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A CLOSER LOOK: LINKING ANNUAL CARBON EMISSIONS AND ECONOMIC PROSPERITY IN CANADA

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Abstract
Canada, a prominent global economy and an OECD member, boasts substantial wealth, but also faces the challenge of being one of the world's largest energy consumers. Per capita energy consumption in Canada is slated to exceed 300 million joules in 2020, a rate three times the global average and among the highest worldwide. Correspondingly, Canada ranks tenth among major global polluters in total carbon emissions and is forecasted to have the highest per capita carbon emissions.
This study delves into the intricate connection between Canada's annual carbon emissions and its economic growth. By examining these interrelated factors, the research aims to provide a deeper understanding of how economic development in Canada influences carbon emissions, and vice versa. Such insights are pivotal for crafting sustainable policies that balance economic prosperity with environmental stewardship in a high-consumption nation like Canada.

1. Introduction

Canada stands as one of the world's wealthiest countries, ranking as the tenth-largest global economy and a member of the Organisation for Economic Co-operation and Development (OECD). According to the International Energy Agency's World Energy Outlook 2021, Canada's per capita energy consumption is set to surpass 300 million joules in 2020, triple the world average and one of the highest per capita energy consumption rates globally. Among the largest global polluters, Canada holds the tenth position in total carbon emissions. On a per capita basis, Canada is projected to have the highest carbon emissions, according to an analysis by Carbon Brief. This study aims to analyze the tangible relationship between Canada's annual carbon emissions and economic growth.

2. Literature Review

The relationship between carbon emissions and economic growth has consistently remained a prominent research topic, with numerous scholars having conducted investigations on the subject.

Michael Tucker (1995) examined the per capita income and carbon emissions of 137 countries over a span of 21 years.[1] The results revealed a positive correlation between carbon emissions and GDP. Furthermore, the

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growth of emissions tends to decelerate in most cases as a country's per capita income increases. Higher income levels may lead to an augmented demand for environmental protection.

Al-mulali and Sab (2012) studied the impact of energy consumption and carbon emissions on GDP growth and financial development across 30 sub-Saharan African countries.[2] Their study highlighted the critical role of energy consumption in promoting economic growth and financial development, although it also brought forth severe pollution consequences. In 2018, Al-Mulali and Sab examined the effect of electricity consumption on economic growth in Middle Eastern countries.[3] The results from cointegration tests demonstrated a long-term relationship between carbon emissions, electricity consumption, and economic growth, with electricity consumption being pivotal in the economic growth of Middle Eastern nations. These two studies underscored that as GDP grows, a country's economic output requires more energy.

The literature review highlights that a country's technological innovation capacity, degree of economic development, economic structure, population composition, and energy structure collectively determine the total volume of carbon emissions. The above studies showcased the relationship between carbon emissions and GDP by comparing actual emission disparities among countries or regions and the effects of energy consumption on developing economies. This study places particular emphasis on Canada's specific time-series data to elucidate the connection between Canada's carbon emissions and GDP. The degree of economic development is represented by the annual total GDP in current US dollars, urban population signifies population composition, and energy structure is delineated by the proportion of fossil fuel energy and renewable energy consumption.

3. Data

The data used in this study are sourced from the World Bank's "World Development Indicators". This dataset is compiled from international sources officially recognized by the World Bank, rendering it authentic and authoritative.[4] It provides the most up-to-date and accurate global development data available. The dataset is classified as public under the Access to Information Classification Strategy, allowing users both within and outside the Bank to access it. The study employs data spanning from 1960 to 2020. However, there are some instances of missing data in the dataset, resulting in varying sample sizes for each variable. The regression models employ approximately 25 to 31 observations.

Given that the units of most individual variables used in this study are percentages, logarithms are employed on the remaining variables for better model interpretation. The primary dependent variable in this study is the natural logarithm of carbon emissions, which is utilized to showcase Canada's carbon emissions. The primary independent variable is the natural logarithm of annual total GDP, which measures Canada's economic growth over time. Social development and economic growth necessitate increased resource input and usage, leading to heightened carbon emissions. Thus, we can hypothesize a positive correlation between annual total GDP and carbon emissions.

