

Empirical Analysis of Inter-Relationship between Economic Growth, Energy Consumption and CO₂ Emissions in Mano Zone Countries

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Abstract

This study seeks to empirically determine the direction of causality between energy consumption (En), Gross Domestic Product (GDP) and CO₂ emissions for a panel of the four Mano River countries from 1980 to 2010. The results show the presence of a bidirectional causality between Gross Domestic Product (GDP) and CO₂ emissions; a unidirectional link from energy consumption (in) to CO₂ emissions. This indicates that economic growth and Energy Consumption (en) have a negative effect on environmental quality in the Mano River countries. In the long term, there appears to be a unidirectional causal relationship from Gross Domestic Product (GDP) to CO₂ emissions. This means that economic growth has a positive effect on CO₂ emissions. All these results indicate that energy is a force for economic growth in the short term, but in the long term it can be a source of environmental destruction. Thus, it is more than urgent to develop more concrete strategies of energy cooperation and exploit the high levels of complementarities and interdependencies between different countries, taking into account the particularities of each country in the economic area.

Keywords

Energy Consumption, Economic Growth, CO₂ Emissions, Mano River

1. Introduction

Since the 1973 oil crisis, security of energy supply has become a major concern for

many oil-importing countries. This has led to a search for more accessible alternative sources of domestic energy supply, which is an integral part of the energy policy of many energy-importing countries (Toth & Rogner, 2006). Indeed, the exponential increase in energy consumption over recent decades in Asian and African countries is justified by impoverishment and industrial expansion. Energy consumption is expected to rise to 159.3 Btu in 2015, 187.8 Btu in 2020, 217.0 Btu in 2025, 246.9 Btu in 2030 and 277.3 Btu in 2035. The average annual percentage change 2007-2035 in Asia is 2.8 per cent, which is higher than other regions, such as countries in the Middle East (2.2 per cent), Central and South America (1.8 per cent) and Africa (1.8 per cent), Lau et al. (2011).

But it is clear that fossil fuels remain the backbone of the world's energy system. Currently, around 81% of all primary energy in the world is derived from fossil fuels, with oil accounting for 31.1%, coal for 28.9% and natural gas for 21.4%. Only 0.8% of the world's primary energy is derived from geothermal, wind, solar or other alternative energy sources. More specifically, wind power accounted for only 0.2% of the global primary energy supply with its 23 m.t.e.p. contribution while direct solar energy represented 0.1% with a result of 12 m.t.e.p. (IEA, 2015). Favennec argued that by 2020, hydrocarbons, i.e., oil and gas, would remain the dominant energy sources and would still cover 60% of commercial energy needs. It is clear that energy consumption is continuing to rise and will do so even more over the next few years, as transport needs increase, and it seems unlikely that alternative fuels will be able to replace petrol and diesel on a massive scale (Favennec, 2002: p. 537).

The exponential increase in energy consumption and the rapid growth in pollutant emissions are likely to have an effect on the general environment: rising sea levels, seasonal variation, changes in climate and weather, ecosystems and habitats. These numerous challenges mean that energy and the quality of the environment are increasingly being taken into account in the design of energy systems and energy policies. Many countries, paying particular attention to the impacts of climate change, are considering ways of adapting to adverse impacts by developing strategies to find unanimous solutions to the problem. They are therefore beginning to invest in diversifying energy sources and seeking stable, secure and clean energy supplies (Toth & Rogner, 2006). In the same vein, these countries have built nuclear power stations not only to reduce dependence on imported oil, but also to increase the supply of secure energy and minimise the price volatility associated with oil imports (Toth & Rogner, 2006; Vaillancourt et al., 2008). It is a fact that the episodic energy crisis, coupled with ozone-depleting energy sources, environmental costs and high-energy consumption, has forced governments around the world to keep a closer eye on their energy supplies. Growing concerns have prompted government interest in Asian and African countries. These include co-operation on energy conservation and the effective use of energy policies. In this context, the long-term relationship between energy consumption and economic growth has been a lively topic of empirical assessment. These two entities reside

in a framework that is gradually deteriorating, i.e., the environment with its corollary of difficulties. These have a considerable impact on the climate, which is subject to regular disturbances. As a result, climate change is now widely identified as a major ecological problem facing the globe. It has become a complex phenomenon resulting from the difficult interactions between three distinct parameters: economic growth, energy and the environment. In the economic literature, the direction of causality—whether the adoption of energy conservation inhibits or stimulates economic growth and environmental quality—has been the subject of much debate. There is a wealth of literature on the relationship between energy consumption, economic growth and pollutant emissions. Studies date back to the seminal work (Bertagnolli & Katz, 1979), and this theme has been stimulated in particular by the global energy context: increasing awareness of global heating, climate change, and the impact of climate change on the environment.

