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CARBON DIOXIDE (CO2) EMISSIONS IN GHANA: AN ATMOSPHERIC HAZARD

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ABSTRACT--

This study investigates trends in Ghana's carbon dioxide (CO2) emissions, utilizing historical data from 1970 to 2022 and applying autoregressive integrated moving average (ARIMA) modeling approach. Time-series data sourced from the World Bank employs carbon dioxide (CO2) emissions from Transport (Energy) (Mt CO2e) as the dependent variable, with autoregressive (AR) and moving average (MA) components as independent variables. Parameter estimation, conducted using generalized least squares (GLS), identifies a positive and statistically significant MA(10) coefficient (0.430044), indicating that 43% of past shocks persist in influencing current emissions. Projections indicate a sharp increase in carbon emissions from 10.9 Mt CO2e in 2023 to 14.7 Mt CO2e in 2042, implying a persistent rise in the concentration of greenhouse gases in the atmosphere. Given these findings, we recommend the implementation of stricter emissions regulations, promotion of cleaner and more sustainable energy sources, and enhancement of public transportation systems to curb future emissions growth.

KEY WORDS: *ARIMA modelling, cardon dioxide (CO2) emissions*---

INTRODUCTION

Carbon dioxide (CO2) emissions represent a significant environmental and atmospheric challenge globally, contributing to climate change and its associated adverse effects (IPCC 2021). In Ghana, CO2 emissions have been steadily rising over the past five decades, largely driven by the transport and energy sectors (World Bank 2023). As a developing nation, Ghana faces increasing urbanization, industrialization, and energy consumption, which exacerbate greenhouse gas emissions and pose risks to environmental sustainability and public health (Kwaka & Aboagye 2014).

The persistent increase in CO2 emissions highlights the need for a comprehensive analysis to understand trends and forecast future emissions. According to (IEA 2022) Ghana's transport sector remains a primary source of carbon emissions due to reliance on fossil fuels and limited adoption of renewable energy technologies. Without effective mitigation strategies, the country may face severe climate-related challenges, including rising temperatures, erratic rainfall patterns, and ecosystem degradation (UNEP 2021).

This study investigates the trends and projections of CO2 emissions in Ghana from 1970 to 2022, utilizing autoregressive integrated moving average (ARIMA) modeling. By providing empirical evidence, it aims to inform policy decisions aimed at reducing emissions and promoting sustainable energy solutions. The rationale for this study stems from the urgent need to address Ghana's growing contribution to greenhouse gas concentrations and to align with global climate targets, such as the Paris Agreement (UNFCCC 2015). Through this research, we aim to offer insights into emission patterns and recommend practical interventions to curb the upward trend in atmospheric CO2 levels.

LITERATURE REVIEW

Globally, carbon dioxide (CO2) emissions have been a central focus of climate change research due to their significant role in global warming and environmental degradation. IPCC (2021) emphasizes that anthropogenic CO2 emissions, primarily from fossil fuel combustion and industrial activities, account for over 75% of total greenhouse gas emissions. Studies by Stern (2007) highlight the economic implications of rising emissions, linking them to declining agricultural productivity, health hazards, and extreme weather events. Global mitigation efforts, including the Paris Agreement (UNFCCC 2015), aim to limit temperature rises through emission reductions and carbon neutrality goals.

In Africa, CO2 emissions are rapidly increasing due to economic growth, urbanization, and reliance on non-renewable energy sources (IEA 2022). The African Development Bank (AfDB, 2019) reports that the energy and transport sectors dominate emissions, reflecting limited infrastructure and technological adaptation. West Africa, in particular, faces challenges related to poor energy efficiency and weak enforcement of environmental regulations (Amegah & Agyei-Mensah 2017). Consequently, regional initiatives such as the African Renewable Energy Initiative (AREI) aim to promote clean energy alternatives to curb emissions growth.

Ghana’s CO2 emissions have surged in recent decades, primarily driven by urbanization, transportation, and industrialization (World Bank 2023). Kwaka & Aboagye (2014) attribute the rise to fossil fuel dependency and insufficient adoption of renewable energy technologies. Policy efforts, such as Ghana’s Renewable Energy Master Plan (Energy Commission of Ghana 2019), highlight the government’s commitment to reducing emissions. However, gaps remain in implementation, enforcement, and public awareness.

This study is guided by the Environmental Kuznets Curve (EKC) hypothesis, which suggests an inverted U-shaped relationship between economic growth and environmental degradation (Grossman & Krueger 1995). Initially, economic growth exacerbates emissions, but at higher income levels, technological improvements and environmental regulations lead to emission reductions. The EKC framework provides insights into the stages of Ghana’s economic development and its impact on emissions.

