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Oil Consumption, CO$_2$ Emission, and Economic Growth: Evidence from the Philippines

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Abstract: This paper attempts to investigate the short- and long-run causality issues among oil consumption, CO$_2$ emissions, and economic growth in the Philippines by using time series techniques and annual data for the period 1965–2012. Tests for unit root, co-integration, and Granger-causality tests based on an error-correction model are presented. Three important findings emerge from the investigation. First, there is bi-directional causality between oil consumption and economic growth, which suggests that the Philippines should endeavor to overcome the constraints on oil consumption to achieve economic growth. Second, bi-directional causality between oil consumption and CO$_2$ emissions is found, which implies that the Philippines needs to improve efficiency in oil consumption in order not to increase CO$_2$ emissions. Third, uni-directional causality running from CO$_2$ emissions to economic growth is detected, which means that growth can continue without increasing CO$_2$ emissions.

Keywords: oil consumption; CO$_2$ emissions; economic growth; Granger-causality; Philippines

1. Introduction

Oil plays an important role in economic growth and industrial development. It should not be surprising to find that there is a close tie between GDP growth and oil supply. In the Philippines, oil consumption ran to about 282 thousand barrels daily in 2012 [1]. In 2011, total primary energy consumption in the Philippines was roughly 1.6 quadrillion Btu. Oil constituted around 40% of total

consumption, both coal and solid biomass and waste made up around 20% each, and the remainder came from natural gas and renewable sources [2]. Moreover, the current economic situation is strongly influenced by supply and demand of oil.

Over the last decades, some studies have been conducted to examine the relationship between oil consumption and economic growth. In a summary of the literature, the empirical findings on the causal relationship between oil consumption and real gross domestic product (GDP) are different from country to country. We do not have any concrete and consistent results yet.

For example, uni-directional causality running from economic growth to oil consumption was detected in Taiwan [3] and Pakistan [4]. That is, people are more likely to demand oil as the economy develops. However, the reverse causality does not exist, which means demand-side management of oil could be adopted since the less use of oil does not hold back economic growth. Uni-directional causality running from oil consumption to economic growth was discovered by Zou and Chau [5] for China and Lee and Chang [6] for Taiwan. An increase in oil consumption could push economic growth in both cases. Shortage of oil supply infrastructure can hinder economic growth. Administers whose country has these cases should cope with growing demand for oil. Yoo [7], Yuan *et al.* [8], and found bi-directional causality in South Korea, China, respectively. In addition, Ghosh [9] reported that there are the short-run bi-directional causality between economic growth and high speed diesel consumption and the existence of a long-run uni-directional causality running from economic growth to high speed diesel consumption in India. On the other hand, Fatai *et al.* [10] and Rufael [11] discovered no causality between oil consumption and economic growth in New Zealand and in Shanghai of China, respectively.

Growth in oil use and the associated green house gases (GHG) emissions have accompanied the economic growth seen after the recovery from the Asian financial crisis. Real GDP has doubled during the past 30 years, and GHG emissions also increase significantly with high dependence on fossil fuel in the Philippines. The Philippines government has opted to phase out oil as a primary fuel for power generation and transport sector. The government continues to promote power sector reforms and development of renewable energy through private sector investment [12]. Recently, some studies dealt with the causality relationship between energy consumption, CO_2 emissions, and economic growth. That is, the question of whether it is really possible to achieve sustained economic growth without increasing energy consumption or GHG has become a topic of special interest.

Bloch *et al.* [13] reported that there is a uni-directional short-run and long-run causality running from income to coal consumption in China. Further, there also exists a bi-directional causality between coal consumption and carbon emissions in short- and long-run Usama [14] found bi-directional causality between oil consumption, CO_2 emissions, and economic growth in the Middle East and North African countries, respectively. Most of the studies examined the relationship between total energy consumption and other factors. Funinhas and Marque [15] suggest bi-directional causality between energy growth in both the long-run and short-run in Portugal, Italy, Greece, Spain and Turkey. The Empirical results of causality tests among energy consumption, CO_2 emissions, and economic growth are shown in Table 1.

