Uncovering short- and long-run relationships between Philippine GDP, population and carbon emissions using Autoregressive Distributed Lag and Cointegration Analysis

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Abstract: The most recent scientific assessments confirm that the warming of the climate system is due to human activities such as burning of fossil fuels and land use change. All over the world, various studies have been conducted to understand the strong connection between economic activity, population growth and carbon emissions. In recent years, plenty of methodologies have been adopted for this purpose, including decomposition analysis, and panel-based methods. This paper utilizes Autoregressive Distributed Lag (ARDL) and Cointegration Analysis to uncover potential long term, short and delayed effects of economic growth and population growth to CO2 emissions in the Philippines. This analysis used data from 1960 to 2014 extracted from the World Bank. The analysis showed that emissions from the Philippines have short and long run relationships with its previous levels, while GDP only contributed slightly in this test. The results uncovered something more than a simple increasing trend for Philippine carbon emissions. Potential causes and recommended policy discourses are presented.

Key Words: Autoregressive Distributed Lag; Cointegration; Carbon Emissions; GDP; Population

1. INTRODUCTION

Southeast Asia is a sub-region of Asia covering more than 3,300 km from north to south and 5,600 km from east to west. It is more of a tropical climate zone with temperatures above 25°C throughout the year. Southeast Asia is made up of 11 countries of which 10 are members of the regional economic organization known as Association of Southeast Asian Nations (ASEAN).

Southeast Asia is recorded to be one of the fastest growing regions in terms of population and urban growth. The coastlines of Southeast Asia are highly vulnerable to the effects of climate change. The issue of climate change is real and urgent in Southeast Asia.

The Philippines on the other hand is an archipelagic country within Southeast Asia located in the Western Pacific Ocean, composed of three main islands – Luzon, Visayas and Mindanao. Its total land area is 298,170 square kilometers and an estimated population of 107.74 million based on Worldometers (2019) estimates, with a total of 7,107 islands.

The Philippine Atmospheric, Geophysical

and Astronomical Services Administration (PAGASA, 2011) reported that the most recent scientific assessments confirm that the warming of the climate system is likely due to human activities such as burning of fossil fuels and land use change. PAGASA also encourages climate change scenario projections as an important step forward in improving our understanding of the complex climate, particularly in the future. Related literatures employing similar methodologies are summarized below.

Sumabat et al, (2015) conducted research on the decomposition of Philippine CO_2 emissions from fuel combustion and electricity generation. The Logarithmic mean Divisia Index (LMDI) method performed in the study quantified the driving forces to changes in Philippine CO_2 emissions from 1991 to 2014. It was concluded that majority of CO_2 emissions can be attributed to economic growth and lifestyle changes of population.

Ozturk et al. (2010) examined the long run relationship issues between economic growth, carbon emissions, energy consumption and employment ratio in Turkey by using autoregressive distributed lag bounds testing approach of cointegration.

Dietz and Rosa (1997) developed a stochastic version of the IPAT model to estimate the effect of population, affluence, and technology on national CO_2 emissions. The results suggested that population and economic growth anticipated over the next decade will exacerbate greenhouse gas emissions.

Mousavi et al. (2017) performed in a systematic manner three variations of decomposition analysis on driving forces of carbon emissions from 2003 to 2014 due to energy consumption of the industry, driving forces of carbon intensity of the electricity generation, and key drivers of carbon emissions due to total fossil fuel combustion. Major findings highlighted that the main driver to Iran's CO_2 emissions are increased consumption, which was responsible for an additional 201.5 MtCO2 since 2004, while technology-related improvements (e.g. energy mix) were only able to offset 7.7 MtCO2.

Sukati (2013) investigated the concept of vector autoregression (VAR) and cointegration using a bivariate model of global prices and headline Consumer Price Index (CPI) in South Africa. It determined how much inflation is driven by oil prices.

After several reviews on previous researches done in the Philippines, there have not been similar studies conducted to understand potential short- and long-run relationships with carbon emissions in the country.

In this study, Autoregressive Distributed Lag (ARDL) and Cointegration Analysis will be used to further analyze the relationship between variables that cause increasing CO_2 emissions. This is similar to Sukati's (2013) approach but the variables to be considered are Gross Domestic Product (GDP), Total Population, and per capita CO_2 emissions.

2. METHODS AND DATA

For this study, data was extracted from the World Bank International Economics Dept. Development Data Group (2019).

There are 2 methods used in this study and each method gives credibility to the data and results obtained from the analysis.

a. Cointegration Analysis
b. Autoregressive Distributed Lag (ARDL)

2.1 Cointegration Analysis

Cointegration analysis is used to establish the relationship between variables, and to get rid of non-stationary and prior restrictions on the lag structure of a model. Econometric analysis of time series data has increasingly diverted towards the use of cointegration and the reason is due to its powerful way of detecting the presence of steady state equilibrium variables to avoid the problems of spurious regression. It is now an overriding requirement for economic models using non-stationary time series data (Nkoro and Aham, 2016).

