
| RESEARCH ARTICLE

Assessing the Impact of GDP, Agriculture, Forestry, and Fishing Value Added, and Livestock Production Index on CO2 Emissions in the Philippines

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| ABSTRACT

This study explored the impact of Agriculture, forestry, and fishing, value added (current US\$), Livestock production index (2004-2006 = 100), and GDP (current US\$) on CO2 emissions. Motivated by loads of recent literature conveying how the Philippines is one of the top contributors to CO2 emissions, this quantitative study worked to determine whether the independent variables have a significant relationship with the dependent variable. They collected secondary data from the World Bank to conduct the study in the Philippines. Specifically, they employed the following variables: (1) Agriculture, forestry, and fishing, value added (current US\$), (2) Livestock production index (2004-2006 = 100), (3) GDP (current US\$), and (4) CO2 emissions. The researchers administered the study using the Multiple Regression Analysis methods. The study found that GDP and Livestock Production Index are significant and positively related to CO2 emissions in the Philippines.

| KEYWORDS

Agriculture, forestry, and fishing, value added (current US\$), Livestock production index, GDP (current US\$), CO2 emissions

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1. Introduction

This section addresses the nexus between the study's dependent variable, CO2 emissions, and the study's independent variables. This chapter includes essential elements of the paper. The following are the: background of the study, statement of the problem, hypotheses, significance of the study, and the scope and limitations.

1.1 Background of the Study

The Philippines is presumed to lead the growth of carbon emissions in Southeast Asia in the next decade. (Rivera, 2019). In 2018, the Philippine Climate Change Assessment Working Group declared that as the country's economy grows, the emissions follow. Carbon dioxide emissions are regarded as the primary driver of climate change. With numerous studies coming out about the looming dangers of climate change, it is imperative for people to start caring about its implications not only to their daily lives but their future as well. According to the United Nations, global fossil CO2 emissions have skyrocketed 62% between 2016-2020. It was also discovered in 2018 that the levels of heat-trapping greenhouse gases had reached a new record of 407.8 parts per million, further displaying how future generations will have a massive obstacle in combating this phenomenon.

According to the Kaya identity (1997), the total carbon emissions resulting from global warming are influenced by economic growth, energy consumption, population growth, and carbon emissions intensity (Kaya and Yokoburi, 1997). Correspondingly, all of these factors mentioned above are on the rise in the Philippines today.

The agriculture sector is known to be one of the major contributors to global greenhouse gas (GHG) emissions. (Seo et al., 2017). As the livestock production index is interconnected with animal agriculture, it is vital to investigate this as well. Animal agriculture is a massive chunk of the agricultural sector. It is said to be the second-largest contributor to human-grade greenhouse gas (GHG)

emissions. Despite these findings, it also cannot be denied that these activities satisfy many of our wants and needs. It is of great essence to fulfil the need to balance the people's needs and wants in a capitalistic system.

On the other hand, standing by and allowing the same practices to continue will surely meet a lot of people's agenda. It is a sector that caters to most, if not all, people from consumers to firms. The study of Grossman entitled "Economic Growth and the Environment" stated that there is no evidence that environmental quality deteriorates steadily with economic growth. (Grossman & Krueger, 1995). Nevertheless, the consensus in the past few years has implied that the state of our environment is dire. With the creation of the Paris Agreement or COP21 being signed by 175 parties, it is apparent that this issue has taken a front seat in global discourse.

The world economy has more than tripled in the past 40 years. (Knox et al., 2014). Thus, the discourse on global warming is complex. Shall we sacrifice the potential of even more growth in the economy, or shall we take preventative measures to an extreme in order to rescue the planet? This paper will provide quantitative results that could aid in discerning an approach that will benefit all parties involved.

1.2 Statement of the Problem

This study aims to answer the following research questions:

1. How much of the changes in CO2 emissions (kt) is explained by the Gross Domestic Product (current US\$)?
2. How much of the changes in CO2 emissions (kt) is explained by the Agriculture, forestry, and fishing value added (current US\$)?
3. How much of the changes in CO2 emissions (kt) are explained by the Livestock production index (2004-2006=100)?
4. Is there a significant relationship between CO2 emissions and Gross Domestic Product (current US\$)?
5. Is there a significant relationship between CO2 emissions and Agriculture, forestry, and fishing, value added (current US\$)?
6. Is there a significant relationship between CO2 emissions and the Livestock production index (2004-2006=100)?

1.3 Hypotheses of the Study

Ho1: There is no significant relationship between CO2 emissions and Gross Domestic Product (current US\$).

Ho2: There is no significant relationship between CO2 emissions and Agriculture, forestry and fishing, value added (current US\$).

Ho3: There is no significant relationship between CO2 emissions and the Livestock production index.

1.4 Significance of the Study

This paper can demonstrate significant implications in the following:

Department of Agriculture. This paper would push them to create more sustainable technologies in their field.

Department of Environment and Natural Resources. This paper could allow them to discern a new approach to handling the Philippines' contribution to carbon emissions.

Local Government Units. This paper could inspire them to create new programs that could help their citizens cope with CO2 emissions.

People in business. The private business sector, specifically the agricultural sector, can take the initiative from the paper's results. They could seek to find more innovative ways of production that could help lessen carbon emissions.

Farmers. This study can help them by shedding light on their importance in our economy. It could also provide them with new ideas regarding their profession that could improve their lives.

Future Researchers. The methods used in this study could inspire them to create a similar study in the field. Given the theories and models analyzed in this paper, it could also make the process easier.

1.5 Scope and Limitations of the Study

The study is focused only on the Philippines with no comparative analysis. The dependent variable in this study is the CO2 emissions measured in (kt). Meanwhile, the independent variables include Agriculture, forestry, and fishing (AFF), value added (current US\$), Livestock production index (LPI), and Gross Domestic Product (GDP) in (current US\$). The time-series data is annual and is collected from the World Bank. The researchers conducted this study to determine if there are significant relationships among the variables stated above. Moreover, the researchers utilized the statistical software EViews to perform all the needed tests that result and discussion required.

2. Literature Review

In this section, the researchers review the various studies related to the study and its variables. They are divided into cross-country, regional, or country-specific studies.

2.1 Cross-Country Studies

In a study entitled "Globalization and carbon emissions: Is there any role of agriculture value-added, financial development, and natural resource rent in the aftermath of COP21?" by Wang et al. (2020), environmental degradation was a prime concern. It focused on G7 countries considering their participation in the Paris Climate Agreement (COP21) and their escalating carbon emissions. Using the CS-ARDL econometric model, they evaluated their empirical analysis's short-run and long-run results. They then discovered that economic globalization, financial development, and natural resources cause carbon emissions to augment. On the contrary, they also learned that agriculture value-added reduces carbon emissions. This indicates that the G7 countries have sophisticated agricultural management technologies that could potentially provide similar results to other countries' CO2 emissions.