This study takes urban population, per capita electricity consumption, renewable energy consumption, and fossil fuel energy consumption as explanatory variables to establish a more comprehensive regression model through multiple regression. Urban areas generally consume more energy than rural areas. We can hypothesize that with the increase in urban population, energy consumption will rise, resulting in higher carbon emissions. Per capita electricity consumption is selected as a variable because energy consumption, whether from renewable or non-renewable sources, inherently incurs energy consumption and subsequently generates carbon emissions. Hence, we can hypothesize a positive correlation between per capita electricity consumption and carbon emissions. Renewable energy, as clean energy, such as wind and solar power, is reusable and reduces carbon emissions. In contrast, fossil fuels such as coal, oil, and natural gas are non-renewable. The primary source of Canada's carbon emissions is the consumption of fossil fuels. The following Table 1 and Table 2 provides detailed information about the variables used in this study and their corresponding data.

Table 1: Variable description

Variable Name	Description	Year	Units	Source
logCO2	Natural log of carbon emission	1990 - 2020	kt	World Bank
logGDP	Natural log of annual total GDP	1960 - 2020	Current US$	World Bank
logUpop	Natural log of urban population	1960 - 2020	People	World Bank
logelec	Natural log of electric power consumption	1960 - 2014	kWh per capita	World Bank
Renew	Renewable energy consumption (% of total final energy consumption)	1990 - 2020	Percentage	World Bank
Fossil	Fossil fuel energy consumption (% of total final energy consumption)	1960 - 2015	Percentage	World Bank

Table 2: Summary of statistics for the variables

Variable	# of Observations	Mean	Standard Deviation	Minimum	Maximum
logCO2	31	5.708869	0.0455121	5.616264	5.763109
logGDP	61	11.60127	0.5223824	10.60705	12.26637
logUPop	61	7.32068	0.1091278	7.092313	7.491353
logelec	55	4.099933	0.1516301	3.748584	4.23716
Renewable	31	21.8971	0.5776111	21.13	23.85
Fossil	56	78.22858	4.728488	71.69827	86.21466

4. Checking the Classical Linear Model (CLM) assumptions

4.1. Assumption 1: Linear in parameters

The model will follow the assumption that is linear in parameters, as below:

Y = β0 + β1x1 + β2x2 + β3x3 + ... + βkxk + e, where Y represents the dependent variable, β0 denotes the intercept term, β1 to βk are the coefficients associated with respective independent variables x1 to xk, and e signifies the error term.

4.2. Assumption 2: Random sampling

Given that the data under examination is sourced from the “World Bank”, it is ascertained that these data points have been systematically collected from diverse global populations through random sampling procedures. Hence, the tenet of random sampling can be reasonably postulated.

4.3. Assumption 3: No perfect collinearity

Multiple Linear Regression (MLR) 3. assumes that each independent variable within the sample dataset possesses variation, precluding the presence of exact linear interrelationships among these independent variables. The following Table 3 presentation expounds upon the outcomes of intercorrelation assessments among all independent variables. Notably, instances of complete collinearity, characterized by a correlation coefficient of 1, are conspicuously absent. Nevertheless, certain correlation coefficients tend toward unity. Hence, a further in-depth assessment of the potential performance of multicollinearity within the context of the multiple linear regression model is necessary. This investigation will be conducted in the subsequent robustness testing section.

Table 3: Correlation test, STATA

	logGDP	logUPop	logelec	Renewable	Fossil

logGDP	1				
logUPop	0.9484	1			
logelec	-0.5221	-0.3933	1		
Renewable	-0.7142	-0.7597	-0.0000	1	
Fossil	0.2265	0.3894	0.3307	-0.5975	1

4.4. Assumption 4: Zero conditional mean

Multiple Linear Regression (MLR) 4. assumes that the values of the explanatory variables must not convey any information concerning the mean of the unobserved factors, denoted as E(ui|xi1, xi2,..., xik), which is equal to zero. However, due to the presence of numerous latent variables influencing the variables under consideration, and the limitations inherent to the available data, the expected value of the error term cannot be rigorously confined to zero. In the linear regression model employed in this study, it is assumed that the conditional mean of the error term adheres to the assumption of zero conditional mean.

