308.

Wei, SZC, Chen Ching-Fu and Z Zhu. (2008). Economic growth and energy consumption revisited—evidence from linear and non-linear Granger causality. *Energy economics*, 30: 3063–3076.

Yuan, J., C Zhao, S Yu and Z Hu. (2007). Electricity consumption and economic growth in China: cointegration and co-feature analysis. *Energy economics*, 29: 1179–1191.

APPENDIX.

Deriving variance decomposition analysis (consider a two-variable case)[2]

$$Y_t = b_{10} - b_{12}EU_t + \gamma_{11}Y_{t-1} + \gamma_{12}EU_{t-1} + \varepsilon_{yt} \quad \text{(A1)}$$

$$EU_t = b_{20} - b_{21}Y_t + \gamma_{21}Y_{t-1} + \gamma_{22}EU_{t-1} + \varepsilon_{EUt} \quad \text{(A2)}$$

$$\begin{aligned} Y_t + b_{12}EU_t &= b_{10} + \gamma_{11}Y_{t-1} + \gamma_{12}EU_{t-1} + \varepsilon_{yt} \\ EU_t + b_{21}Y_t &= b_{20} + \gamma_{21}Y_{t-1} + \gamma_{22}EU_{t-1} + \varepsilon_{EUt} \end{aligned} \quad \text{(A3)}$$

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}\begin{bmatrix} Y_t \\ EU_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{EUt} \end{bmatrix} \quad \text{(A4)}$$

$$\begin{aligned} &\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}^{-1}\begin{bmatrix} Y_t \\ EU_t \end{bmatrix} = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}^{-1}\begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \\ &\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}^{-1}\begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} + \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}^{-1}\begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{EUt} \end{bmatrix} \end{aligned} \quad \text{(A5)}$$

We can re-write equation A5 as follows:

$$\begin{aligned} x_t &= A_0 + A_1 x_{t-1} + e_t \\ y_t &= a_{10} + a_{11}y_{t-1} + a_{11}EU_{t-1} + e_{1t} \\ EU_t &= a_{20} + a_{21}y_{t-1} + a_{22}EU_{t-1} + e_{2t} \end{aligned} \quad \text{(A6)}$$

where, $x_t = \begin{bmatrix} Y_t \\ EU_t \end{bmatrix}$, $A_0 = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}^{-1}\begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix}$, $A_1 = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}^{-1}\begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}$

$e_t = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}^{-1}\begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{EUt} \end{bmatrix}$, and suppose $B = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}$

Next, we take one period ahead of equation A6 and taking conditional expectation as follows:

[2] The idea in mathematical derivation of variance decomposition analysis is adopted from Enders (2010).

$$x_{t+1} = A_0 + A_1 x_t + e_{t+1} \tag{A7}$$
$$E_t x_{t+1} = A_0 + A_1 x_t \tag{A8}$$

Thus

$$x_{t+1} - E_t x_{t+1} = e_{t+1}$$

In the case of two steps ahead, forecast of x_{t+2} is

$$x_{t+2} = A_0 + A_1 x_{t+1} + e_{t+2}$$
$$x_{t+2} = A_0 + A_1 (A_0 + A_1 x_t + e_{t+1}) + e_{t+2}$$
$$x_{t+2} = A_0 + A_1 A_0 + A_1 A_1 x_t + A_1 e_{t+1} + e_{t+2} \tag{A9}$$
$$E_2 x_{t+2} = A_0 + A_1 A_0 + A_1 A_1 x_t$$
$$x_{t+2} - E x_{t+2} = A_1 e_{t+1} + e_{t+2}$$

In the case of three steps ahead, forecast of x_{t+3} is

$$x_{t+3} = A_0 + A_1 x_{t+2} + e_3$$
$$x_{t+3} = A_0 + A_1 (A_0 + A_1 x_{t+1} + e_{t+2}) + e_3$$
$$x_{t+3} = A_0 + A_1 A_0 + A_1 A_1 x_{t+1} + A_1 e_{t+2} + e_3$$
$$x_{t+3} = A_0 + A_1 A_0 + A_1 A_1 (A_0 + A_1 x_t + e_{t+1}) + A_1 e_{t+2} + e_3 \tag{A10}$$
$$x_{t+3} = A_0 + A_1 A_0 + A_1 A_1 A_0 + A_1 A_1 A_1 x_t + A_1 A_1 e_{t+1} + A_1 e_{t+2} + e_3$$
$$E_3 x_{t+3} = A_0 + A_1 A_0 + A_1 A_1 A_0 + A_1 A_1 A_1 x_t$$
$$x_{t+3} - E_3 x_{t+3} = A_1 A_1 e_{t+1} + A_1 e_{t+2} + e_3$$

In this case we have a 2 by 2 matrix, thus we can simplify the notation as follows:
One period ahead

$$x_{t+1} - E_t x_{t+1} = e_{t+1} = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}^{-1} \begin{bmatrix} \varepsilon_{yt+1} \\ \varepsilon_{EUt+1} \end{bmatrix} = \frac{1}{1 - b_{12} b_{21}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{yt+1} \\ \varepsilon_{EUt+1} \end{bmatrix} \tag{A 11}$$