Bismark Ameyaw's 2018 study assessed the relationship between GDP and carbon emissions in several West African countries from 2007 to 2014. They detected a unidirectional causality between the GDP and emissions. It was deduced that highly realistic and accurate carbon emissions are essential in implementing an attainable environmentally-friendly energy policy.

According to Crippa et al. (2021), Through a new global food emissions database called (EDGAR-FOOD), the researchers found that the immense contribution came from agriculture and land use/land-use change activities (71%).

2.1.1 GDP- CO2 emissions

Mardani et al. (2018) stated that prioritizing the need to develop energy resources sustainably is emphasized in this 2018 paper entitled Carbon dioxide (CO2) emissions and economic growth: A systematic review of two decades of research from 1995 to 2017. The relationship between CO2 emissions and economic growth was tackled. They concluded that a reduction in emissions might not be a good idea due to it playing a part in economic growth. They concluded that since CO2 emissions contribute to economic growth, a reduction in emissions may not be a desirable outcome in emerging and developed nations.

The paper analyzed the impact of agricultural, livestock, fishery, and human forestry activities on greenhouse gas emissions. Their objective was to build a model of greenhouse gases being changed due to human activities' factors. To achieve this, they employed the ADL-model where current values of the series depend both on past values of the series and on current and past values of other time series as their theoretical model. The method includes the following main stages: inspection of the time series of the variables for their stationarity using Dickey-Fuller test; the choice of the endogenous variable lags, which have a strong correlation with the variable value in the last period; check the tightness of the endogenous variable's connection with the exogenous variables, exogenous variables' test of multicollinearity; testing the significance of autocorrelation coefficients using the Ljung-Box Q-test; verification of the pair correlation coefficients for their significance using Student's t-test; determination of model coefficients using regression analysis; test of the regression equation and the regression equation coefficients' significance. (Mirolyubova et al., 2017).

A 2019 study entitled "The Relationship between Economic Growth, Energy Consumption and Carbon Dioxide Emissions: Evidence from Central Asia" is also related to this paper. It utilized a panel dataset collected from five Central Asian countries, including Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan. They collected 100 observations from two decades' worth of data (1998-2017). Using the Vector Autoregressive (VAR) model, they explored the causality between economic growth, energy consumption, and CO2 emissions in the previously mentioned Central Asian countries. The usage of this model was due to its ability to interpret the endogenous variables only by their history and apart from deterministic regressors. They found that per capita energy consumption has a direct relationship with per capita GDP.

Meanwhile, per capita, CO₂ emissions negatively affect per capita GDP. Ultimately, this study was able to prove that these Central Asian countries' economic growth is still majorly dependent on energy consumption. It propounds the idea of creating better policies that can tackle economic growth and sustainable development in Central Asia.

According to de Oliveira & Lima (2020), a modified version of the Lewis dual economy model is presented with environmental implications between environmental quality and economic growth. It tackled the possible long-run effects of a pollution abatement rule in developing economies. They found that environmental quality is positively related to labor productivity and profits. In addition, they found that the pollution abatement requirement develops an ecological development trap by its negative and positive effects on profitability in the modern sector.

2.1.2 Livestock production

With the perils of climate change in mind, researchers Appiah et al. conducted a study with the objective of examining the causal relationship between agriculture production and carbon dioxide emissions in emerging economies from 1971 to 2013. Through the use of the FMOLS and DOLS, they found that a 1% increase in economic growth, crop production index, and livestock production index generated an increase in carbon dioxide emissions by 17%, 28%, and 28% , respectively. Their causality direction was explored with a PMG estimator. They concluded by suggesting the need to change farming production techniques and a more environmentally friendly agricultural technology method.

2.2 Regional Studies

In Thomas et al.'s (2018) study, published by the Journal of Cleaner Production, he evaluated the relationship between GHG emissions per capita (a measure of environmental degradation) and GDP per capita in Canada's provincial/territorial levels between 1990 and 2014. They tested the validity of the EKC hypothesis and its application to Canada and its provinces. It utilized both pooled and fixed-effects regression models. It was based on panel data (cross-sectional time-series data) for Canadian provinces and territories from 1990 to 2014. Their model's dependent variable was GHG emissions per capita. Meanwhile, GDP per capita (measured in thousands of constant 2007 dollars), GDP per capita squared, trade openness (measured as the sum of exports and imports as a percentage of GDP), and time trend are used as explanatory variables in their models.

In 2017, researchers Fei and Lin computed for CO₂ efficiency in 30 provinces of China. They found that: Generally, most provinces and regions did not perform efficiently in energy consumption and CO₂ emissions in China's agricultural sector. Moreover, their agricultural sector's contribution to emissions is compelled to increase even more in the future due to agricultural mechanization.

With CO₂ emissions being the most important among energy-related GHG emissions, the researchers of the study entitled "Energy-related CO₂ emission in European Union agriculture: Driving forces and possibilities for reduction" made use of the Index Decomposition Analysis (IDA) and analyzed the main drivers behind energy-related CO₂ emission across agricultural sectors of European countries. They discovered that France, Finland, Sweden, Denmark, the Netherlands, Poland, and Belgium have the highest potential to reduce emissions.

Additionally, in a 2017 paper from the Journal of Cleaner Production, the decoupling of carbon dioxide (CO₂) emissions from agricultural economic growth in 30 Chinese provinces from 1997-2014 was investigated. They found that fertilizer, in-season rice cultivation, and cattle generated the most CO₂ emissions in the categories of agricultural production activities, farming, and livestock husbandry, respectively.

2.3 Country-Specific Studies

2.3.1 Livestock, Agriculture

The following studies are about how the changes in CO₂ emissions are impacted by different variables. The study of Rehman et al. (2021), Their VECM results show that forestry production, rainfall, and temperature negatively affect carbon dioxide emissions. Crops production, livestock production, energy use, and population growth have a negative effect on carbon dioxide emissions. However, there is a positive effect between forestry production, crop production, livestock production, population growth, rainfall, and temperature in the short run. Usage in energy has a negative effect on carbon dioxide emissions. Granger Causality test results show that there is a unidirectional relationship between the variables. Another paper by Rehman et al. (2019) demonstrated carbon dioxide emissions' association with the cropped area, energy use, fertilizer offtake, gross domestic product per capita, improved seed distribution, total food grains, and water availability in Pakistan for the period of 1987-2017. With the autoregressive distributed lag (ARDL) bounds testing technique, cointegration was applied to demonstrate the causality linkage among study variables from the evidence of long-run and short-run analyses. Overall, they found that the long-run effects are more robust than the short-run dynamics regarding the impact of explanatory variables on carbon dioxide emission, thus making the findings heterogeneous. This paper of Chen et al. (2016) forecasted input and output variables for China's six industries during the 13th Five-Year Plan by using an EBMDEA model to analyze the distribution efficiency of the industries. Among the six

major sectors in China, only agriculture, forestry, animal husbandry, and fisheries achieved an efficient initial allocation of carbon emission rights. In contrast, industry and transportation, warehousing, and the postal service exhibited low allocative efficiency.