To date, no study that focuses on the causality relationship between oil consumption, CO_2 emissions, and real GDP with respect to Philippines has been carried out. Thus, the purpose of this paper is to investigate the causality among oil consumption, CO_2 emissions, and economic growth, and to obtain policy implications of the investigation. The remainder of the paper is organized as follows.

Section 2 provides an overview of the methodology adopted here. Section 3 explains the data employed and presents the results and discussions. Some conclusions are made in the final section.

Table 1. Empirical results of causality tests between energy consumption, CO_2 emissions, and economic growth.

Countries	Periods	Causality Relationship	Sources
BRICs	1971–2005	Short run: C→Y, E→CY Long run: YC→E, CE→Y Strong: C→EY, E→CY, Y→E	Pao and Tsai [16]
Central America (6)	1971–2004	short run: E→CY, Y→CE long run: EY→C, YC→E	Apergis and Payne [17]
China	1960–2007	long run: Y→E, E→C	Zhang and Cheng [18]
	1981–2006	long run: Y→CE, C→E, E→YC	Chang [19]
CIS	1992–2004	short run: E→CY, Y→CE long run: EY→C, CY→E	Apergis and Payne [20]
Europe (19)	1960–2005	short run: (Denmark) Y→C,E (Greece) Y→E (Italy) E→C, Y→CE (Swiss) E→Y, Y→E long run: (Denmark) EY→C (Greece) EY→C (Iceland) EY→C (Italy) EY→C, YC→E (Portugal) EY→C (Swiss) EY→C EC→Y	Acaravci and Ozturk [21]
Greece	1977–2007	short run: Y→C, E→C long run: Y→EC, E→C, C→E strong: Y→EC, E→C	Hatzigeorgiou *et al.* [22]
Iran	1967–2007	long run: Y→CE	Lotfalipour *et al.* [23]
Malaysia	1971–1999	short run: Y→E long run: CE→Y, YC→E strong: CE→Y, Y→E	Ang [24]
France	1960–2000	short run: E→Y long run: EY→C, CY→E	Ang [25]
South Africa	1965–2006	C→Y, E→YC	Menyah and Wolde-Rufael [26]
Turkey	1960–2005	short run: C→EY, E→C, Y→C long run: EY→C, EC→Y	Halicioglu [27]
	1968–2005	long run: CE→Y	Ozturk and Acaravci [28]

Note: Y, E, and C indicate real GDP, energy consumption, and CO_2 emissions, respectively.

2. Methodology

2.1. Granger-Causality and Stationarity

We employed the Granger-causality test to determine the direction of causality [29,30]. This test is simple and straightforward and represents a convenient and general method for detecting any presence of a causality relationship between variables. According to this test, a time series (*X*) is said to Granger-cause another time series (*Y*) if the prediction error of the current series *Y* declines through the

use of past values of *X* in addition to past values of *Y*. The Granger-causality test is selected in this study over other alternative techniques because of the favorable Monte Carlo evidence reported by Geweke *et al.* [31].

The Granger-causality test requires the time series of variables to be stationary. It has been shown that the use of non-stationary data in causality tests can lead to spurious results [32]. Therefore, following Engle and Granger [33], we first tested the unit roots of *X* and *Y* to confirm the stationarity of each variable. For this, we employed the Phillips-Perron (PP) test because this test is known to be robust to serial correlation and time-dependent heteroscedasticity [34]. If any variable is found to be non-stationary, we must compute the differences and then apply the causality test with the differenced data.

2.2. Co-Integration

The concept of co-integration can be defined as a systematic co-movement between two or more economic variables over the long run. According to Engle and Granger [33], if *X* and *Y* are both non-stationary, one would expect that a linear combination of *X* and *Y* would be a random walk process. However, the two variables may have a property whereby a particular combination of *X* and *Y* (e.g., $Z = X - bY$) is stationary. Thus, if such a property holds true, then we can assume that *X* and *Y* are co-integrated.

If *X* and *Y* are non-stationary and co-integrated, then any standard Granger-causal inferences will be invalid, and a more comprehensive causality test based on an error correction model (ECM) is needed [33]. However, if *X* and *Y* are both non-stationary, and the linear combination of the series of the two variables is non-stationary, then the standard Granger-causality test should be adopted [35]. Therefore, testing the co-integration property of the series of oil consumption, CO_2 emissions, and economic growth is required before performing the Granger-causality test. When both series are integrated in the same order, we can test for the presence of co-integration. For this, we employ the Johansen co-integration test [36].