4.5. Assumption 5: Homoskedasticity

Multiple Linear Regression (MLR) 5. assumes that the values of the explanatory variables must not contain information about the variance of unobserved factors. The following Figure 1 illustrate residualfitted value plots and normal quantile-quantile (Q-Q) plots for each variable. Observing the residualfitted value plots, it is evident that residuals exhibit no discernible patterns. Furthermore, the normal QQ plot shows a linear alignment between the actual residuals of the model and the theoretical residuals of an ideal model, indicative of a normally distributed residual distribution.[5] Hence, it can be inferred that the model conforms to Assumption 5.

Additionally, the homoskedasticity of variances within the model is further substantiated through White's test and the Breusch-Pagan test. Both tests evaluate the null hypothesis of homoscedasticity of residual variances, that variances are constant.[6] The p-values from both tests exceed 10%, thereby compelling acceptance of the null hypothesis of homoscedasticity. By combining these tests and diagnostic plots to proves the absence of heteroscedasticity within our regression model, thereby obviating the necessity for any heteroscedasticity corrections.

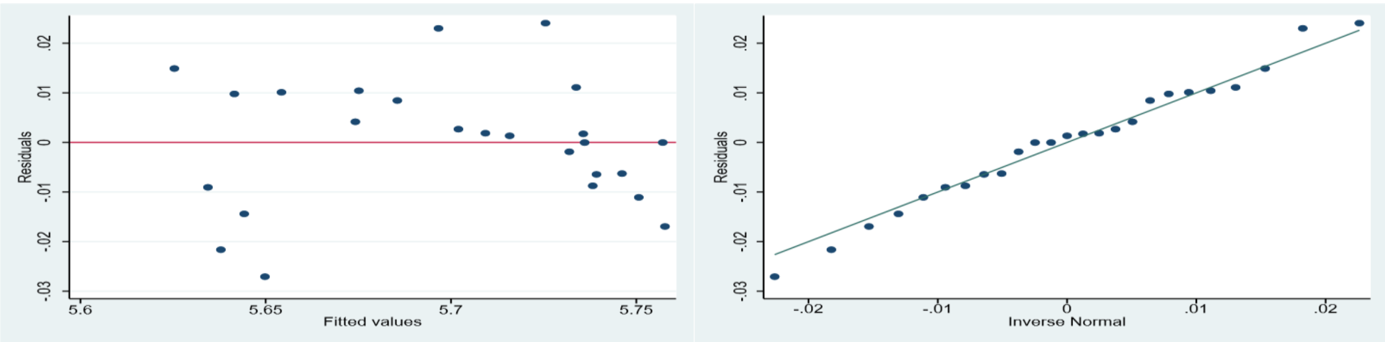

Figure 1: Residual vs fitted plot, and Normal Q-Q plot, STATA

4.6. Assumption 6: Normality of error terms

Multiple Linear Regression (MLR) 6. assumes that the unobserved factors are normally distributed around the population regression function. The Figure 2 below illustrates residuals exhibiting a bellshaped distribution. The x-axis denotes residuals, while the y-axis represents the density of the dataset. This histogram validates the results of the normality test applied to the model. A Skewness & Kurtosis test was conducted using STATA to assess normality.[7] The outcome, based on 25 observations, yields a skewness probability of 0.7461, indicating an asymptotic normal distribution (given a skewness p-value 0.9482 which is far greater than 10% level, implying acceptance of the null hypothesis that the data conforms to a normal distribution). This further proved that our model conforms to Assumption 6.