Meanwhile, in another study published by the Journal of Cleaner Production in 2020, the input and output method to study the CO₂ emissions in Chongming Island in China due to some difficulties in finding the data for CO₂ emissions in the years 2002-2012. Using the SDA (Structural decomposition analysis), they looked into the variables that can affect CO₂ emissions. The results show that Gross Capital Formation affects consumption-based emissions.

According to Driha et al., the interaction between electricity consumption and agricultural activities has an additional pernicious effect on the environment. Through their 2019 study, it was discovered as it investigated the environmental Kuznets curve (EKC) hypothesis for Brazil, Russia, India, China, and South Africa (BRICS) from 1990–2014, with consideration to agricultural activities, energy use, trade openness, and mobile use as driving forces of environmental degradation. They employed the Dynamic Ordinary Least Squares (DOLS) and the Fully Modify Ordinary Least Square (FMOLS) for long-run regression to test the impact of selected independent variables on carbon emissions in BRICS.

In a paper published in 2017 from Shandong University's School of Economics entitled Forest, agriculture, renewable energy, and CO₂ emission, they explored the impacts of renewable energy consumption, agriculture, and forest on CO₂ emission in Pakistan. Through annual data from 1990 to 2014, the ARDL approach was used to estimate the long-run impacts of renewable energy consumption, agricultural production, and forest area on CO₂ emissions. The results are presented in CO₂ emission. This positive relationship shows that the rise in agricultural production increases CO₂ emissions in Pakistan. The general form of the model was $CO_2t = f(REC, AGRI, FOREST)$.

In the interim, studies about reducing emissions in the agricultural sector have arisen. A 2017 paper by the Tokyo University of Science deduced that it is possible to harvest spinach of high calibre while reducing carbon dioxide emissions through the elevated CO₂ emissions treatment. Along with numerous other studies, they also figured out that the agricultural sector was one of the highest contributors to the continuous changes in CO₂ emissions in a certain country. (Seo et al., 2017)

2.3.2 Other factors that can affect the changes in CO2 emissions.

Caia et al. (2020) used the input and output method to study the CO₂ emissions in Chongming Island in China due to some difficulties finding the data for CO₂ emissions in 2002-2012. Using the SDA (Structural decomposition analysis), they look into the variables that can affect CO₂ emissions. The results show that Gross capital Formation affects consumption-based emissions. A similar model was used by Wang et al. (2020); they also used the input and output approach in the study. To determine the factors that affect the changes in the CO₂ emissions, they used the Index Decomposition Analysis–Log Mean Divisia Index (LMDI). The findings show that carbon emissions in forest product industries have declined during the last twenty years. They found out that the driving factor that changes the Carbon dioxide emissions is the energy intensity in the production and economic input, which have changed continuously. The same method was used by the 2020 paper by Yu et al., entitled Energy-related CO₂ emissions and structural emissions' reduction in China's agriculture: An input-output perspective, the input-output method, an energy consumption model, and a structural decomposition analysis were availed in order to research China's agriculture sector's energy-related CO₂ emissions and structural emissions' reduction from 2007-2017. "The research results show that the input structure effect and the energy intensity effect inhibited the growth of energy-related CO₂ emissions in China's agriculture, with the reduction effect of energy intensity effect being the more prominent, whereas the final demand effect and the energy structure effect contributed to promoting China's agricultural energy-related CO₂ emissions' growth, with the final demand effect being the greater promoting factor." (Yu et al., 2020) Additionally, they found that China's energy structure effect does not benefit their emissions.

With China being considered a large agricultural country and the world's lead-carbon emissions contributor, this research was created to scrutinize the CO₂ emissions in their agricultural sector by using the geographically weighted regression (GWR) model. In addition, the Stochastic impacts Regression on Population, Affluence, and Technology (STIRPAT) model was employed to construct the study's econometric model. In conclusion, they learned that their central region experienced greater effects of economic growth on CO₂ emissions than their eastern and western regions due to the variances in their fixed-asset investment on agricultural infrastructure and agricultural exports. (Lin & Xu, 2017).

On account of Taiwan being one of the top 20 countries with the most carbon emissions, the researchers aimed to impart suitable measures for carbon emissions. They focused on the following variables: population growth, economic growth, and carbon emissions in Taiwan. They made use of the analytic tool of Stochastic Impacts by Regression on Population, Affluence

and Technology (STIRPAT) to discern whether their variables can express their individual effects on the total amount of carbon emissions. They came up with seven models through the STIRPAT tool. Two of which were successful and were proposed to predict the Carbon Emissions impact due to population and economic growth in Taiwan by 2025. (Liao & Yeh, 2017).

Another research followed the general EKC model, where the quadratic effect of income and GDP on CO₂ emissions is assumed to explore the hypothetical EKC while examining the determinants of CO₂ release. Its goal was to analyze the effects of the agricultural subsectors on CO₂ emissions instead of investigating agriculture as a whole. It employed the ARDL method to test the cointegration among the variables. They found that crops and fisheries have a significant, negative association with the release of emissions. Moreover, the improvement in fisheries contributed to the reduction of carbon emissions in the long run. Therefore, livestock had a positive but insignificant relationship with carbon emissions, which implies that livestock farms have minimal impact on the environmental damages.

The input and output analysis was used to figure out the allocation of carbon dioxide emissions with the sectors that had been focused on in a 2017 Chinese study published by the Journal of Cleaner Production. In which they determined that the electric power and heat supply sector had the biggest contribution in emission reduction, with an expected emission reduction of 1825.98 million tons (for emission intensity reduction targets of 60%) and 2673.69 million tons (for emission intensity reduction targets of 65%) by 2030, followed by the sectors of non-metallic mineral products, the chemical industry, metal smelting and pressing, the transport and storage industry, agriculture/forestry/animal husbandry/fishery, the food and tobacco processing industry, and the production and distribution of fuel gas. Based on the emissions reduction shares, the industries/sectors are benchmarked for their carbon emission reduction responsibilities". (He et al., 2017) Furthermore, the researchers suggested that policymakers impart their expertise in finding ways to help these sectors abate their emissions.

A study analyzed the causal relationship between CO₂ emissions, energy consumption, the addition of three development sectors, and household final consumption expenditure in Indonesia using annual data from 1975 to 2014. They used ADF and PP unit root tests, Johansen cointegration test, and Granger causality test based on vector error correction modelling and deduced that although CO₂ emissions and energy consumption have a mutual effect, CO₂ emissions are inclined to have a greater effect on energy consumption. "CO₂ emissions, energy consumption, the added of industry sector and household final consumption expenditure have a significant effect on the added value of agriculture sector and service sector, while the added value of agriculture sector is a key factor that drove increases in the added value of service sector." (Nugraha & Osman, 2018)

In the Netherlands, a paper by Coenen et al. (2017) discovered that CO₂ emissions have increased above the level in the base year 1990 in 2015 (+ 1.5%). This increase was offset by the reduction in the emissions since 1990 of methane, nitrous oxide and fluorinated gases (CH₄, N₂O and F-gases). This study implied that the reduction of Methane, which is consistently present in agriculture, helped make up for their CO₂ emissions increase. In the study of Anna Riekkola and Sandberg (2017) Sweden's goal to convert to a carbon-neutral energy system by 2045, the researchers conducted this study to examine whether they can achieve this through three reduction measures. They found that electricity, district heating, and space heating can be close-to-zero emissions as early as 2025. However, their transport sector and energy-intrusive industries have shown to be a challenge. To combat this, they have proposed using forestry residues present in the agriculture sector.