2.3. Error-Correction Model

The In the ECM procedure, *X* and (or) *Z* Granger-cause(s) *Y* if either the estimated coefficients on lagged values of *X* and (or) *Z* or the estimated coefficient on the lagged value of the error term from the co-integration regression are (is) statistically significant. Similarly, *Y* and (or) *Z* Granger-cause(s) *X* if either the estimated coefficients on lagged values of *Y* and (or) *Z* or the estimated coefficient of the error term from the co-integration regression are (is) statistically significant. In the same manner, *X* and (or) *Y* Granger-cause(s) *Z* if either the estimated coefficients on the lagged values of *X* and (or) *Y* or the estimated coefficient on the lagged value of the error term from the co-integration regression are (is) statistically significant. This procedure specifically allows for a causal linkage between two or more variables stemming from an equilibrium relationship, thus characterizing the long-run equilibrium alignment that persists beyond the short-run adjustment.

If three variables are non-stationary, but they become stationary after the first differencing, and co-integrated, the ECMs for the Granger-causality test can be specified accordingly as follows:

$$\Delta Y_t = \beta_{10} + \sum_{i=1}^{L_{11}} \beta_{11i} \Delta Y_{t-i} + \sum_{j=1}^{L_{12}} \beta_{12j} \Delta X_{t-j} + \sum_{k=1}^{L_{13}} \beta_{13k} \Delta Z_{t-k} + \beta_{14} \varepsilon_{t-1} + u_{1t} \tag{1}$$

$$\Delta X_t = \beta_{20} + \sum_{i=1}^{L_{21}} \beta_{21i}\Delta X_{t-i} + \sum_{j=1}^{L_{22}} \beta_{22j}\Delta Y_{t-j} + \sum_{k=1}^{L_{23}} \beta_{23k}\Delta Z_{t-k} + \beta_{24}\varepsilon_{t-1} + u_{2t} \tag{2}$$

$$\Delta Z_t = \beta_{30} + \sum_{i=1}^{L_{31}} \beta_{31i}\Delta Z_{t-i} + \sum_{j=1}^{L_{32}} \beta_{32j}\Delta X_{t-j} + \sum_{k=1}^{L_{33}} \beta_{33k}\Delta Y_{t-k} + \beta_{34}\varepsilon_{t-1} + u_{3t} \tag{3}$$

where X_t, Y_t, and Z_t represent the natural logarithms of oil consumption, CO_2 emission, and real GDP, respectively; Δ is the difference operator; L's are the number of lags, β's are parameters to be estimated, μ_t's are the serially uncorrelated error terms, and ε_{t-1} is the error correction term (ECT) , which is derived from the long run co-integration relationship $Y_t = \eta_0 + \eta_1 X_t + \eta_2 Z_t + \varepsilon_t$, where η represents the parameters to be estimated and ε_t is an error term. The co-integration vector equation is estimated by the use of a canonical co-integrating regression method suggested by Park [37].

In each equation, the change in the dependent variable is caused not only by their lags, but also by the previous period's disequilibrium in the level, ε_{t-1}. Given such a specification, the presence of short-run and long-run causality can be tested [33]. Let us consider Equation (1). If the estimated coefficients on the lagged values of oil consumption (β_{12}) are statistically significant, then it is implied that oil consumption Granger-causes real GDP in the short run. This test can be conducted by a joint F-test, whose null hypothesis is that all coefficients of ΔX are zero ($\beta_{121} = \beta_{122} = \ldots = 0$). Similarly, if the estimated coefficients on the lagged values of CO_2 emissions (β_{13}) are statistically significant, then the implication is that CO_2 emission Granger-causes real GDP in the short run. On the other hand, long-run causality can be found by testing the significance of the estimated coefficient of ECT (β_{14}) by a t-test. Finally, the strong Granger-causality running from oil consumption to GDP can be determined through a joint test of the statistical significance of β_{12}'s and β_{14} by the joint F-test. The strong Granger-causality from CO2 emissions to GDP can be determined through a joint test of the statistical significance of β_{13}'s and β_{14} by a joint F-test. Similarly, we can examine whether real GDP and CO_2 emissions Granger-cause oil consumption through Equation (2) and whether real GDP and oil consumption Granger-cause CO_2 emissions through Equation (3).