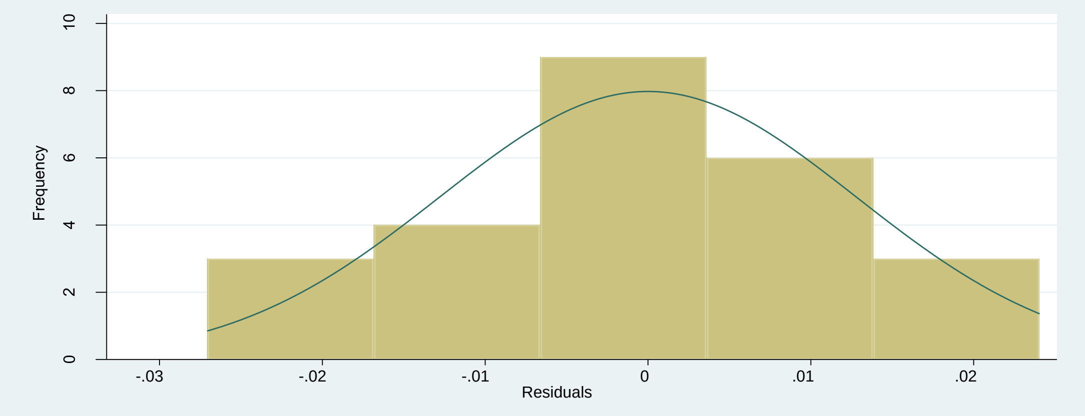

Figure 2: Histogram of residuals of mulitiple linear regression model, STATA

5. Model

Each regression model will provide the standard errors for each parameter. N represents the number of observations, R square represents a measure of the goodness of fit of the model. All data have been processed utilizing STATA.

5.1. Simple linear regression model: logCO2 =β0 + β1logGDP + e

In our initial analysis, we examine the direct association between Canada's carbon emissions and the annual total GDP. This evaluation is performed using a simple linear regression model, wherein the influence of annual total GDP growth on carbon emissions is assessed in isolation from the potential impact of any other variables. The sample size required for simple regression is notably larger compared to that necessary for multiple regression. This larger sample size enhances the randomness of the sample.The outcomes of the model are presented below:

logCO2 = 3.324 + 0.198 (logGDP)

n = 31, R square = 0.7462

In the context of the simple regression model, a 1% increase in the annual total GDP corresponds to an approximate 0.198% increase in carbon emissions. This finding signifies that heightened economic growth in a nation is associated with a proportionate increase in carbon emissions, signifying a positive correlation between the two variables. This observation aligns with our initial hypothesis. The R square is approximately 0.7462. This value indicates the model's efficacy in explaining the observed variability, thereby substantiating its goodness of fit. Approximately 75% of the aggregate variance in carbon emissions is attributable to the change in the annual total GDP, whereas the remaining 25% encompasses variations that are independent of annual total GDP. The T-value for logGDP stands at 9.23, while the corresponding P-value is recorded as 0.000. This signifies the statistical significance of logGDP in relation to logCO2, even at the most stringent significance level of 1%.

5.2. Multiple linear regression model: logCO2 = β0 + β1(logGDP) + β2(logUpop) + β3(logelec) + β4Fossil + β5Renew + e

This model delineates the interrelationships among various factors, including carbon emissions, annual total GDP, urban population, per capita electricity consumption, proportion of renewable energy consumption, and proportion of fossil fuel energy consumption within the context of Canada. In pursuit of comprehensively analyzing the influence of all explanatory variables on the dependent variable, the dataset spans the timeframe from 1990 to 2014, encompassing a total of 25 observations for each variable.The outcomes of the multiple regression model are presented below:

logCO2 = -5.567 + 0.060(logGDP) + 0.850(logUpop) + 0.944(logelec) + 0.004Fossil - 0.002Renew

n = 25, R square = 0.9898

The outcomes of the multiple regression analysis are consistent with our initial hypothesis. Specifically, annual total GDP, urban population, per capita electricity consumption, and the proportion of fossil fuel energy consumption exhibit positive correlations with carbon emissions. For every 1% increase in these explanatory variables, there is a corresponding percentage increase in carbon emissions that aligns with their respective slope coefficients. While the proportion of renewable energy consumption displays a negative correlation with carbon emissions. For every 1% rise in the proportion of renewable energy consumption in total final energy consumption, there is a reduction of approximately 0.002% in carbon emissions. Both fossil fuel energy and renewable energy consumption appear to exert minor economic impact on carbon emissions, with effects only 0.002% and 0.004%.