2.3.3 GDP to CO₂ emissions

Meanwhile, Cherni and Jouini (2017) are also exploring the possibility of renewable energies as an alternative to conventional energies. A paper entitled "An ARDL approach to the CO₂ emissions, renewable energy, and economic growth nexus: Tunisian evidence" delved into the relationship between CO₂ emissions, renewable energy consumption and economic growth through the use of the Autoregressive Distributed Lag model. Overall, the researchers found that economic growth significantly contributed to Tunisia's fossil fuel consumption, the leading source for CO₂ emissions. Be that as it may, cutting back on fuel consumption was discovered to lead to economic growth troubles. Hence, this study established the importance of renewable energy to combat the incessant upsurge of the CO₂ emissions found in the atmosphere.

Further studies explored this concept, just like a 2019 Chinese study that investigated the drivers of carbon dioxide (CO₂) emission (million metric tons) in the top 10 emitting countries. They also utilized the Logarithmic Mean Divisia Index (LMDI) decomposition to carefully inspect the influencing factors of CO₂ emissions change. They found that the economic growth effect was the most significant influencing factor. Their study discovered that the CO₂ emission change significantly affects population and income, especially in China and the United States of America.

A study by Aye and Edoja on the effect of economic growth on CO₂ emission in developing countries found that economic growth has a negative effect on emissions in the low growth regime but has a positive effect in the high growth regime. Researchers Aye and Edoja's findings are against the Environmental Kuznets Curve (EKC).

Rahman and Kashem's 2017 paper named "Carbon emissions, energy consumption and industrial growth in Bangladesh: Empirical evidence from ARDL cointegration and Granger causality analysis," In Bangladesh, GDP as a determinant for CO2 emissions is not appropriate. (Rahman & Kashem, 2017). This is due to over 70% of their GDP coming from their service and agricultural sectors. In order to perform their study with their goal of examining whether CO2 emissions are derivatives of economic growth and consumption, or an environmental dilemma, they analyzed the empirical cointegration, long and short-run dynamics, and causal relationships among industrial production, energy consumption, and CO2 emissions in the case of Bangladesh for 1972–2011.

2.4 Theoretical Framework

In this section, relevant theories that are concerned with the study's variables are investigated.

2.4.1 The Lewis Model

Nobel laureate W. Arthur Lewis formulated a theory of development in which surplus labor from the traditional agricultural sector is transferred to the modern industrial sector, the growth of which absorbs the surplus labour, promotes industrialization, and stimulates sustained development. (Todaro & Smith, 2015). He was also behind the Lewis two-sector model, which was developing countries' most used theory when it came to the development process in surplus-labor around the 1960s and early 1970s.

Lewis defined *surplus labor* as the portion of the rural labor force whose marginal productivity is zero or negative. It was often stated as "disguised unemployment in agriculture." He was very much of the mindset that the agricultural sector's workforce could be better used in the modern industrial sector. He was a staunch advocate for industrialization, which he believed would stimulate sustained development. He was of this philosophy as he believed that the modern sector routinely reinvests their profits. Thus, the process of self-sustaining growth along with employment expansion comes to fruition, assuming that all the surplus rural labor is integrated into the industrial sector.

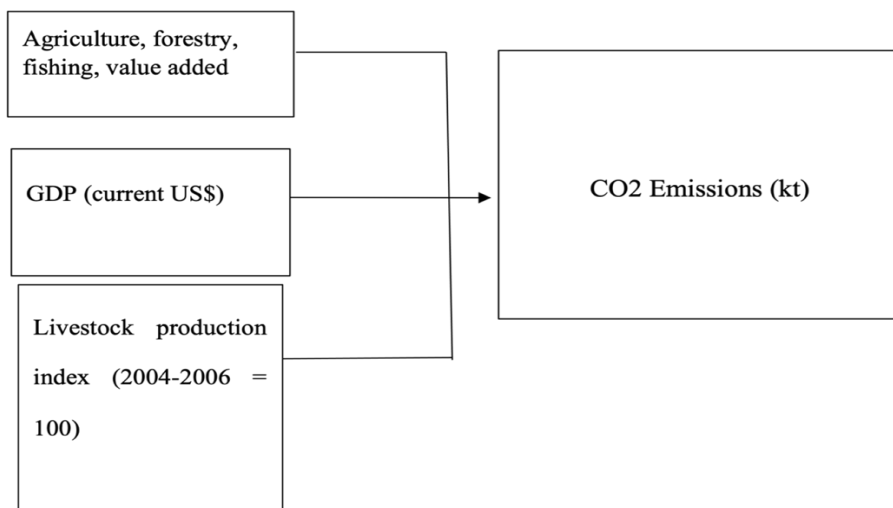
2.4.2 Green Solow Model

Brock and Taylor (2004) studied how the effects of technological advancement, for which a determinant of economic growth in the Solow Growth Model, has emitted waste emissions which can lead to environmental degradation. Heavily associated with the Environmental Kuznets Curve, this model spawned an EKC relationship between the flow of pollution emissions and income per capita and the stock of environmental quality and income per capita. The model is described to have exogenous technological progress in both goods production and abatement that leads to continual growth and environmental quality. It followed a model that created presumptions that emissions are determined through economic activity and changes that can influence the techniques utilized in the intensity of abatement.

2.4.3 Environmental Kuznets Curve

Agarwal (2021) described this hypothesis that was originated by Simon Kuznets in the 1950s as a curve employed to graph the concept that as an economy develops, market forces increase and economic inequality decreases. Subsequently, this hypothesis claims that the environment initially suffers. However, at a later time, the relationship between the environment and society recuperates. This hypothesis is instrumental in executing the study as it could explain the future implications of the paper's results.

2.5 Conceptual Framework



2.5 Synthesis

The theories and concepts above are leaning towards indicating the need to decrease carbon emissions through new agricultural methods that are sustainable and are able to meet the needs of the consumers. However, some studies and models are of the philosophy that carbon emissions and economic growth are negatively related. This presents the dilemma of whether to continue the practices that could induce harm to the planet in order to generate higher economic growth or to urgently continue the attempt to fix the environmental damages that we have caused.

2.6 Definition of terms

CO2 emissions (kt). Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during the consumption of solid, liquid, and gas fuels and gas flaring.