3. Results and Discussion

3.1. Data

In order to examine whether there is a causal relationship between oil consumption, CO_2, and economic growth, data covering the period 1965–2012 are used. The choice of the starting period was constrained by the availability of data on oil consumption from the BP [1]. Oil consumption is expressed in terms of thousand bbl daily. We employed real GDP in Peso as a proxy for economic growth from World Bank [38]. Finally, CO_2 emissions per year were in million ton. The data of CO_2 emissions was obtained from BP [1].

3.2. Results of Unit Roots and Co-Integration Tests

When testing for unit roots, co-integration, and causality, we have chosen to use probability values of 0.05 and 0.1 in this study, which are appropriate levels of significance to be used with small sample sizes such as that used here. We employed the PP test to verify the stationarity of the time series data.

The test results for levels and first-differences are summarized in Table 2. The null hypothesis is that the series of all the variables would be non-stationary, which means each variable has a unit root. According to the first run of the PP test, the *p*-value exceeds 0.05, and thus the null hypothesis cannot be rejected. This implies that this data set was non-stationary. However, the *p*-value for the first-differenced data set is less than 5%, and thus, the null hypothesis can be rejected; that is, the first-differenced data are stationary.

Table 2. Results of Phillips-Perron (PP) unit root tests.

Variables	Levels		First differences	
	PP values	***p*-values**	**PP values**	***p*-values**
Oil consumption (*X*)	−6.24 [4]	0.727	−21.88 [3]**	0.048
CO_2 emissions (*Y*)	−10.00 [10]	0.436	−41.33 [2]**	0.001
GDP (*Z)*	−7.31 [8]	0.639	−44.19 [2]**	0.000

Note: The numbers inside brackets are the optimum lag lengths determined using the Akaike information criterion described in Pantula *et al.* [39]. The *p*-values are calculated under the null hypothesis of non-stationarity. ** indicates the rejection of the null hypothesis at the 5% level.

However, the standard unit root tests are known to have reduced power if the time series contains structural break. Therefore, we have considered unit root tests that allow for a level shift at a known point in time. Lanne *et al.* [40] propose the unit root test for the model, which is based on estimating the deterministic term by a generalized least squares (GLS) under the unit root null hypothesis and subtracting it from the original series. Then, augmented Dickey-Fuller (ADF) type tests are applies to the adjusted series. This study employs ADF unit root test that allows for structural break and the test results are presented in Table 3. The test statistics is lower than the critical values at the 10% level which are tabulated in Lanne *et al.* [40]. The test results provide evidence of non-sationarity in three series when breaks are allowed. Hence, the variables are non-stationary when level but stationary at their first differences. The Granger-causality tests are run with the first differenced data.

Table 3. Results of unit root tests with structural break.

Variables	Optimal lags	Break points	Test statistics	Inferences
Oil consumption (*X*)	6	1984	−2.77	Non-stationary
CO2 emissions (*Y*)	10	1987	−2.19	Non-stationary
GDP (*Z)*	1	1985	−1.58	Non-stationary

Note: The test is based on Lanne *et al.* [40]. The numbers inside brackets are the optimum lag lengths determined using the Akaike information criterion described in Pantula *et al.* [39]. Break points are computed which minimizes the generalized least squares objective function used the parameters of the deterministic part.

We conducted a co-integration test to determine the presence of a long-run causality relationship among the three individually non-stationary variables. In a co-integration test, if three series are integrated of the same order and the linear combination of the three series has no unit root, then it is stationary, that is, there is a long-run causality relationship. Table 4 shows the results of the Johansen co-integration test for the three series. The null hypothesis that the number of co-integrating equations would be zero was rejected at the 10% level, but the null hypothesis that the number of co-integration

equations would be at most one and tow could not be rejected. This implies that there was one co-integration equation. We can conclude that oil consumption, CO_2 emissions, and real GDP were co-integrated and showed an inherent co-movement tendency in the long run. Based on these results, we employed the ECM for the Granger-causality test.