The conceptual framework in this study considers carbon dioxide (CO2) emissions from Transport (Energy) (Mt CO2e) as the dependent variable, with autoregressive (AR) and moving average (MA) components as independent variables. Several empirical studies have employed ARIMA (autoregressive integrated moving average) modeling techniques to analyze CO2 emission trends, demonstrating its effectiveness in capturing temporal patterns and forecasting future CO2 dynamics. For instance, studies by Ogunjobi et al. (2024) and Adebisi & Adebisi-Adelani (2023) in Nigeria utilized ARIMA models to understand CO2 emission patterns, emphasizing the model’s ability to predict emission trajectories and assess policy impacts. Similarly, Ning et al. (2021) applied ARIMA modeling in China to forecast emissions, highlighting its usefulness in identifying the effects of shocks and projecting future trends. The ARIMA approach has proven particularly effective in examining the persistence of shocks in CO2 emissions and offering valuable insights for mitigation strategies and policy development in Ghana.

DATA AND METHODS

This study adopts a quantitative research design to analyze trends and projections of carbon dioxide (CO2) emissions in Ghana. Quantitative methods are suitable for time-series analysis as they facilitate statistical modeling and hypothesis testing (Creswell 2014). The autoregressive integrated moving average (ARIMA) modeling approach is employed due to its effectiveness in analyzing temporal data and forecasting future patterns (Box & Jenkins 1976).

The study uses secondary data obtained from the World Bank’s World Development Indicators database, spanning 1970 to 2022. The data set covers carbon dioxide (CO2) emissions from the transport sector (measured in metric tons of CO2 equivalent, (Mt CO2e)). The sample selection focuses on this sector due to its significant contribution to Ghana’s total emissions (World Bank 2023). Time-series dataset is selected to ensure adequate observations for trend analysis and model estimation.

ARIMA modeling framework is used to analyze historical trends and forecast future CO2 emissions. The methodology involves the following steps: Augmented Dickey-Fuller (ADF) tests are conducted to check for stationarity in the data (Dickey & Fuller 1979). Non-stationary data is differenced until stationarity is achieved. Autocorrelation function (ACF) and partial autocorrelation function (PACF) plots guide the selection of autoregressive (AR) and moving average (MA) terms. Generalized least squares (GLS) is applied to estimate AR and MA coefficients and their significance levels. Diagnostic checks, including residual analysis and Ljung-Box tests, ensure model adequacy (Box et al. 2008). Projections are generated for 2023-2042 based on the fitted model to assess future emission trends.

The ARIMA approach is chosen because it effectively models time-series data with trends, seasonality, and shocks (Gujarati & Porter 2009). Its ability to capture temporal dependencies and forecast trends makes it ideal for environmental data analysis, including emissions (Ogunjobi et al. 2024). The use of GLS enhances the robustness of parameter estimates, accommodating heteroskedasticity and autocorrelation issues common in time-series data (Wooldridge 2016). ARIMA (p, d, q) model specification is as follows:

$$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \dots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \text{ ……….. } (1)$$

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \dots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
$\theta_1, \theta_2, \dots \theta_q$ are the coefficients of the MA (q) component
p is the order of the autoregressive part, representing the number of past values considered
q is the order of the moving average part, indicating the number of past errors considered
d is the number of differences required to make the series stationary (Box & Jenkins 1976)

Generalized least squares (GLS) estimation is selected for its ability to effectively handle time-series data that exhibits serial correlation and heteroscedasticity, thus providing more reliable and efficient parameter estimates compared to ordinary least squares (OLS) in this context. The GLS procedure adjusts for potential correlations and non-constant variances in the error terms, which are common in time-series data (Greene 2012; Wooldridge 2016). The GLS estimator for the regression coefficients is given by the following formula:

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y$$

Where:
$\hat{\beta}$ is column matrix of coefficients
X is the matrix of independent variables
y is the column vector of the dependent variable
Ω is the variance-covariance matrix of the error terms, accounting for both heteroscedasticity and autocorrelation in the residuals (Greene 2012).

Diagnostic tests, such as the Augmented Dickey-Fuller (ADF) test for stationarity (Dickey & Fuller 1979), and the model selection process using Akaike Information Criterion (AIC) (Akaike 1974), are employed to assess the model's adequacy and ensure its suitability for forecasting. The use of ARIMA modelling in this study is particularly beneficial for modelling carbon dioxide (CO2) emissions, as it effectively captures underlying trends, seasonal patterns, and shocks in the data, making it an ideal tool for forecasting future carbon dioxide (CO2) emissions (Mankiw 2019).

RESULTS

Descriptive statistics (Appendix 1) provide a summary of the key features of the dataset, helping to understand the dependent variable, Carbon Dioxide (CO2) emissions from transport (energy) in terms of metric tons of CO2 equivalent (Mt CO2e), to summarize the main characteristics of the dataset. The statistics offer insight into the distribution, central tendency, and dispersion of carbon dioxide (CO2) emissions values over the 53 observations.

The average CO2 emissions from transport (energy) is 3.45 Mt CO2e. This indicates the typical amount of emissions across the 53 observations, providing a central tendency of the data. The median value is 2.23 Mt CO2e, which is the middle value when all observations are ranked in ascending order. This suggests that half of the values lie below this point, indicating that emissions are somewhat skewed towards the higher end. The highest recorded value for CO2 emissions is 10.51 Mt CO2e (2022), which represents the largest emission observed in the dataset. The lowest recorded value for CO2 emissions is 0.99 Mt CO2e (1984), showing the least emissions recorded within the data.