Agriculture, forestry, and fishing, value added (current US\$) - Agriculture corresponds to ISIC divisions 1-5 and includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. The origin of value added is determined by the International Standard Industrial Classification (ISIC), revision 3. Data are in current U.S. dollars.

Livestock production index (2004-2006 = 100) - The agricultural production index is prepared by the Food and Agriculture Organization of the United Nations (FAO). The FAO indices of agricultural production show the relative level of the aggregate volume of agricultural production for each year in comparison with the base period 2014-2016. They are based on the sum of weighted quantities of different agricultural commodities produced after deductions of quantities used as seed and feed weighted in a similar manner. Precisely, the livestock production index includes meat and milk from all sources, dairy products such as cheese, eggs, honey, raw silk, wool, and hides and skins.

GDP (current US\$) - GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars. Dollar figures for GDP are converted from domestic currencies using single year official exchange rates. An alternative conversion factor is used for a few countries where the official exchange rate does not reflect the rate effectively applied to actual foreign exchange transactions. The variables are defined from the study's data source—the World Bank.

3. Methodology

In this section, the study's research design, research locale, sampling techniques, and econometric techniques will be laid out to assist in fulfilling the paper's objectives.

3.1 Research Design

This paper aims to dissect the relationship between components of the Philippine economy, specifically: Agriculture, forestry, and fishing, value added (AFF) in (current US\$), Livestock production index (LPI) (2004-2006 = 100), and Gross Domestic Product (GDP) in (current US\$) to the nation's CO2 emissions (kt). For this paper, a quantitative correlational approach will be utilized. This approach will give prominence to the relationship between the dependent variable, Carbon dioxide emissions (kt), and the independent variables, Agriculture, forestry, and fishing, value added (current US\$), Livestock production index (2004-2006 = 100), and GDP (current US\$). According to McCombes (2020), a correlational research design measures a relationship between two variables without the researcher controlling either of them. Along with the objective to ascertain whether there is a positive correlation, a negative correlation, or a zero correlation.

3.2 Research Locale

The researchers gathered the data on CO2 emissions, Agriculture, forestry, and fishing, value added (current US\$), Livestock production index (2004-2006 = 100), and GDP (current US\$) in the Philippines from the open-data website of the World Bank.

3.3 Sample and Sampling Techniques

World Bank Indicators Data Table

Indicator	Observations	Available data (years)
Agriculture, forestry, and fishing, value added (current US\$)	45	1972-2016

Livestock production index (2004-2006 = 100)	45	1972-2016
GDP (current US\$)	45	1972-2016
CO2 emissions (kt)	45	1972-2016

The table above indicates all the observations that can be found on the World Bank website.

3.3.1 Dependent Variable

CO2 emissions (kt)

3.3.2 Independent Variables

- i. Agriculture, forestry, and fishing, value added (current US\$)
- ii. Livestock production index (2004-2006 = 100)
- iii. GDP (current US\$)

3.4 Econometric Model

This study will utilize a multivariate Ordinary Least Square (OLS) regression model presented as:

Model 1:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n + \varepsilon$$

$$C = \beta_0 + \beta_1 AFF + \beta_2 LPI + \beta_3 GDP + \varepsilon$$

$$C = f(AFF, LPI, GDP)$$

C = Carbon dioxide emissions (kt)

LPI = Livestock production index (2004-2006 = 100)

GDP = Gross Domestic Product (current US\$)

ε = Error term

Model 2:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n + \varepsilon$$

$$C = \beta_0 + \beta_1 LPI + \beta_2 GDP + \varepsilon$$

$$C = f(LPI, GDP)$$

C = Carbon dioxide emissions (kt)

AFF = Agriculture, forestry, and fishing, value added (current US\$)

LPI = Livestock production index (2004-2006 = 100)

GDP = Gross Domestic Product (current US\$)

ε = Error term

Independent Variables	Assumptions	Sign
Agriculture, forestry, and fishing, value added (current US\$)	As Agriculture, forestry, and fishing, value added (current US\$), CO2 emissions increase, vice versa.	(+)
Livestock production index (2004-2006 = 100)	As Livestock production increases, CO2 emissions increase, vice versa.	(+)
GDP (current US\$)	As GDP increases, CO2 emissions Increase vice versa.	(+)

3.5 Instrumentation

The researchers utilized Econometric Views (EViews) to conduct the study. The following treatments will be employed: coefficient of determination (R²), individual hypothesis testing, the t-test, the F test, p-values, the Jarque-Bera Normality test, the Variance Inflation Factor (VIF) test, the test for heteroscedacity's White test, the Durbin-Watson test, the Breusch-Godfrey test, the Autoregressive Model Results, and the Ramsey RESET test.

3.6 Procedures

The researchers collected data from the World Bank in April 2021. The researchers proceeded with the actual regression proper in the first semester of the current school year in order to conduct the fourth and fifth chapter of the paper through the free trial student version of the software EViews.

3.7 Ethical Consideration

The researchers worked on this paper with careful deliberation of all the sources of data and information used. They employed the World Bank's public domain to properly source their data, and all other literature review information is carefully cited accordingly.

3.8 Statistical analysis

The following econometric treatments will be vital to the results of the study. They will be defined accordingly from the book of Gujarati, "Basic Econometrics." published by the McGraw Hill Companies in 2004.

3.9 Coefficient of Determination

The coefficient of determination or R² (multiple regression) is a summary measure that tells how well the sample regression line fits the data. It is the most commonly used measure of the goodness of fit of a regression line. If its value equals 100% or 1, it will be considered a perfect fit.

3.10 Hypothesis Testing for the Individual Significance of Parameters

The theory of hypothesis testing is concerned with developing rules or procedures for deciding whether to reject or not reject the null hypothesis. The t-test will investigate whether the regression coefficients are notably different from 0. The null hypothesis must be rejected to indicate that the individual regressor is notably different from 0.

The formula is:

$$t = \frac{\widehat{\beta}_2 - \beta_2}{\text{se}(\widehat{\beta}_2)} = \frac{(\widehat{\beta}_2 - \beta_2) \sqrt{\sum x_i^2}}{\sigma}$$

3.11 Hypothesis Testing for the Overall Significance of the Model

In testing for the overall significance of the model, the F test will be used. This test must generate a greater F-statistic value than the critical F-value in order to reject the null hypothesis. This would imply that the regression coefficients are equal to 0 or ($\beta_1 = \beta_n = 0$). The critical F-value is found through the F-table. EViews will be able to generate these results. It will also provide the p-value of the F-statistics. This will also supply a decision on whether the null hypothesis will be rejected. It must be less than the level of significance.