2.2 Autoregressive Distributed Lag

ARDL analysis is an approach used in dealing with variables that are integrated in varying order zero or one. The long run relationship is tested through the F statistic (Wald test). In this approach, the relationship of the series is said to be established when the F-statistic exceeds the critical value band (Nkoro and Aham, 2016).

ARDL operates under the premise that past values influence current values, making it popular in analyzing nature, economics, and other time varying processes.

Requirements for application of ARDL

- If the F-statistic (Wald test) establishes that there is a single, long-run relationship and data sample is small or infinite, the ARDL model error coefficient becomes more reliable due to the random data results without specific pattern.

- If the F-statistic (Wald test) indicates there is a multiple long run relationship, ARDL approach will not be advisable but instead, a more complex approach is needed.
- If the trace and maximal eigenvalues of the F-statistic indicates there is a single long run relationship, ARDL can be used instead of alternative approach.

3. RESULTS AND DISCUSSION

Data from 1960 to 2014 was extracted from World Bank for Philippine Gross Domestic Product (GDP), per capita CO_2 Emissions (CE), and Total Population (TP) on a yearly basis.

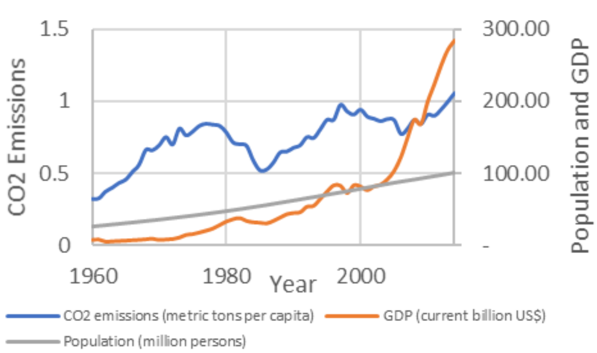

Fig. 1. Philippine GDP, CO_2 emissions, and Total Population

3.1 Cointegration Test

To test for the relationship or correlation between GDP, CE, and TP, the study applied cointegration test using data analysis and statistics software for Microsoft Excel. The results are summarized below.

Table 1. VAR order estimation

Number of lags	AIC	HQ	BIC
1	62.785	62.916	63.129
2	59.036	59.298	59.724
3	58.156	58.549	59.189
4	**55.769**	56.294	57.146
5	58.567	59.222	60.288

Legend:
AIC: Akaike's Information Criterion
BIC: Bayesian Information Criterion
HQIC: Hannan Quinn Information Criterion

In selecting the number of lags, the commonly used method in time series analysis is the AIC and BIC, and this study made used of AIC. Lag length indicates where the variables are persistent and shows significant relationships.

The number of lags indicated by VAR order of estimate according to AIC as shown in Table 1 is 4. Lag 4 is the point where the final prediction error (FPE) is minimal across all analysis AIC, BIC, and HQIC. The values of BIC and HQIC were included in Table 1 for comparison.

After the determination of the number of lags, the data is tested for cointegration.

At None, Cointegration condition:

- Null Hypothesis (Ho): There is no cointegration if statistic equals critical value
- Alternative Hypothesis (H1): There is cointegration if Ho fails

At most 1, Cointegration condition:

- Null hypothesis: There is a cointegration if statistic is not equal to critical value.
- Alternative hypothesis: There is no cointegration if Ho fails.

Table 1. Lambda maximum test

H_o (Number of cointegrating equations)	Statistic	Critical value	p-value
None	60.723	17.797	< 0.0001
At most 1	7.885	11.225	0.182
At most 2	0.443	4.130	0.569

Lambda maximum test indicates 1 cointegrating relation(s) at the 0.05 level.

At None, the lambda statistic (60.723) exceeds the critical value (17.797). Therefore, rejecting the null hypothesis and suggesting that the time series variables CE, GDP, and TP are cointegrated. The alternative hypothesis is selected. Lambda maximum test indicates 1 cointegrating relation(s) at the 0.05 level from the cointegration test result. Similarly, for the trace test, trace statistic (69.052) exceeds the critical value (24.275) at table 2, thus rejecting the null hypothesis. As per maximum zero, CE, and GDP, and TP are cointegrated therefore select the alternative hypothesis which states that there is cointegration if H0 fails at none cointegration condition.

Table 3. Trace test

H_o (Number of cointegrating equations)	Statistic	Critical value	p-value
None	69.052	24.275	< 0.0001
At most 1	8.329	12.321	0.212
At most 2	0.443	4.130	0.569

Trace test indicates 1 cointegrating relation(s) at the 0.05 level.

With At most 1, the trace statistic 8.329 is less than the critical value of 12.321, meaning we cannot reject the null hypothesis condition. There is a cointegration relationship between CE, GDP, and TP. Same with the Lambda max test, 7.885 is less than 11.225 which establishes the fact that there is indeed a long-term relationship between the variables. This is true for the null hypothesis (At most 1) testing conditions since H0 does not equal H1.