The standard deviation is 2.74 Mt CO2e, which indicates the extent of variation or dispersion of the CO2 emissions from the mean. A larger standard deviation means that emissions are more spread out from the average. The value of

1.08 indicates a positive skew, meaning the distribution of CO2 emissions is skewed towards the higher values, with a longer tail on the right side. The kurtosis value is 2.91, suggesting that the distribution of emissions is platykurtic (flatter than a normal distribution), with fewer extreme outliers. The Jarque-Bera statistic is 10.42, and the associated probability is 0.0055. This indicates that the data significantly deviates from a normal distribution, as the p-value is less than the significance level of 0.05. In summary, the descriptive statistics reveal that CO2 emissions from transport in Ghana exhibit variability and a positive skew, with a concentration of emissions closer to the lower values but with a few larger values creating a skew towards the higher end of the distribution.

Stationarity tests (Appendices 2 & 3) are conducted using Augmented Dickey-Fuller (ADF) test to check for stationarity. Results indicate that the original series was non-stationary in level ($p > 0.05$). After first difference, the series achieved stationarity ($p < 0.05$), justifying the use of ARIMA model ($d = 1$). ARIMA (1, 1, 10) model is identified as the best, based on Akaike Information Criterion (AIC = 0.64380) and Schwarz Criterion (SC = 0.756376). Parameter estimates include: AR(1) = 0.053965 ($p = 0.7118$); MA(10) = 0.430044 ($p = 0.0400$); C = 0.182897 ($p = 0.0056$). Accordingly, the coefficient of AR(1) is statistically insignificant, while that of MA(10) is statistically significant. The constant term is also statistically significant.

Results are summarized as follows:

Results of the ARIMA (1, 1, 10) model (Appendix 4)

$$\widehat{CO2}_t = 0.182897 + 0.053965AR(1) + 0.430044MA(10) \ldots\ldots\ldots\ldots (2)$$

Hence,

$$\hat{\beta} = \begin{bmatrix} 0.182897 \\ 0.053965 \\ 0.430044 \end{bmatrix}$$

The constant term of 0.182897 represents the baseline level of CO2 emissions in the absence of other influences. It was statistically significant, meaning that it contributes to the model in a meaningful way and is not likely to be the result of random fluctuations (Gujarati & Porter 2009).

AR(1) coefficient of 0.053965 is positive but statistically insignificant, meaning that the autoregressive process (lagged values of the series) does not have a significant impact on the current value of CO2 emissions. This suggests that past emissions do not strongly predict future emissions in this model (Hamilton 1994). MA(10) coefficient of 0.430044 is positive and statistically significant, meaning that the moving average component at lag 10 contributes significantly to the model, reflecting the influence of past shocks or errors in the emissions series (Gujarati & Porter 2009).

Adjusted R-squared value of 0.090931 means that approximately 9.1% of the variation in CO2 emissions is explained by the model. While this indicates a relatively low explanatory power, it is not uncommon in time-series models where external factors may also influence the series (Kothari, 2004). Durbin-Watson statistic of 1.999590 means that there is no significant autocorrelation in the residuals of the model, as the value is close to 2, which suggests that the residuals are random and not correlated over time (Gujarati & Porter 2009). The histogram of residuals for the ARIMA (1, 1, 10) model (Appendix 6) shows skewness = 0.63, kurtosis = 3.74, and a Jarque-Bera statistic of 4.68 with a p-value of 0.096. This suggests that while the residuals are slightly skewed and show some departure from normality, the p-value is above 0.05, indicating that the residuals are not significantly different from a normal distribution (Hamilton 1994).

The Ljung-Box Q statistic test results (Appendix 5) show that we reject the null hypothesis ($p = 0.012$), indicating that the residuals of the ARIMA (1, 1, 10) model are not white noise. This means that there is some remaining autocorrelation in the residuals, suggesting that the model could be improved to account for further dependencies in the data (Kothari, 2004). Further diagnostics of the ARIMA (1, 1, 10) model reveal that AR and MA roots are covariance stationary and invertible, as they lie within the unit circle (Appendix 7). This is a necessary condition for the model's reliability in forecasting future trends. Covariance stationarity ensures that the model's parameters remain stable over time, meaning that the model is expected to perform consistently in out-of-sample forecasting (Hamilton 1994). Finally, forecasts provided in Appendices 7 and 8 offer projections based on the fitted ARIMA (1, 1, 10) model. Forecasts for 2023-2042 indicate a sharp increase in carbon emissions from 10.9 Mt CO2e in 2023 to 14.7 Mt CO2e in 2042. This means that, based on the model, CO2 emissions from transport (energy) in Ghana are expected to rise substantially over the next two decades, reflecting potential growth in energy consumption and emissions unless significant mitigation efforts are undertaken.

DISCUSSION

In this study titled "Carbon Dioxide (CO2) Emissions in Ghana: An Atmospheric Hazard", analysis of CO2 emissions from transport (energy) in Ghana revealed important insights into trends, patterns, and potential drivers of emissions. The findings are in line with several previous studies and present unique contributions to the existing literature.