The formula is:

$$F = \frac{(\hat{\beta}_2 \sum y_i x_{2i} + \hat{\beta}_3 \sum y_i x_{3i}) / 2}{\sum \hat{u}_i^2 / (n - 3)} = \frac{ESS/df}{RSS/df}$$

3.12 Test for Multicollinearity

Multicollinearity occurs when a "perfect" or exact linear relationship among some or all explanatory variables of a regression model exists. The researchers will test for this through the Variance Inflation Factor (VIF) and Tolerance Statistics (TOL). The VIF is an indicator of multicollinearity. The larger the value of VIF, the more "troublesome" or collinear the variables are. The TOL is the inverse of the VIF. The closer its value is to zero, the greater the degree of collinearity of that variable with the other regressors.

The formulas are:

$$VIF = \frac{1}{1-R^2} \qquad TOL = \frac{1}{VIF}$$

3.13 Test for Serial Correlation

Serial Correlation or the term autocorrelation may be defined as "correlation between members of series of observations ordered in time [as in time series data] or space [as in cross-sectional data]." In the regression context, the classical linear regression model assumes that such autocorrelation does not exist in the disturbances, u_i .

Symbolically,

$$E(u_i u_j) = 0 \quad i \neq j$$

The Durbin-Watson test and the Breusch-Godfrey Serial Correlation LM test will be used to test for this in the model. The Durbin-Watson d statistic is the ratio of the sum of squared differences in successive residuals to the RSS. It will yield a d_L (lower bound) and a d_U (upper bound). The closer the d statistic is to 0, the greater the evidence of positive serial correlation. Meanwhile, the Breusch-Godfrey Serial Correlation LM test tests for autocorrelation by allowing nonstochastic regressors, such as the lagged values of the regressand, higher-order autoregressive schemes, such as AR(1), AR(2), etc.; and AR (3) simple or higher-order moving averages of white noise error terms. To reject the null hypothesis of this test, the chi-square probability of the auxiliary regression's product of observation, R^2 , and the p -values of the regressors, estimated in the test, must be greater than the level of significance.

3.14 Test for Heteroscedasticity

Heteroscedasticity occurs when the standard deviations of a predicted variable (monitored over different independent variables' values or related to prior time periods) are non-constant. (Hayes, 2020). The researchers will test for this through the use of the White test. This will show whether the model possesses pure heteroscedasticity or specification error, or both.

3.15 Test for Misspecification

Misspecification or specification error transpires when the model omits relevant variables or underfits a model or includes unnecessary variables or overfits the model. The Ramsey Regression Specification Error Test (RESET) and the Davidson and MacKinnon J Test will be applied to detect whether this is present in the model.

3.16 Test for Normality

To test for normality, the researchers will make use of a histogram of residuals. It is a simple graphic device test used to learn something about the shape of the PDF of a random variable. In order to conduct this test, the researchers will divide the values of the variable of interest into suitable intervals. Then, in each class interval, rectangles equal in height to the number of observations in that class interval will be erected. A bell-shaped normal distribution curve on the histogram will indicate if the model fits the assumption that the error term is normally distributed.

4. Results and Discussion

This section presents detailed discussions of the statistical results calculated, their interpretation, and the outcome of tests of the hypotheses.

4.1 Presentation and Analysis of Data

In this regression analysis, the researchers use CE as their dependent variable and GDP, LPI, and AFF as independent variables with the application of Multiple Regression Analysis. The researchers employed the World Bank as their source of data. To be precise, the variables, specifically CO2 emissions and GDP, were measured in the following unit of measurements: CO2 emissions in kiloton (kt) and GDP in current US\$. The data is comprised of years 1972 to 2016 with an equivalent of 45 years number of observations.

Table 1: Multiple Regression Results

Dependent Variable: CE Method: Least Squares Date: 10/07/21 Time: 01:23 Sample: 1972 2016 Included observations: 45					
Variable	Coefficient	Std. Error	t-Statistic	Prob.	
C	18556.60	3392.790	5.469421	0.0000	
GDP	1.66E-07	5.62E-08	2.952748	0.0052	
LPI	717.1487	93.02725	7.709017	0.0000	
AFF	-9.39E-07	4.55E-07	-2.061124	0.0457	
R-squared	0.947476	Mean dependent var	58135.56		
Adjusted R-squared	0.943632	S.D. dependent var	25349.12		
S.E. of regression	6018.355	Akaike info criterion	20.32770		
Sum squared resid	1.49E+09	Schwarz criterion	20.48829		
Log likelihood	-453.3733	Hannan-Quinn criter.	20.38757		
F-statistic	246.5300	Durbin-Watson stat	0.371793		
Prob(F-statistic)	0.000000				

This study used Multiple Regression analysis to estimate the relationship between a dependent variable and independent variables. As shown in Table 1, since the computed t-value probability of the independent variables such as GDP, LPI, and AFF are less than five (5) percent level of significance, therefore accept null hypothesis which states that there is a significant impact between X and Y variable, when taken as an individual variable. The coefficients of GDP and LPI are positive, which indicate a direct impact on CE. On the other hand, the coefficient of AFF is negative, which indicate an inverse impact on CE.

In this study, the application of the F-test was utilized to test the overall significance of the independent variables to the dependent variable, CE. Since the computed F-value of 246.5300 has a probability of 0.0000, which is less than five (5) percent level of significance, therefore reject the null hypothesis, which states that the explanatory variables have no significant effect on the explained variable when taken collectively.

One of the problems that the researchers observed in estimating the model is the presence of multicollinearity.

Table 2: Variance Inflation Factors Results

Variance Inflation Factors Date: 10/07/21 Time: 01:29 Sample: 1972 2016 Included observations: 45			
Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	11511026	14.30115	NA
GDP	3.16E-15	64.94086	30.36874
LPI	8654.069	36.82887	7.451820
AFF	2.07E-13	77.03673	23.86676

A Variance Inflation Factor (VIF) detects multicollinearity in regression analysis. Multicollinearity is when there is a correlation between predictors such as independent variables in a model; its presence can adversely affect your regression results. The VIF estimates how much the variance of a regression coefficient is inflated due to multicollinearity in the model.

Based on the results in Table 2, since the computed Centered VIF of variable LPI is 7.4518, which is less than 10, then it indicates that there is no presence of perfect multicollinearity on this variable. On the other hand, the computed Centered VIF of variables GDP is 30.3687, and AFF is 23.8668, which are greater than 10, then it indicates that there is multicollinearity among these variables. Overall, we failed to accept the null hypothesis, which states that there is no perfect multicollinearity among regressors. The researchers decided to drop the insignificant variable to resolve the multicollinearity problem in the regression model and came up with the new regression results presented below.