Table 4: Estimation Results

Dependent Variable: logCO2		
Independent variables	**Simple linear regression model**	**Multiple linear regression model**
logGDP	0.198***	0.060**
	(0.021)	(0.023)
logUpop		0.850***
		(0.101)
logelec		0.944***
		(0.107)
Renew		-0.002
		(0.005)
Fossil		0.004***
		(0.001)
Intercept	3.323***	-5.567***
	(0.258)	(0.744)
Number of observations	31	25
R-squared	0.7462	0.9898
Adjusted R-squared	0.7374	0.9871

*significant at *10%, **5%, ***1%

In the context of the multiple regression analysis, in contrast to the simple regression model, the influence of annual total GDP on carbon emissions diminishes from a significance level of 1% to 2%. The model's R square increases to 0.9898, indicating that approximately 99% of the variation in the dependent variable can be explained by the variations in the explanatory variables logGDP, logUpop, logelec, Fossil, and Renew. This signifies a substantial enhancement in explanatory power compared to the simple regression model, underscoring the utility of incorporating multiple explanatory variables. By assessing the t-values and p-values for each explanatory variable, we establish their respective statistical significance. Notably, with the exception of "Renew", which exhibits a p-value of 0.675, all other explanatory variables possess p-values below the 5% level threshold. This indicates that, except for renewable energy consumption, all other explanatory variables provide strong statistical inference. Table 4 presents the outcomes and specifics of two linear regression models.

6. Extensions

6.1. Robustness Tests

6.1.1. The F-test

We evaluate the model's significant explanatory capacity by employing an F-test when considering multiple explanatory variables. A comparative analysis is conducted between the unrestricted model and the restricted model to ascertain whether the variables logUpop, logelec, Fossil, and Renew collectively exert a significant influence on the explained variable logCO2. Both traditional F-test computation methods and STATA's F-test calculation method will be utilized to compute the F-statistic value.

- **Unrestricted model:** logCO2 = -5.567 + 0.060(logGDP) + 0.850(logUpop) + 0.944(logelec) + 0.004Fossil -0.002Renew
- **Restricted model:** logCO2 = 3.324 + 0.198 (logGDP)
- **Null Hypothesis:** β2 = β3 = β4 = β5 = 0
- **Alternative Hypothesis:** One of them is not equal to 0

The F statistic for the model follows: F = $[(SSSSRRrr - SSSSRRuurr)/\ ]/S[\ SSRRuurr/(n - k - 1)]$

Table 5: The F-Statistic

SSR Unrestricted Model	0.000513661
SSR Restricted Model	0.015773719
Number of restrictions	4
Number of observations in unrestricted model	25
Number of variables in unrestricted model	5
F-Statistic	141.13984

At the 1% significance level, the critical value of F(4,19) is approximately 4.50.[8] According to Table 5, the calculated F-statistic value (141.13984) significantly surpasses the critical value (4.50). Hence, we can reject the null hypothesis at a 99% confidence level, indicating joint significance of these four explanatory variables. Through STATA's F-test, the computed F(4,19) statistic remains substantial at 128.24 and the associated p-value is small than 1% level. Consequently, we reject the null hypothesis, indicating a notable fitting advantage of the multiple regression model over the simpler alternative. Additionally, except for renewable energy consumption, all other four explanatory variables hold statistically significant meaning regarding the natural logarithm of carbon emissions.

6.1.2. Multicollinearity test

While evaluating the assumptions of the Classical Linear Model (CLM), we conducted tests to assess the absence of perfect collinearity among our independent variables. However, we observed that the correlation between logGDP and logUpop is exceedingly close to 1. The Table 6 below displays the results of testing for multicollinearity in the multiple linear regression model. According to the empirical rule for Variance Inflation Factor (VIF), values exceeding 10 indicate severe multicollinearity that requires correction. Both logGDP (17.80) and logUpop (14.78) have VIF values exceeding 10. This indicates the need for model modification.