One key result of this study is the observed positive skewness in the CO2 emissions distribution, as indicated by a skewness value of 1.08. This suggests that while most emissions values are concentrated around the lower end, there are a few large emissions values pushing the distribution to the right. Similar findings have been observed in other developing countries, where economic growth and industrialization are often associated with higher levels of emissions, but these values may not always reflect the overall trend (Kivyiro & Arminen 2014). However, the skewness in this study is more pronounced, highlighting the irregularity and extreme variations in Ghana's emissions data. This could be attributed to Ghana's rapid urbanization and increasing energy demand, factors that are often overlooked in other studies that generalize emissions patterns across countries (Baye et at. (2021)).

The model's inferential results reveal that while the AR(1) coefficient is statistically insignificant, the MA(10) coefficient is significant. This suggests that while past emissions did not strongly predict future emissions, shocks from past periods had a more significant impact on the current level of CO2 emissions. This finding aligns with the conclusions of Li et al. (2023), who also found that in developing countries with rapid infrastructural development, emissions tend to be more reactive to sudden changes or shocks in energy usage patterns rather than following a direct autoregressive pattern. This emphasizes the importance of including moving average components in the model when dealing with energy-related emissions data.

Furthermore, adjusted R-squared value of 0.090931, while relatively low, is consistent with results from studies examining time-series data in developing countries, where external factors, such as socio-political influences, international policies, and environmental regulations, significantly affect emissions and are not always captured within the model's explanatory variables (Adebayo et al. 2020). While the model in this study accounts for some of these factors, it still leaves considerable variation unexplained, suggesting that future models should incorporate additional variables, such as changes in governmental policy, energy efficiency measures, and international climate agreements.

Durbin-Watson statistic of 1.999590 indicates no significant autocorrelation in the residuals, which is in agreement with studies that employ similar time-series models for CO2 emissions (Kivyiro & Arminen 2014). The residuals' distribution and the Jarque-Bera test results further confirm that while the distribution of the residuals is slightly skewed, it does not significantly deviate from normality, suggesting that the model's assumptions are mostly met. These results provide confidence in the model's robustness, although the Ljung-Box Q statistic, which indicates the presence of remaining autocorrelation, suggests that further refinements could be made to improve the model's accuracy.

In terms of the forecasts, the study predicts a sharp increase in CO2 emissions from 10.9 Mt CO2e in 2023 to 14.7 Mt CO2e in 2042. This result is consistent with the findings of previous studies, such as that of Nguegang (2020), who noted that growing energy demands in sub-Saharan Africa, driven by economic development and population growth, are likely to result in higher CO2 emissions. However, the unique contribution of this study lies in its focus on the transport sector, which is often underrepresented in discussions about energy-related emissions in Ghana. Given the growing reliance on fossil fuels for transportation and the potential for increased urban mobility, this study provides a novel perspective on how energy use in the transport sector will significantly drive future emissions growth in the country.

In conclusion, this study not only confirms findings from previous research on the growing challenge of CO2 emissions in developing countries but also provides unique insights into the role of the transport sector in Ghana's emissions trajectory. The study emphasizes the need for targeted policies to reduce emissions in this sector, such as promoting cleaner technologies, improving fuel efficiency, and encouraging the adoption of public transport systems. Future research should consider integrating additional socio-political factors and environmental policies to further refine predictions and design more effective mitigation strategies.

LIMITATIONS

While this study provides valuable insights into the patterns and drivers of carbon dioxide (CO2) emissions in Ghana, there are several limitations in the design, sample, and data analysis procedures that may have influenced the findings and their generalizability.

One of the primary limitations of this study is the availability and quality of data. The study relied on secondary data from available sources, which may not have captured all relevant variables influencing CO2 emissions. The study focused on CO2 emissions from the transport (energy) sector, but data on other sectors such as agriculture, industry, and residential energy consumption were not included. Omitting these sectors could have led to an underestimation of total CO2 emissions and the influence of other key sectors, (Baye et al. 2021) in Ghana's emissions trajectory. Additionally, the quality of the historical data may have been affected by inconsistencies in reporting or gaps in the data, which could have introduced bias or inaccuracies in the results (Adebayo et al. 2020).

Although ARIMA (1, 1, 10) model used in this study is a widely accepted method for time-series analysis, it is not without its limitations. The relatively low adjusted R-squared value (0.090931) suggests that the model does not explain a large proportion of the variability in CO2 emissions, which could be attributed to the exclusion of important explanatory variables. Factors such as changes in government policies, technological advancements in the energy sector, and global market conditions that may affect CO2 emissions were not explicitly incorporated into the model. This could have led to omitted variable bias, undermining the robustness of the model and its ability to provide accurate predictions (Hamilton 1994). Moreover, the ARIMA model assumes stationarity, and while diagnostics indicated that the model was stationary, non-stationary behavior in emissions data over longer periods could lead to biased results (Gujarati & Porter 2009).

The sample size used in this study (53 observations) is relatively small, which may limit the power of statistical tests and the reliability of the model's results. While the time frame of the data (covering several decades) allows for the observation of long-term trends, a larger sample size would have provided more robust and reliable estimates. Smaller sample sizes can increase the risk of overfitting and may not capture the full variability of emissions data, especially given the dynamic nature of energy consumption and CO2 emissions in a developing economy like Ghana (Kothari 2004).