Table 4. Results of Johansen co-integration tests.

Null hypotheses	Likelihood ratio test statistic	*p*-values
The number of co-integrating equations is zero ($R = 0$)	36.63	0.027
The number of co-integrating equations is at most one ($R \leq 1$)	14.43	0.158
The number of co-integrating equations is at most two ($R \leq 2$)	0.04	0.620

Note: The optimal lag length was chosen as 9 by using the Akaike information criterion described in Pantula *et al.* [39]. The *p*-values were calculated under the corresponding null hypothesis. *R* denotes the number of co-integrating equations.

3.3. Results of the Error-Correction Model and Granger-Causality Tests

As previously stated, if the series of three variables are non-stationary and the linear combination of the three variables is stationary, then the ECM rather than the standard Granger-causality test should be employed. Therefore, we conducted an ECM to investigate both short-run and long-run causality. In the ECM, the first difference of each endogenous variable (oil consumption, CO_2 emissions, and real GDP) was regressed on the one-period lag of the co-integrating equation and the lagged first differences of all endogenous variables in the system, as shown in Equations (1), (2) and (3). We chose the lag lengths (*L* in Equations (1), (2) and (3) by using the Akaike information criterion [39].

The results of the tests on causality are presented in Table 5. Significance levels of 5% and 10% are used for causality tests. In order to check for the appropriateness of the estimation results of the ECM, we conduct two types of specification tests. We check the model stability using CUSUM and CUSUMSQ tests suggested by Brown *et al.* [41]. The results of both tests suggest that the null hypothesis of absence of structural break cannot be rejected at the 5% level. In addition, we conduct a Durbin-Watson test to detect the presence of the first-order autocorrelation in the residuals from the regression analysis, but the null hypothesis of no autocorrelation cannot be rejected. In this case, we estimated the statistics of Durbin-*h*, because of lagged dependent variables.

Let us first discuss the estimation results for Equation (1). The estimated coefficients for the lagged values of changes in oil consumption (ΔX) are statistically significant at the 5% level, which implies the presence of short-run causality running from oil consumption to economic growth. Similarly, those in CO_2 emissions (ΔY) are also statistically significant at the 5% level, which indicates the existence of short-run causality running from CO_2 emissions to economic growth. The statistical significance, at the 5% level, of the coefficient for the ECT in Equation (1) suggests that there are long-run causality not only from oil consumption to economic growth but also from CO_2 emissions to economic growth. The statistical significance, at the 5% level, of the estimated coefficients for the lagged values of changes in oil consumption (ΔX) and the coefficient of the ECT in Equation (1) shows the presence of strong causality from oil consumption to economic growth. Moreover, we can find strong causality running from CO_2 emissions to economic growth at the 5% level.

Table 5. Results of causality tests based on the error-correction model.

Null Hypotheses	Source of Causality (Independent Variables)						
	Short-Run			Long-Run	Joint (Short/Long-Run)		
	F-values			*t*-values	*F*-values		
	ΔZ	ΔX	ΔY	ε_{t-1}	$\Delta Z, \varepsilon_{t-1}$	$\Delta X, \varepsilon_{t-1}$	$\Delta Y, \varepsilon_{t-1}$
Oil consumption and/or CO$_2$ emissions do not cause economic growth		7.244**	8.515**	−3.890**		17.777**	17.601**
		(0.010)	(0.006)	(0.000)		(0.005)	(0.000)
Economic growth and/or CO$_2$ emissions do not cause oil consumption	2.996**		2.490*	−2.118**	4.762**		2.713*
	(0.045)		(0.086)	(0.042)	(0.007)		(0.061)
Oil consumption and/or economic growth do not cause CO$_2$ emissions	1.825	5.320**		1.439	2.793*	5.590**	
	(0.175)	(0.009)		(0.158)	(0.074)	(0.007)	

Notes: X, Y, and Z indicate oil consumption, CO$_2$ emissions, and economic growth, respectively. The optimal lag lengths are selected by using the Akaike information criterion described in Pantula *et al.* [39]. The numbers in parenthesis are *p*-values calculated under the null hypothesis of no causality. * and ** imply the rejection of the null hypothesis at the 10% and 5% levels, respectively.