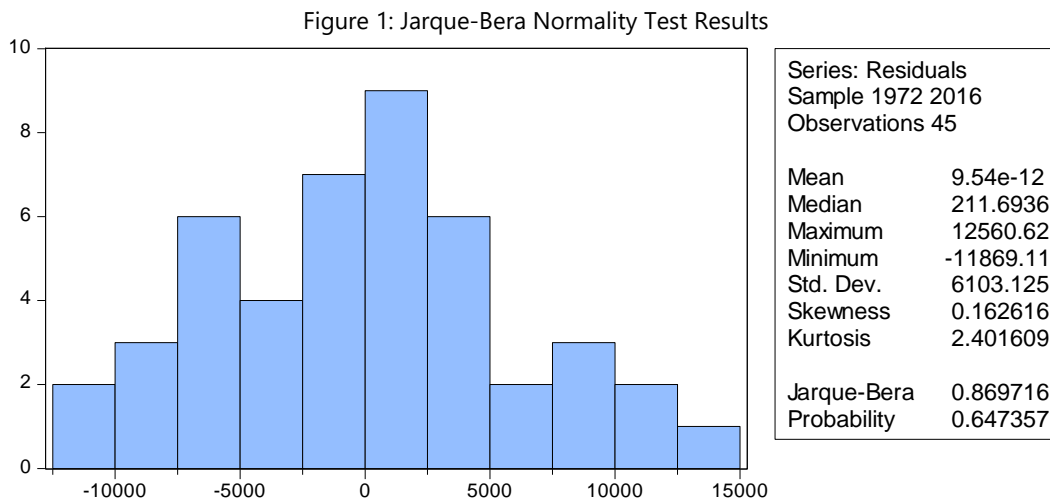
Table 3: Multiple Regression Results without AFF

Dependent Variable: CE				
Method: Least Squares				
Date: 10/07/21 Time: 01:31				
Sample: 1972 2016				
Included observations: 45				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14497.24	2867.475	5.055752	0.0000
GDP	6.54E-08	2.89E-08	2.260548	0.0290
LPI	717.5447	96.55737	7.431278	0.0000
R-squared	0.942033	Mean dependent var		58135.56
Adjusted R-squared	0.939273	S.D. dependent var		25349.12
S.E. of regression	6246.747	Akaike info criterion		20.38185
Sum squared resid	1.64E+09	Schwarz criterion		20.50229
Log likelihood	-455.5916	Hannan-Quinn criter.		20.42675
F-statistic	341.2770	Durbin-Watson stat		0.348288
Prob(F-statistic)	0.000000			

Based on the new regression results as shown in Table 3, the computed t-value probability of the independent variables such as GDP and LPI are less than five (5) percent level of significance, therefore accepting null hypothesis which states that there is a significant impact between X and Y variable when taken as an individual variable. The coefficients of GDP and LPI are still positive in this model, which indicates a direct impact on CE.

The F-test was utilized to test the overall significance of the independent variables to the dependent variable, CE. Since the computed F-value of 341.2770 has a probability of 0.0000, which is less than five (5) percent level of significance, therefore reject the null hypothesis, which states that the explanatory variables have no significant effect on the explained variable when taken collectively.

This model is better than the first one, as observed by the researchers. Thus, the researchers continued to present the other tests of multiple regression analysis.



The researchers used the Jarque-Bera Normality Test to determine whether the residuals are normally distributed or not normally distributed. Based on the results shown in Figure 1, since the p-value of Jarque-Bera statistics is 0.6473, which is greater than the five (5) percent chosen level of significance, therefore we do not reject the null hypothesis, which states that the data is normally distributed. In addition, to say that the residuals are perfectly symmetrical around the mean, a skewness of zero (0) and kurtosis of three (3) should be evident. Figure 2 shows that the skewness in the model is 0.1626, and the kurtosis is 2.4016. Thus, the researchers observed that the residuals are symmetrical around the mean.

Table 4: Variance Inflation Factors Results without AFF

Variance Inflation Factors			
Date: 10/07/21 Time: 01:32			
Sample: 1972 2016			
Included observations: 45			
Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	8222411.	9.482086	NA
GDP	8.36E-16	15.93499	7.451788
LPI	9323.325	36.82871	7.451788

Moreover, the Variance Inflation Factor (VIF) test was utilized again in order to detect multicollinearity in regression analysis. Multicollinearity is when there is a correlation between predictors such as independent variables in a model; its presence can adversely affect your regression results. The VIF estimates how much the variance of a regression coefficient is inflated due to multicollinearity in the model.

Based on the results in Table 4, since the computed Centered VIF of variables GDP and LPI are 7.4518, which is less than 10, therefore accept the null hypothesis, which states that there is no perfect multicollinearity among regressors.

Table 5: Heteroskedasticity Test: White Results

Heteroskedasticity Test: White				
F-statistic	4.622853	Prob. F(5,39)	0.0021	
Obs*R-squared	16.74562	Prob. Chi-Square(5)	0.0050	
Scaled explained SS	10.22284	Prob. Chi-Square(5)	0.0692	
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Date: 10/07/21 Time: 01:33				
Sample: 1972 2016				
Included observations: 45				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.47E+08	83933134	-1.752994	0.0875
GDP	-0.005103	0.002406	-2.120865	0.0403
GDP^2	-1.89E-14	7.13E-15	-2.652077	0.0115
GDP*LPI	0.000143	5.70E-05	2.502402	0.0166
LPI	13729400	6559843.	2.092946	0.0429
LPI^2	-218723.0	96468.34	-2.267303	0.0290
R-squared	0.372125	Mean dependent var	36420392	
Adjusted R-squared	0.291628	S.D. dependent var	43605166	
S.E. of regression	36700215	Akaike info criterion	37.79803	
Sum squared resid	5.25E+16	Schwarz criterion	38.03892	
Log likelihood	-844.4557	Hannan-Quinn criter.	37.88783	
F-statistic	4.622853	Durbin-Watson stat	1.168206	
Prob(F-statistic)	0.002083			

One of the important assumptions of the classical linear regression model is that the variance of each disturbance term u_i , conditional on the chosen values of the explanatory variables, is some constant number equal to σ^2 . The heteroskedasticity Test: White is applied in this regression analysis, and based on the result presented in Table 5, with 45 included observations and degrees of freedom 5 and 39, the computed p-value of 0.0021 is less than the five (5) percent chosen level of significance; therefore, we failed to accept the null hypothesis which states that there is no higher-order serial correlation in the model. Heteroscedasticity can arise because of the presence of outliers (either very small or very large) in relation to the observations in the data. The inclusion or exclusion of such an observation, especially if the sample size is small, can substantially alter regression analysis results. A variable can be regarded as an outlier because the given values of other variables are much larger. In situations such as this, it would be hard to maintain the assumption of homoscedasticity. In this study, LPI has low values compared to other variables. Thus, for further studies, the researchers recommend using other variables with a large value and including more observations to lessen the risk of committing this problem.