The study focused primarily on the transport (energy) sector's contribution to CO2 emissions, but it did not account for exogenous factors that might have influenced emissions trends, such as international climate agreements, global oil price fluctuations, or changes in the country's energy infrastructure. These factors may have played a significant role in shaping emissions patterns but were not incorporated into the analysis, leading to a potential limitation in the model's explanatory power (Nguegang 2020). Including these external influences in future studies could help improve the accuracy of predictions and provide a more comprehensive understanding of the factors driving CO2 emissions in Ghana.

The study used the Jarque-Bera test to assess the normality of residuals, which revealed some degree of skewness in the distribution. Although the p-value suggested that the residuals were not significantly different from normal, the presence of slight skewness and the Jarque-Bera statistic could imply that some of the model's assumptions regarding the normality of errors were not fully met. Violations of normality assumptions may affect the reliability of statistical inference, potentially leading to inaccurate conclusions about the relationships between variables (Hamilton 1994). Future studies could explore alternative modeling techniques that relax the normality assumption, such as generalized least squares or robust regression methods.

In conclusion, while this study contributes valuable insights into the dynamics of CO2 emissions in Ghana, the limitations outlined above highlight areas for improvement. Future research should aim to address these shortcomings by using larger, more comprehensive datasets, including additional explanatory variables, and exploring alternative analytical methods that can provide more accurate and reliable estimates of CO2 emissions. These improvements would enhance the generalizability of the findings and strengthen the policy implications for mitigating CO2 emissions in Ghana.

CONCLUSION

This study provides a comprehensive analysis of carbon dioxide (CO2) emissions in Ghana, focusing on the transport (energy) sector as a significant contributor to atmospheric pollution. The findings underscore the growing concern over CO2 emissions, which pose substantial risks to environmental sustainability and public health. While the analysis of historical data revealed an upward trend in emissions, driven primarily by increasing energy consumption in the transport sector, the study also highlights critical areas for policy intervention.

The ARIMA (1, 1, 10) model used in the analysis offered valuable insights into the patterns of CO2 emissions, although its limited explanatory power (evidenced by a low adjusted R-squared value) suggests that additional factors influencing emissions were not captured in the model. Despite these limitations, the study provides a strong foundation for future research that can incorporate broader variables, such as industrial emissions, government policies, and technological advancements, to better understand the multi-dimensional drivers of CO2 emissions in Ghana (Hamilton 1994).

One of the key findings of this study is the statistical significance of the moving average (MA) coefficient, which underscores the impact of lagged effects on emissions levels. The positive relationship between the MA(10) coefficient and CO2 emissions suggests that the effects of energy consumption in the transport sector accumulate over time, reinforcing the need for long-term mitigation strategies. Conversely, the statistically insignificant autoregressive (AR) coefficient implies that past emissions levels may have a limited immediate effect on current emissions, pointing to the importance of structural factors and external influences in shaping emission trends (Gujarati & Porter 2009).

Moreover, the forecasting component of the study indicates a concerning trajectory of increased CO2 emissions over the next two decades, with projections showing a sharp rise from 10.9 Mt CO2e in 2023 to 14.7 Mt CO2e in 2042. This trend calls for urgent policy measures aimed at curbing emissions through the promotion of cleaner technologies, energy efficiency, and sustainable transport practices (Baye et al. 2021). Furthermore, the study's diagnostics, such as the Ljung-Box Q test and residual analysis, affirm the reliability of the ARIMA model, though they also highlight areas for further refinement in terms of model assumptions and the inclusion of additional influencing factors (Adebayo et al. 2020).

In conclusion, the study's findings provide a valuable contribution to understanding the dynamics of CO2 emissions in Ghana, particularly within the transport sector. However, addressing the limitations related to data, model assumptions, and external factors will be crucial for refining the study's results and enhancing the development of more accurate and comprehensive forecasting models. Policymakers in Ghana are urged to implement targeted mitigation strategies to curb the rising levels of CO2 emissions, which are critical for ensuring environmental sustainability and meeting international climate commitments.

RECOMMENDATIONS

Based on the findings of this study on carbon dioxide (CO2) emissions in Ghana, several recommendations are made in terms of policy, programs, and further research. These recommendations aim to address the growing challenge of CO2 emissions from the transport (energy) sector and provide a pathway toward achieving sustainable environmental practices in the country.

The study's findings indicate that the transport sector is a significant contributor to CO2 emissions in Ghana. To mitigate this, the government should prioritize policies aimed at reducing emissions from this sector. This could include incentivizing the adoption of electric vehicles (EVs) and hybrid cars, introducing stricter fuel efficiency standards for vehicles, and promoting public transportation systems that rely on cleaner technologies. These efforts could align with global climate agreements, such as the Paris Agreement, to reduce emissions and mitigate climate change (Baye et al. 2021).