To address multicollinearity without compromising the overall quality of the regression model, we propose merging "logGDP" and "logUpop" into a single variable "logGDP/Upop," which represents the average GDP per capita for urban areas annually. By dividing the annual total GDP (logGDP) by urban population (logUpop), we create this new composite variable "logGDP/Upop". This new economic index accounts for the relationship between economic scale and population size. Upon reevaluation of the model for multicollinearity, the VIF values for all independent variables are now below [10]. The Table 7 presents the multicollinearity results of the adjusted multiple linear regression model. Adhering to the empirical rule for VIF, the new model no longer exhibits multicollinearity issues.

Table 6: Multicollinearity results before modified, STATA

Variable	**Initial VIF**
logGDP	17.80
logUpop	14.78

logelec	2.41
Renew	4.24
Fossil	2.32
Mean VIF	8.31

Table 7: Multicollinearity results after modified, STATA

Variable	**Modified VIF**
logGDP/Upop	4.56
logelec	2.41
Renew	4.22
Fossil	1.92
Mean VIF	3.28

6.2. Modified multiple linear regression model Modified multiple linear regression model: logCO2 = β0 + β1(logGDP/Upop) + β2(logelec) + β3Fossil + e

We have determined that there is no significant statistical relationship between "Renew" and "logCO2". Through the above multicollinearity tests, we identified multicollinearity between "logUpop" and "logGDP". To address this issue, we propose combining "logGDP" and "logUpop" into a new variable named "logGDP/Upop". By eliminating "Renew" and introducing the new variable "logGDP/Upop", we proceeded to conduct another round of multiple linear regression analysis on the model. The outcomes of the modified multiple regression model are presented below:

logCO2 = -0.613 + 0.276(logGDP/Upop) + 1.011(logelec)+ 0.011Fossil

n = 25, R square = 0.9220

Based on the outcomes, all the remaining explanatory variables still align with our initial hypothesis. Specifically, per capita electricity consumption and fossil fuel energy consumption continue to exhibit a positive correlation with carbon emissions. Furthermore, the new explanatory variable "logGDP/Upop" also maintains a positive correlation with carbon emissions, suggesting that the new economic index retains a similar relationship to the annual total GDP. Even after the modification and removal of two explanatory variables, the model continues to offer a significantly high degree of explanation, with an R square value of 0.92. All explanatory variables in this modified model exhibit p-values below 0.01, signifying statistical significance at the 1% level. Table 8 displays the outcomes of the adjusted multiple linear regression model.

Table 8: Estimation Results of modified model

Dependent Variable: logCO2	
Independent variables	**Modified Multiple linear regression model**
logGDP/Upop	0.276***
	(0.024)
logelec	1.011 ***
	(0.253)
Fossil	0.011 ***
	(0.002)
Intercept	-0.613
	(1.055)
Number of observations	25
R-squared	0.9220
Adjusted R-squared	0.9109

*significant at *10%, **5%, ***1%

6.3. Autocorrelation test

Due to the time series nature of the data used in this study, it is imperative to explore autocorrelation to assess whether errors within the regression model are mutually independent. Autocorrelation arises when errors in a regression model are correlated or dependent over time. This investigation was conducted using STATA, employing the Durbin-Watson test and the Breusch-Godfrey LM test to estimate the autocorrelation of errors in the model.

The Durbin-Watson statistic ranges from 0 to 4, and according to empirical rules, values between 1.5 and 2.5 indicate the absence of autocorrelation among errors.[9] The Durbin-Watson test's null hypothesis assumes no first-order autocorrelation. The null hypothesis for the Breusch-Godfrey LM test posits no serial correlation.