Let us move on to Equation (2). The estimated coefficients for the lagged values of changes in real GDP (ΔZ) are statistically significant at the 5% level, which implies the presence of short-run causality running from economic growth to oil consumption. Similarly, those in CO$_2$ emissions (ΔY) are also statistically significant at the 10% level, which indicates the existence of short-run causality running from CO$_2$ emissions to oil consumption. The statistical significance, at the 5% level, of the coefficient for the ECT in Equation (2) suggests that there are long-run causality not only from economic growth to oil consumption but also from CO$_2$ emissions to oil consumption. The statistical significance, at the 10% level, of the estimated coefficients for the lagged values of changes in real GDP (ΔZ) and the coefficient of the ECT in Equation (2) shows the presence of strong causality economic growth to oil consumption. In addition, we can detect strong causality running from CO$_2$ emissions to oil consumption at the 10% level.

Finally, let us look into the estimation results for Equation (3). The estimated coefficients for the lagged values of changes in real GDP (ΔZ) are not statistically significant at the 10% level, which implies the absence of short-run causality running from economic growth to CO$_2$ emissions. However, those in oil consumption (ΔX) are statistically significant at the 5% level, which indicates the existence of short-run causality running from oil consumption to CO$_2$ emissions. The statistical insignificance, at the 10% level, of the coefficient for the ECT in Equation (3) suggests that there do not exist long-run causality not only from oil consumption to CO$_2$ emissions but also from economic growth to CO$_2$ emissions. The statistical significance, at the 10% level, of the estimated coefficients for the lagged values of changes in real GDP (ΔZ) and the coefficient of the ECT in Equation (3) shows the presence of strong causality economic growth to CO$_2$ emissions. Moreover, we can discover strong causality running from oil consumption to CO$_2$ emissions at the 5% level.

3.4. Discussions

Figure 1 summarizes the results of the causality tests. Three important findings emerge from the results. First, we found that a bi-directional causality between oil consumption and economic growth.

This study lends support to the argument that oil consumption stimulates economic growth with feedback effect. A high level of oil consumption leads to high level of real GDP, though there are many other factors contributing to economic growth, and oil is only one of such factors. The oil consumption infrastructure shortage may restrain the economic growth in the Philippines. Space and water heating, and cooking in homes and businesses, processing heat for industry, and production in industries such as electricity generation, mechanical power and transportation demand a substantial amount of oil infrastructure. In order not to adversely affect economic growth, efforts must be made to encourage government and industry to increase oil supply investment. Furthermore, one could reasonably expect that economic growth enhances oil consumption. Households, because of their higher income, have come to consume more and more oil (gasoline, diesel, *etc.*). Economic growth causes expansion in the industrial and commercial sectors where oil has been used as a basic input.