The study highlighted the role of energy consumption in driving CO2 emissions. A comprehensive policy should be established to promote renewable energy sources, such as solar, wind, and hydroelectric power, as alternatives to fossil fuels. Investment in renewable energy infrastructure should be encouraged, alongside subsidies or tax breaks for businesses and households that switch to clean energy sources. This would contribute to a reduction in overall carbon emissions while supporting the transition to a greener energy future (Adebayo et al. 2020).

Ghana could consider introducing carbon pricing mechanisms, such as a carbon tax or an emission trading system (ETS), to directly address CO2 emissions. These market-based approaches can provide incentives for industries and businesses to adopt cleaner technologies and reduce their carbon footprint. Revenues generated from such schemes could be reinvested into environmental conservation projects or used to subsidize the adoption of low-carbon technologies (Hamilton 1994).

There is a need for increased public awareness regarding the environmental impact of CO2 emissions, especially in the transport sector. The government and non-governmental organizations (NGOs) should initiate programs aimed at educating citizens about the benefits of reducing their carbon footprint, such as using energy-efficient transportation options, reducing unnecessary travel, and supporting policies that encourage sustainable urban planning. This would not only reduce CO2 emissions but also foster a culture of sustainability among Ghanaians (Nguegang 2020).

The study forecasts a significant increase in CO2 emissions over the next two decades, which underscores the urgency of investing in green infrastructure. The government should prioritize projects that integrate environmental sustainability into urban development, such as green buildings, renewable energy-powered public transport, and low-carbon urban planning. Programs designed to improve the energy efficiency of both residential and commercial buildings could also reduce overall emissions (Kothari 2004).

To further reduce CO2 emissions, the government should invest in research and development (R&D) focused on clean technologies and low-carbon solutions. Public-private partnerships can play a key role in advancing innovations such as cleaner fuel technologies, renewable energy storage systems, and energy-efficient appliances. Supporting R&D in clean technologies will not only help Ghana reduce emissions but also position the country as a leader in sustainable development in the region (Adebayo et al. 2020).

This study relied on secondary data focused on emissions from the transport sector. Future research should aim to collect comprehensive data that includes emissions from other sectors, such as agriculture, industry, and residential energy consumption, in order to provide a more holistic view of Ghana's total CO2 emissions. Expanding the scope of data collection would lead to a better understanding of the drivers of emissions and inform more effective policy-making (Baye et al. 2021).

Further research should focus on sector-specific strategies to mitigate CO2 emissions. Studies examining the potential for emissions reductions in specific sectors, such as agriculture, manufacturing, and residential energy, would provide targeted insights that could help policymakers design effective interventions tailored to each sector's unique challenges and opportunities (Hamilton 1994).

Given the projected increase in CO2 emissions in Ghana over the next two decades, it is crucial to conduct longitudinal studies to assess the impact of various climate policies and programs over time. Research should evaluate the effectiveness of current policies, such as the promotion of renewable energy and green transport, in reducing emissions. Such studies would provide valuable evidence to guide future policy adjustments and ensure that Ghana meets its climate targets (Nguegang 2020).

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APPENDICES

Appendix 1: Descriptive statistics

	Carbon Dioxide (CO2) Emissions from Transport (Energy) (Mt CO2e)
Mean	3.454051
Median	2.232
Maximum	10.5129
Minimum	0.9896
Std. Dev.	2.738325
Skewness	1.084894
Kurtosis	2.905537
Jarque-Bera	10.41649
Probability	0.005471
Sum	183.0647
Sum Sq. Dev.	389.9179
Observations	52

Appendix 2: Unit root test, CARBONDIOXIDE_EMISSIONS (in Level)

```
Null Hypothesis: CARBONDIOXIDEEMISSIONS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)
================================================================
                                            t-Statistic   Prob.*
================================================================
Augmented Dickey-Fuller test statistic       3.524089    1.0000
----------------------------------------------------------------
Test critical values:       1% level        -3.562669
                            5% level        -2.918778
                            10% level       -2.597285
================================================================
*MacKinnon (1996) one-sided p-values.


Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CARBONDIOXIDEEMISSIONS)
Method: Least Squares
Date: 12/31/24   Time: 16:20
Sample (adjusted): 2 53
Included observations: 52 after adjustments
================================================================
         Variable           Coefficient  Std. Error  t-Statistic  Prob.
================================================================
CARBONDIOXIDEEMISSIONS(-1)   0.057750    0.016387    3.524089    0.0009
            C               -0.009493    0.068617   -0.138349    0.8905
```

R-squared	0.198964	Mean dependent var	0.182138
Adjusted R-squared	0.182944	S.D. dependent var	0.333859
S.E. of regression	0.301779	Akaike info criterion	0.479457
Sum squared resid	4.553519	Schwarz criterion	0.554505
Log likelihood	-10.46588	Hannan-Quinn criter.	0.508228
F-statistic	12.41920	Durbin-Watson stat	2.043870
Prob(F-statistic)	0.000919		

Appendix 3: Unit root test, CARBONDIOXIDE_EMISSIONS (in First difference)