3.2 Using ARDL to test for contributing factors

Table 4. ARDL result using 1 lag

Using lag 1	Coefficients	*t Stat*	*P-value*
Intercept	9.44E-02	2.87E+00	5.94E-03
CE-1	8.94E-01	1.64E+01	**1.02E-21**
GDP-1	3.60E-13	1.70E+00	**9.48E-02**
TP-1	-4.34E-10	-5.97E-01	5.53E-01

Table 5. ARDL result using 2 lags

Using lag 2	Coefficients	t Stat	P-value
Intercept	1.10E-01	2.18E+00	3.47E-02
CE-1	9.05E-01	6.08E+00	**2.23E-07**
CE-2	-2.86E-02	-1.96E-01	8.46E-01
GDP-1	5.75E-13	5.09E-01	6.13E-01
GDP-2	-2.59E-13	-2.16E-01	8.30E-01
TP-1	-8.42E-09	-1.07E-01	9.15E-01
TP-2	8.17E-09	1.02E-01	9.19E-01

Table 6. ARDL result using 3 lags

Using lag 3	Coefficients	t Stat	P-value
Intercept	9.58E-02	1.72E+00	9.21E-02
CE-1	8.75E-01	5.74E+00	**9.55E-07**
CE-2	2.27E-01	1.07E+00	2.92E-01
CE-3	-2.44E-01	-1.60E+00	1.16E-01
GDP-1	1.01E-12	8.63E-01	3.93E-01
GDP-2	-3.52E-13	-2.10E-01	8.34E-01
GDP-3	-4.68E-13	-3.50E-01	7.28E-01
TP-1	-2.17E-08	-4.36E-02	9.65E-01
TP-2	5.51E-08	5.19E-02	9.59E-01
TP-3	-3.36E-08	-5.90E-02	9.53E-01

The confidence interval considered is 95%. Since the p-values of CE-1 and CE-4 in Table 7 are lower than 0.05, this means that the emissions of the immediate previous year and that from 4 years ago significantly affects the CE of the current year.

Table 7. ARDL result using 4 lags

Using lag 4	Coefficients	t Stat	P-value
Intercept	9.80E-02	1.61E+00	1.16E-01
CE-1	7.75E-01	5.09E+00	**1.01E-05**
CE-2	2.63E-01	1.26E+00	2.14E-01
CE-3	1.57E-01	7.39E-01	4.64E-01
CE-4	-3.96E-01	-2.61E+00	**1.29E-02**
GDP-1	8.26E-13	7.16E-01	4.78E-01
GDP-2	5.74E-13	3.46E-01	7.32E-01
GDP-3	-1.49E-12	-8.99E-01	3.74E-01
GDP-4	-1.53E-13	-1.07E-01	9.16E-01
TP-1	8.78E-08	1.16E-01	9.08E-01
TP-2	-2.86E-08	-1.23E-02	9.90E-01
TP-3	-2.23E-07	-8.60E-02	9.32E-01
TP-4	1.65E-07	1.60E-01	8.74E-01

On a critical note, increases in emissions are generally due to pressures from a growing population and economy, as indicated in previous studies. However, when pressures from having high emissions in previous years catch up, emissions peak due to the infiltration of cleaner energy alternatives and clean energy policies (at least within the immediate decade in the Philippines). But interestingly, efforts seem to have not been sustained very well in the Philippines. This can be due to poor follow-through and erratic decision-making, especially pertaining to the country's primary energy mix. This erratic behavior is discussed in Sumabat et al. (2016).

Another possible explanation is the emissions' extreme sensitivity to dips in the economy. Around the year 1980, GDP declined a little bit, while in 2000, economic growth stalled primarily because of the global financial crisis. Coincidentally, these were the same years when emissions per capita also experienced a decline.

4. CONCLUSIONS

The cointegration test and ARDL model adjoins that there is a long run relationship between present and past emissions. GDP on the other hand contributes slightly on the factors that affect CE. This paper meets its objective by identifying possible short- and long-run relationships with emissions.

A learning from this study is to test for cointegration before conducting other related analysis because the cointegration test can attest to the reliability of the data.

Based on the results, the following policy implications are recommended for further consideration:

1. Obvious as it may seem, long-term energy planning has to be improved. Currently, poor follow-through of clean energy initiatives is observed.
2. Research and development on the decarbonization of the Philippine economy has to be strengthened. Economies will continue to grow, and the sustainable solutions would have to catch up real soon.
3. Explore how circular economy practices may be integrated locally.

For future work, the interactions between various factors have to be looked into, in addition to the individual effect. This is in order to better understand the role of economic growth and population to the periodic behavior of Philippine CO_2 emissions. In shorter-term studies (10 to 15 years period), economic activity and population growth have been observed to be straightforwardly strong contributors to increasing emissions. However, analyzing a far-reaching data set (55 years) in this study, the emissions per capita revealed far more than a simple increasing trend.

5. ACKNOWLEDGMENTS

The first author would like to thank the Almighty God for the strength and the insights to carry out this research work. The first author would also like to acknowledge his wife, Rochelle F. Nnadiri for the support and encouragement. The same goes to Mr. Edward and Morela Mistie Ohaebuka for their mentorship.

This research was supported by the Commission on Higher Education Grants-in-Aid program of the Philippines under Res. No. 873-2017.

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