Figure 1. Causality relationship for the Philippines.
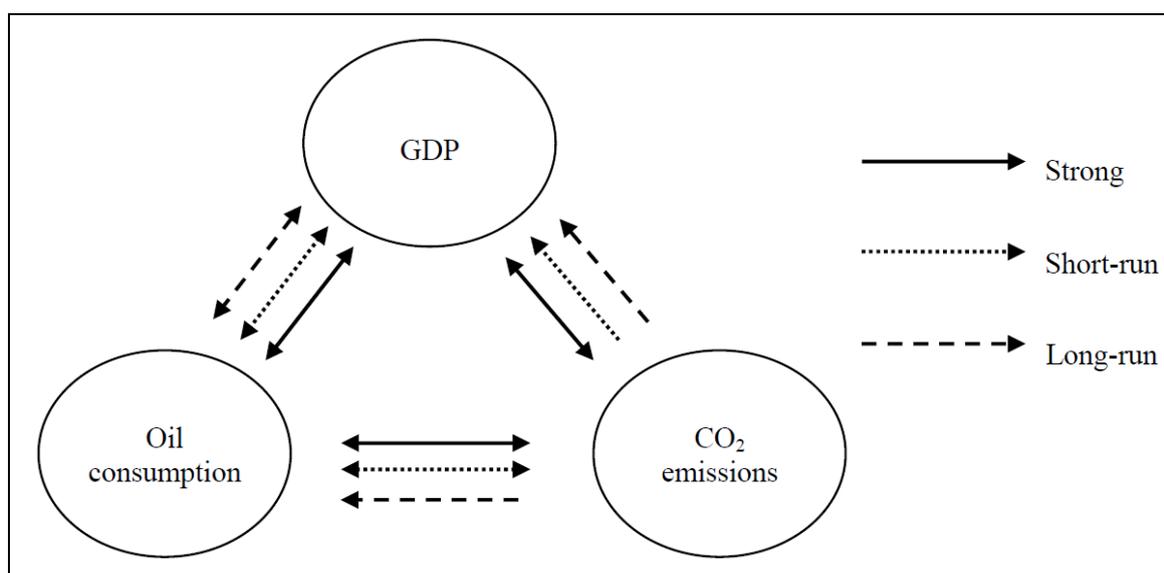
Second, a bi-directional causal relationship between oil consumption and CO_2 emissions is detected. Currently, oil is the biggest resource that emits CO_2 in the Philippines. Therefore, the efficiency in oil consumption is extremely important and has a major impact. If more renewable energy is subsequently used, the causal relationship between oil consumption and CO_2 emissions might be weakened because renewable energy produces less, or no, CO_2 emissions.

However, we need to note that the results in Table 5 strongly support causality from CO_2 emissions to oil consumption, but weakly support the reverse causality [42]. There are short-run, long-run, and strong causality from CO_2 emissions to oil consumption. On the other hand, there exist short-run and strong causality from oil consumption to CO_2 emissions, but long-run causality does not exist. This difference in the interpretation evidence of causality may be important. The notion that oil consumption has not been strongly causal in CO_2 emissions does offer hope that oil consumption can be increased without increasing CO_2 emissions, as long as policy continues to foster efficiency and support a shift from dirtier fossil fuels.

Finally, there is a uni-directional causality running from CO_2 emissions to economic growth. Increasing CO_2 emissions is linked to inducing more economic growth. This means that the economic

development of the Philippines is dependent on CO_2 emissions. Thus, implementing the policies of mitigating CO_2 emissions may adversely affect economic growth. The Philippines needs to reduce domestic CO_2 emissions minimizing their impact on its economy, and to maintain its existing industrial structure, which is not very energy-intensive, and emphasize the development of renewable energy sources. Moreover, for the purpose of reducing CO_2 emissions, energy needs to be used more efficiently and directed toward using more clean energy source in order not to produce the consequent deteriorating economic side effects.

Previous studies in the case of the Philippines have provided only the causality between economic growth and consumption. Rafiq and Salim [43] suggested uni-directional causality from energy consumption to economic growth for strong causality and in the long-run, but no causality in the short-run. Apergis and Tang [44] founded that energy consumption Granger-cause economic growth. Although the previous results do not correspond with ours, the findings are based on total energy consumption, not oil consumption.

4. Conclusions

The policy-makers in the Philippines are interested in the causal relationship between oil consumption, CO_2 emissions, and economic growth. This study attempted to examine the causal relationship among them. Specifically, Granger-causality tests were performed using time series techniques in a framework in which both traditional and additional channels of causality could be exposed. This study provided new evidence in terms of the causality relationship among oil consumption, CO_2 emissions, and real GDP as well as the direction of causality with respect to the Philippines. We obtained three important findings from the examination. First, there is bi-directional causality between oil consumption and economic growth, which suggests that the Philippines should endeavor to overcome the constraints on oil consumption to achieve economic growth. Second, bi-directional causality between oil consumption and CO_2 emissions is found, which implies that the Philippines needs to improve efficiency in oil consumption in order not to increase CO_2 emissions. Third, uni-directional causality running from CO_2 emissions to economic growth is detected, which means that growth can continue without increasing CO_2 emissions.

Author Contributions

Kyoung-Min Lim, Seul-Ye Lim and Seung-Hoon Yoo conceived and designed the study. The data were collected and analyzed by Seul-Ye Lim and Kyoung-Min Lim.

Conflicts of Interest

The authors declare no conflict of interest.

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