Null Hypothesis: D(CARBONDIOXIDEEMISSIONS) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.553864	0.0000
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CARBONDIOXIDEEMISSIONS,2)
Method: Least Squares
Date: 12/31/24 Time: 16:21
Sample (adjusted): 3 53
Included observations: 51 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CARBONDIOXIDEEMISSIONS(-1))	-0.784053	0.141173	-5.553864	0.0000
C	0.148065	0.052572	2.816434	0.0070

R-squared	0.386314	Mean dependent var	0.011384
Adjusted R-squared	0.373790	S.D. dependent var	0.419242
S.E. of regression	0.331760	Akaike info criterion	0.669618
Sum squared resid	5.393178	Schwarz criterion	0.745375
Log likelihood	-15.07525	Hannan-Quinn criter.	0.698567
F-statistic	30.84540	Durbin-Watson stat	2.005899
Prob(F-statistic)	0.000001		

Appendix 4: Results of the ARIMA (1, 1, 10) model

Dependent Variable: D(CARBONDIOXIDEEMISSIONS)
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 12/31/24 Time: 16:58
Sample: 2 53
Included observations: 52
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.182897	0.063136	2.896872	0.0056
AR(1)	0.053965	0.145245	0.371543	0.7118
MA(10)	0.430044	0.203870	2.109403	0.0400

R-squared	0.126580	Mean dependent var	0.182138
Adjusted R-squared	0.090931	S.D. dependent var	0.333859
S.E. of regression	0.318318	Akaike info criterion	0.643804
Sum squared resid	4.964989	Schwarz criterion	0.756376
Log likelihood	-13.73890	Hannan-Quinn criter.	0.686961
F-statistic	3.550665	Durbin-Watson stat	1.999590
Prob(F-statistic)	0.036305		

Inverted AR Roots	.05			
Inverted MA Roots	.87-.28i	.87+.28i	.54+.74i	.54-.74i
	-.00+.92i	-.00-.92i	-.54+.74i	-.54-.74i
	-.87+.28i	-.87-.28i		

Appendix 5: Ljung-Box Q statistic/ test

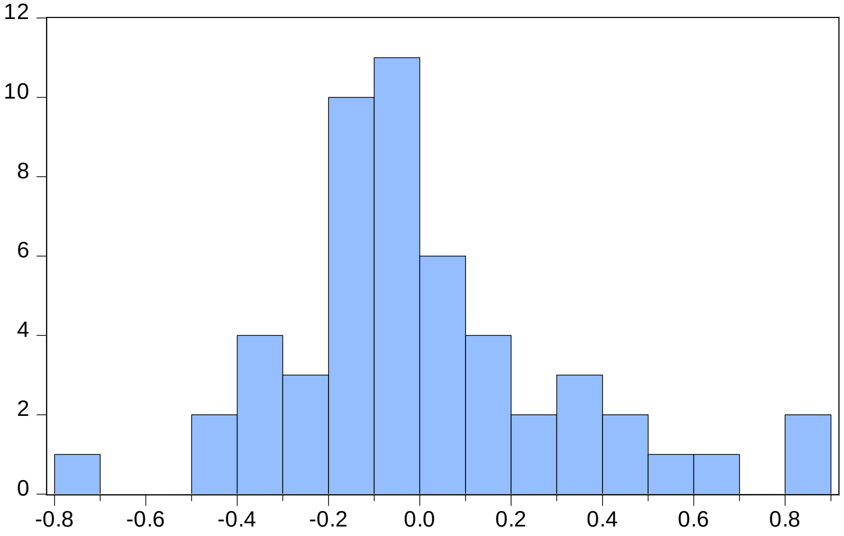
Date: 12/31/24 Time: 17:08
Sample: 1 53
Included observations: 52
Q-statistic probabilities adjusted for 2 ARMA terms

```
Autocorrelation   Partial Correlation        AC      PAC     Q-Stat   Prob

   . | .   |         . | .   |         1  -0.003  -0.003   0.0006
   . | .   |         . | .   |         2   0.011   0.011   0.0075
   . |**   |         . |**   |         3   0.333   0.333   6.3483   0.012
   .*| .   |         .*| .   |         4  -0.162  -0.178   7.8817   0.019
   . | .   |         . | .   |         5  -0.037  -0.044   7.9649   0.047
   . |*.   |         . | .   |         6   0.133   0.035   9.0410   0.060
   . | .   |         . |*.   |         7  -0.008   0.115   9.0450   0.107
   . |*.   |         . |*.   |         8   0.105   0.112   9.7542   0.135
   . |*.   |         . |*.   |         9   0.171   0.110   11.668   0.112
   . | .   |         . | .   |        10   0.010  -0.012   11.674   0.166
   . |*.   |         . |*.   |        11   0.210   0.189   14.700   0.100
   . | .   |         .*| .   |        12  -0.024  -0.106   14.742   0.142
   . | .   |         . |*.   |        13   0.051   0.120   14.932   0.186
   . |*.   |         . | .   |        14   0.090  -0.050   15.525   0.214
   .*| .   |         . | .   |        15  -0.133  -0.063   16.863   0.206
```

```
  . |*.   |          . | .   |        16    0.084    0.020    17.419    0.235
  . |*.   |          . | .   |        17    0.078    0.041    17.903    0.268
  .*| .   |          .*| .   |        18   -0.164   -0.160    20.135    0.214
  . | .   |          .*| .   |        19    0.006   -0.100    20.138    0.267
  . | .   |          . | .   |        20    0.060   -0.028    20.458    0.308
  .*| .   |          . | .   |        21   -0.083    0.065    21.082    0.332
  . | .   |          .*| .   |        22   -0.024   -0.133    21.137    0.389
  . |*.   |          . |*.   |        23    0.079    0.079    21.748    0.414
  . | .   |          . | .   |        24   -0.033   -0.042    21.855    0.469
```