6.3.1. The simple regression model: logCO2 = β0 + β1logGDP + e

The Durbin-Watson statistic is merely 0.268, indicating strong positive autocorrelation. This observation is supported by The Breusch-Godfrey LM test's p-value of 0.000, significantly lower than 1%. Thus, we reject the null hypothesis, concluding that the simple regression model's errors exhibit significant positive autocorrelation. After modifying the simple regression model through STATA, the Durbin-Watson statistic increases to 1.597, signifying the absence of autocorrelation. The corrected model yields logCO2 = 3.922 + 0.149(logGDP), indicating that a 1% increase in annual GDP corresponds to an approximately 0.149% increase in carbon emissions. This economic impact reduction of 0.049% is in line with our initial hypothesis that Canada's GDP positively correlates with its carbon emissions. The p-value for logGDP remains statistically significant at 0.005 (less than 1% level).

6.3.2. The initial multiple regression model: logCO2 = β0 + β1(logGDP) + β2(logUpop) + β3(logelec) + β4Fossil + β5Renew + e

The Durbin-Watson statistic is around 2.3 (DW = 2.268). The Breusch-Godfrey LM test yields a pvalue of 0.3782 which is greater than 10% level, leading us to accept the null hypothesis, indicating no significant autocorrelation among the model's errors over time.

6.3.3. The modified multiple regression model: logCO2 = β0 + β1(logGDP/Upop) + β2(logelec) + β3Fossil + e

The Durbin-Watson statistic is only 0.737, less than 2 and close to 0, suggesting positive autocorrelation. The Breusch-Godfrey LM test yields a p-value of 0.0054 which is less than 1% level, leading us to reject the null hypothesis, indicating significant autocorrelation among the errors in the modified model. With STATA-based adjustments, the corrected model's Durbin-Watson statistic increases to 2.824, remaining above the empirical rule's interval [1.5, 2.5]. Therefore, the autocorrelation issue in the model persists.

6.3.4. The new multiple regression model: logCO2 = β0 + β1 (logGDP/Upop) + β2Fossil + e

Table 9: Estimation Results with Autocorrelation test

	Dependent Variable: logCO2			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Independent variables	**Simple linear regression model**	**Multiple linear regression model**	**Modified Multiple linear regression model**	**New Modified Multiple linear regression model**
logGDP	0.149***	0.060**		
	(0.049)	(0.023)		
logUpop		0.850***		
		(0.101)		
logGDP/Upop			0.074	0.162***
			(0.053)	(0.047)

logelec		0.944***	0.871***	
		(0.107)	(0.205)	
Renew		-0.002		
		(0.005)		
Fossil		0.004***	0.005***	0.005**
		(0.001)	(0.002)	(0.002)
Intercept	3.922***	-5.567***	1.487*	4.603***
	(0.596)	(0.744)	(0.837)	(0.288)
Number of observations	30	25	24	25
R-squared	0.2463	0.9898	0.6237	0.4134
Adjusted R-squared	0.2194	0.9871	0.5672	0.3600

*significant at *10%, **5%, ***1%

In an attempt to address autocorrelation, the explanatory variable "logelec" was removed. The initial Durbin-Watson statistic is 0.641, which increases to 2.140 after adjustments, falling within the 1.5 to 2.5 range, indicating the correction of autocorrelation. The corrected outcome is logCO2 = 4.603 + 0.162(logGDP/Upop) + 0.005Fossil.

As the new economic index, "logGDP/Upop," representing Canada's annual average GDP per capita for urban areas, grows by 1%, carbon emissions in Canada increase by 0.162%. Fossil fuel energy consumption retains its initial hypothesis, continuing to exhibit a positive correlation with carbon emissions. Compared to the initial multiple regression model, its economic impact remains minimal, at only 0.005%. Both explanatory variables maintain p-values below 5% level, signifying statistical significance in relation to logCO2. Table 9 showcases the regression outcomes of each model following autocorrelation testing.

7. Conclusion

On a holistic level, developed countries emit a higher volume of carbon as they experience economic growth, which in turn exerts substantial negative impacts on global climate. Every nation needs to seek a balance between economic growth and carbon neutrality, taking responsibility for reducing carbon emissions amid rapid economic expansion and thereby contributing to the construction of a shared human destiny.

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