Table 6: Durbin Watson Test Result

R-squared	0.942033	Mean dependent var	58135.56
Adjusted R-squared	0.939273	S.D. dependent var	25349.12
S.E. of regression	6246.747	Akaike info criterion	20.38185
Sum squared resid	1.64E+09	Schwarz criterion	20.50229
Log likelihood	-455.5916	Hannan-Quinn criter.	20.42675
F-statistic	341.2770	Durbin-Watson stat	0.348288
Prob(F-statistic)	0.000000		

Another test that is performed in Multiple Regression analysis is the Durbin Watson Test (DW). DW Test is a measure of autocorrelation and is also called serial correlation in residuals from regression analysis. Autocorrelation is the similarity of a time series over successive time intervals. It can lead to underestimates of the standard error and can cause you to think predictors are significant when they are not. The Durbin Watson test reports a test statistic, with a value from 0 to 4, where 2 is no autocorrelation, 0 to <2 is positive autocorrelation which is common in time-series data, and >2 to 4 is negative autocorrelation which is less common in time-series data. A rule of thumb is that test statistic values in the range of 1.5 to 2.5 are relatively normal. Based on the regression results presented in Table 1, since the computed Durbin-Watson statistic is 0.3483, therefore we failed to accept the null hypothesis, which states that there is no first-order autocorrelation.

Table 7: Autoregressive Model Results

Dependent Variable: CE				
Method: Least Squares				
Date: 10/07/21 Time: 07:25				
Sample (adjusted): 1974 2016				
Included observations: 43 after adjustments				
Convergence achieved after 3 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.127431	0.153157	7.361264	0.0000
AR(2)	-0.091224	0.159594	-0.571599	0.5707
R-squared	0.980895	Mean dependent var	59491.02	
Adjusted R-squared	0.980429	S.D. dependent var	25110.64	
S.E. of regression	3512.888	Akaike info criterion	19.21166	
Sum squared resid	5.06E+08	Schwarz criterion	19.29358	
Log likelihood	-411.0507	Hannan-Quinn criter.	19.24187	
Durbin-Watson stat	1.965734			

To correct the first-order serial correlation in the model, an autoregression model was utilized wherein the researchers forecast the variable of interest using a linear combination of past values of the variable. The term autoregression indicates that it is a regression of the variable against itself. A rule of thumb for Durbin Watson is that test statistic values in the range of 1.5 to 2.5 are relatively normal. Based on the regression results presented in Table 7, since the computed Durbin-Watson statistic is 0.19657, therefore accept the null hypothesis, which states that there is no first-order autocorrelation.

Table 8: Ramsey RESET Test Results

Ramsey RESET Test			
Equation: UNTITLED			
Specification: CE C GDP LPI			
Omitted Variables: Squares of fitted values			
	Value	df	Probability
t-statistic	0.500945	41	0.6191
F-statistic	0.250946	(1, 41)	0.6191
Likelihood ratio	0.274589	1	0.6003
F-test summary:			
	Sum of Sq.	df	Mean Squares
Test SSR	9970195.	1	9970195.
Restricted SSR	1.64E+09	42	39021849
Unrestricted SSR	1.63E+09	41	39730426
Unrestricted SSR	1.63E+09	41	39730426

To test the stability in the regression, the Ramsey RESET test was utilized, as shown in Table 8. Based on the result, the t-statistic and F-statistic computed p-value is 0.6191, which is greater than the five (5) percent chosen level of significance, therefore accepting the null hypothesis, which states that there is no misspecification error.

5. Conclusion

This chapter summarises the study’s overall findings and their implications.

5.1 Summary

This study aims to evaluate the trends and relationship of the determinants, namely Gross Domestic Product, Agriculture, forestry, and fishing, value-added, and Livestock production index that affects the changes in the CO2 emissions in the country. Through the use of time-series data from 1972-to 2016, the study’s target was reached through Multiple Regression Analysis. Initially, the study employed AFF as one of its variables. However, the Variance Inflation Factor (VIF) test detected multicollinearity. The researchers then decided to drop this variable and proceed with a new model with CO2 emissions, GDP, and LPI as their variables. Numerous econometrics tests were employed to conduct the study. Namely, the researchers utilized the following: Jarque-Bera Normality Test, Variance Inflation Factor (VIF) test, the heteroskedasticity Test: White, Durbin Watson Test (DW), and the Ramsey RESET test.

Model 1 Summary of Results:

	CO2 emissions	Gross Domestic Product	Livestock Production Index	Agriculture, forestry, and fishing, value-added
Coefficient	18556.60	1.66E-07	717.1487	-9.39E-07
t-value	5.469421	2.952748	7.709017	-2.061124
R-squared	0.947476	0.947476	0.947476	0.947476
F-value	246.5300	246.5300	246.5300	246.5300

Model 2 Summary of Results:

	CO2 emissions	Gross Domestic Product	Livestock Production Index
Coefficient	14487.24	6.54E-08	717.5447
t-value	5.055752	2.260548	7.431278
R-squared	0.942033	0.942033	0.942033
F-value	341.2770	341.2770	341.2770

5.2 Conclusion

This study discovered that Gross Domestic Product and Livestock Production Index are significant and positively related to CO2 Emissions in the Philippines. This result explicitly supports the Green Solow Model, interconnected with the Environmental Kuznets Curve. Meanwhile, the Agriculture, Forestry and Fishing value-added or the AFF variable was detected to have a negative relationship and as an insignificant factor to CO2 Emissions. Additionally, this decision was also settled due to the Variance Inflation Factor (VIF) result where multicollinearity was detected. This is why the researchers decided to drop this variable from the model and present and run a new model where GDP and LPI are the only variables that are considered in the model. The R-squared of the model suggests that 94.2% of the variability in CO2 emissions can be explained by the independent variables in the study. Furthermore, as indicated by the result of the F-test and the entire diagnostic test, model 2's overall model is significant and shows no evidence of multicollinearity, serial correlation, heteroscedasticity and misspecification.

According to the National Integrated Climate Change Database and Information Exchange System, the Philippines is the third most vulnerable country to climate change, according to the 2017 world risk report. Furthermore, threats to our natural ecosystems, coral loss, declining rice yields, more intense droughts, higher sea-level rise, water scarcity, and labor productivity are all claimed to be in great danger due to climate change. Therefore, despite CO2 emissions and GDP being revealed to be positively related in the study. The balance of promoting economic growth and controlling the emissions we generate per year is ever so relevant, especially at this time.

5.3 Recommendations

The researchers of this paper recommend the following:

- **To future researchers.** Since the data available was not specific to an area in the Philippines, future researchers could redesign the idea of the paper by examining the variables in regions of the Philippines. This could allow for a more specific result and gather a more comparative study. To consider other types of greenhouse gases, as CO2 emission is not the only type of greenhouse gasses that other industries are emitting.
- **To the Academe.** Since the only method that the researchers used is the Ordinary Least Squares (OLS) regression, the researchers suggested exploring more on the other contributing factors that affect the CO2 emissions in the Philippines through using other economic methods such as Granger Causality Test. This could enable future researchers to determine if the variables have a two-way relationship.
- **To policymakers.** Given the results of the study, the researchers would like to recommend policymakers to further advocate for sustainability in all sectors as it could be instrumental in decreasing CO2 emissions without aggressively affecting economic activity. This could even allow for new sectors to emerge, given that sustainable products would be filling a space in the market.

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