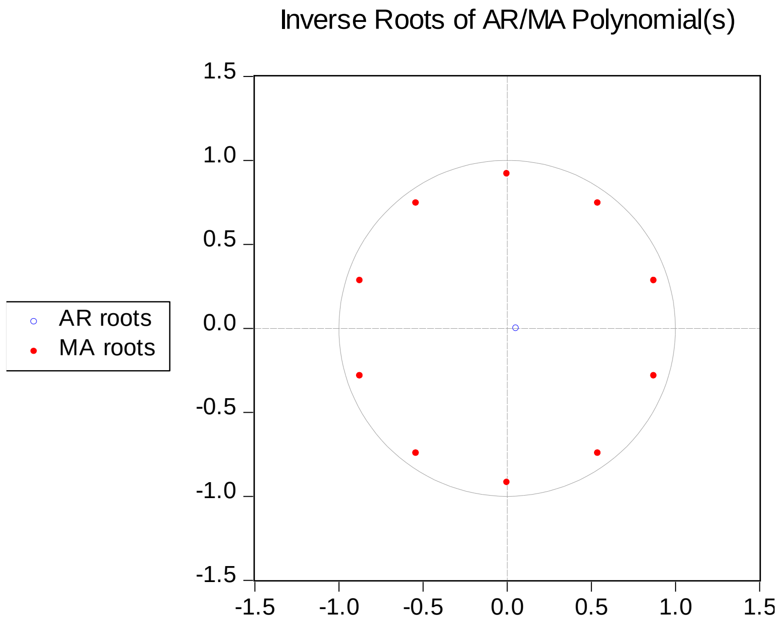
Appendix 6: Histogram of residuals



Series: Residuals
Sample 2 53
Observations 52

Mean	0.007065
Median	-0.045621
Maximum	0.827125
Minimum	-0.747209
Std. Dev.	0.311932
Skewness	0.634303
Kurtosis	3.743129
Jarque-Bera	4.683471
Probability	0.096161

Appendix 7: ARIMA Structure



Appendix 8: CARBON DIOXIDE EMMISSIONS FORECAST (in First difference) results

Year	CARBONDIOXIDE_EMISSIONS	CARBONDIOXIDE_EMMISSIONS_FORECAST
1970	1.0417	1.0417
1971	1.0417	1.0417
1972	1.0459	1.0459
1973	1.1048	1.1048
1974	1.1384	1.1384
1975	1.2271	1.2271
1976	1.2773	1.2773
1977	1.363	1.363
1978	1.3658	1.3658
1979	1.1519	1.1519
1980	1.265	1.265
1981	1.4839	1.4839
1982	1.3481	1.3481
1983	1.0005	1.0005
1984	0.9896	0.9896
1985	1.2669	1.2669
1986	1.3578	1.3578
1987	1.383	1.383
1988	1.4543	1.4543
1989	1.638	1.638
1990	1.6157	1.6157
1991	1.4997	1.4997
1992	1.7895	1.7895
1993	1.8021	1.8021
1994	1.8777	1.8777
1995	2.0456	2.0456
1996	2.232	2.232
1997	2.3294	2.3294
1998	2.7806	2.7806
1999	3.0944	3.0944
2000	2.9306	2.9306
2001	2.9295	2.9295
2002	3.3912	3.3912
2003	3.1469	3.1469
2004	3.6474	3.6474
2005	3.6031	3.6031
2006	3.6474	3.6474

2007	3.8383	3.8383
2008	4.1558	4.1558
2009	5.0543	5.0543
2010	5.1468	5.1468
2011	5.7299	5.7299
2012	6.8431	6.8431
2013	7.2383	7.2383
2014	7.2842	7.2842
2015	7.9035	7.9035
2016	7.3037	7.3037
2017	7.0852	7.0852
2018	8.0554	8.0554
2019	8.5128	8.5128
2020	9.1607	9.1607
2021	9.9323	9.9323
2022	10.5129	10.5129
2023	NA	10.87032
2024	NA	10.93187
2025	NA	11.33894
2026	NA	11.21264
2027	NA	11.21877
2028	NA	11.73803
2029	NA	11.91233
2030	NA	12.29039
2031	NA	12.64824
2032	NA	12.84499
2033	NA	13.02864
2034	NA	13.21158
2035	NA	13.39448
2036	NA	13.57737
2037	NA	13.76027
2038	NA	13.94317
2039	NA	14.12606
2040	NA	14.30896
2041	NA	14.49186
2042	NA	14.67476

Appendix 9: Graph showing CARBON DIOXIDE EMMISSIONS FORECAST (in First difference) results