Two periods ahead

$$x_{t+2} - E x_{t+2} = A_1 e_{t+1} + e_{t+2} = A_1 \left[\frac{1}{1 - b_{12} b_{21}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{yt+1} \\ \varepsilon_{EUt+1} \end{bmatrix} \right] + \frac{1}{1 - b_{12} b_{21}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{yt+2} \\ \varepsilon_{EUt+2} \end{bmatrix} \tag{A12}$$

Thus for the n-period forecast error $x_{t+n} - E_t x_{t+n}$ is

$$x_{t+n} - E_t x_{t+1} = \sum_{i=0}^{n-1} \phi_i \varepsilon_{t+n-i} \text{ , where } \phi_i = \frac{A_1^i}{1 - b_{12} b_{21}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \quad \text{(A13)}$$

Focusing only on the Y_t sequence, we see that the n-step-ahead forecast error is

$$Y_{t+n} - E_t Y_{t+n} = \phi_{11}(0)\varepsilon_{yt+n} + \phi_{11}(1)\varepsilon_{yt+n-1} + \ldots + \phi_{11}(n-1)\varepsilon_{yt+1}$$
$$+ \phi_{12}(0)\varepsilon_{EUt+n} + \phi_{12}(1)\varepsilon_{EUt+n-1} + \ldots + \phi_{12}(n-1)\varepsilon_{EUt+1} \quad \text{(A14)}$$

Denote the n-step-ahead forecast error variance of Y_{t+n} as $\sigma_y(n)^2$:

$$\sigma_y(n)^2 = \sigma_y^2 \left[\phi_{11}(0)^2 + \phi_{11}(1)^2 + \ldots + \phi_{11}(n-1)^2\right]$$
$$+ \sigma_z^2 \left[\phi_{12}(0)^2 + \phi_{12}(1)^2 + \ldots + \phi_{12}(n-1)^2\right] \quad \text{(A15)}$$

The proportion of $\sigma_y(n)^2$ due to shocks from the economic growth $\{\varepsilon_{yt}\}$ and from energy consumption $\{\varepsilon_{EUt}\}$ sequence are

$$\frac{\sigma_y^2 \left[\phi_1 \ (0)^2 + \phi_1 \ (1)^2 + \ldots + \phi_1 \ (n-1)^2\right]}{\sigma_y(n)^2} \quad \text{(A16)}$$

and

$$\frac{\sigma_{EC}^2 \left[\phi_{11}(0)^2 + \phi_{11}(1)^2 + \ldots + \phi_{11}(n-1)^2\right]}{\sigma_y(n)^2} \quad \text{(A17)}$$

The forecast error variance decomposition shows the proportion of the movement in a sequence due to its 'own' shocks versus shocks from the other variables. If ε_{EUt} shocks explain none of the forecast error variance of Y_t at all forecast horizons, we can say that the $\{Y_t\}$ sequence is exogenous. In this circumstance, $\{Y_t\}$ evolves independently of the ε_{EUt} shocks and of the $\{Y_t\}$ sequence. However, if ε_{EUt} shocks can explain all the forecast error variance of Y_t at all forecast horizons, we can say that the $\{Y_t\}$ sequence is endogenous.

However, to solve the variance decomposition we need a restriction on the matrix B. As we have seen from equations A1 and A2 or what we called a primitive system, it contains ten parameters (b_{10}, b_{20}, γ_{11}, γ_{12}, γ_{21}, γ_{22}, b_{12}, b_{21}, σ_Y, and σ_{EU}), but VAR estimation yields only nine parameters (a_{10}, a_{20}, a_{12}, a_{20}, a_{21}, a_{22}, σ_Y, σ_{EU} and $\sigma_{EU,Y}$). Thus, to solve the primitive system, we need to restrict one of the parameters in the primitive equation. Suppose we restrict $b_{21}=0$ in matrix B; this means Y_t does not have a contemporaneous effect on EU_t. This restriction similarly with, say, ε_{Yt} and ε_{EUt} shocks affects the contemporaneous value of Y_t but only ε_{EUt} shocks affect the contemporaneous value of EU_t. Thus the observed values of e_{2t} are completely attributed to pure shocks to the (EU_t) sequence. Decomposing residuals in this triangular fashion is called Cholesky decomposition. Mathematically, we can write it as follows:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \begin{bmatrix} 1 & b_{12} \\ 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{EUt} \end{bmatrix}$$
$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \begin{bmatrix} 1 & -b_{12} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{EUt} \end{bmatrix} = \begin{bmatrix} \varepsilon_{yt} - b_{12}\varepsilon_{EUt} \\ \varepsilon_{EUt} \end{bmatrix} \tag{A18}$$

From equation A18 we can conclude that all the observed errors from $\{e_{2t}\}$ sequence are attributed to ε_{EUt} shocks. We also can say that ε_{EUt} shock has contemporaneous effect on Y_t and on EU_t. On the other hand, ε_{Yt} shock has no direct effect on EU_t, but there is an indirect effect in that lagged values of Y_t affect the contemporaneous value of EU_t. Thus if we see the order of equation A18, an ε_{EUt} shock directly affects e_{1t} and e_{2t}, but an ε_{Yt} shock does not affect e_{2t}. Hence, EU_t is said to be 'causality prior' to Y_t. Finally we can conclude that ordering is very important in Cholesky decomposition and as n increases, the variance decompositions should converge.