Thus, the literature on energy saving distinguishes three branches. The first branch focuses on the relationship between economic growth and the environmental connection of pollutants. It attempts to verify the validity of the Environmental Kuznets Curve (EKC) hypothesis. The CEK hypothesis states that there is an inverse U-formed relationship between different pollutants and per capita income (i.e., environmental degradation increases up to a certain level while income rises; after that, it starts to decrease after a turning point). Consequently, the CEK hypothesis expresses a well-defined relationship between growth and environmental quality (see Grossman & Krueger, 1995). A second branch of research has looked at the relationship between energy consumption and economic growth. Since the study led by Lise and Van Montfort (2007), a voluminous causality literature (Belloumi, 2009; Tsani, 2010; Omri, 2013) and there is no consensus in the results. The third group of studies has emerged from the combination of two groups of studies that seek to analyse the relationship between economic growth, energy consumption and pollutant emissions. These include studies by Ang (2007), Halicioglu (2009), Aroui et al. (2012), Cowan et al. (2014) and Kasman and Duman (2015). The results of these studies differ from country to country. The mixed results reflect several factors, including institutional differences between countries, model specifications and econometric approaches.

In recent decades, some research has focused on renewable energy and its role in increasing growth and global fighting-against heating. The new trend in the energy economics literature is to decompose the effects of renewable and non-renewable energy consumption on the economy, but there are few studies that have focused on the causal relationship between CO₂ emissions, renewable and/or non-renewable energy consumption and economic growth. Sadorsky (2009) analyses the relationship between renewable energy consumption, GDP and CO₂ emissions in the G7 countries from 1980-2005. Panel cointegration evaluations prove that a 1% increase in real income increases per capita renewable energy consumption in the G7 countries by 8.44% or 7.24% according to the FMOLS or DOLS evaluation technique, and a 1% increase in CO₂ emissions increases per

capita renewable energy consumption in the G7 countries by 5.23% (FMOLS technique). Thus, real GDP and CO₂ emissions have had positive effects on the consumption of renewable and/or non-renewable energy.

Energy is necessary for national economic production and, consequently, economic growth and the development of society, but it is also a major source of greenhouse gas emissions, which in turn damage the environment.

Specifically, this study seeks to determine the causal effects of non-renewable energy consumption and carbon emissions on environmental quality in the Mano River countries. It also assesses the causal link between energy consumption and long-term economic growth. Finally, it investigates the causal effect between GDP and CO₂ emissions in relation to environmental quality in the Mano River countries. In addition to the introductory section (section 1), the rest of the work is organised as follows: section 2 describes the data and the econometric model. Statistical and empirical results will be reported in Section 3 based on the model results, conclusions will be drawn and some economic policy implications will be provided in Section 4 (Appendices).

2. Methodology

This section investigates the relationship between energy consumption, CO₂ emissions and economic growth for the Mano River countries, using more recently developed panel data methods. We also explore the mutual influence between these variables using the Granger causality test. The methodology used is that of panel data. The data used are secondary and cover the period from 1986 to 2010 from the World Bank database (World Bank, 2022). To achieve the desired goal, the econometric models used emanate from those of Soytaş et al., (2007), Ang (2009) and Akpan and Akpan (2012). These models have been adopted by Belaïd and Zrelli (2016). Modifications to the model result in the following general econometric model:

$$LCO_{2it} = a_{it} + \beta_1 Lgdp_{it} + \beta_2 Len_{it} + \beta_3 Lpop_{it} + \beta_4 Ltcu_{it} + \varepsilon_{it} \quad (1)$$

$L(.)$ presents the logarithm.

2.1. Description of Variables

All variables are taken from the World Bank's World Development Indicator for the year 2023.

The model's dependent variable is carbon dioxide (CO₂) emissions; this is the indicator that measures the level of atmospheric degradation of the environment. It is used to monitor environmental degradation. It is for this reason that countries have been asked to reduce their CO₂ emissions by 2° Celsius every year since the COP21 climate conference in 2016 in Paris, France. The explanatory variables of interest are Gross Domestic Product (GDP) per capita in constant US Dollars. It is the macroeconomic indicator mainly used to assess economic growth. It represents all the wealth obtained over the course of a year. An increase in GDP systematically leads to an increase in the rate of economic growth. Secondly, Energy

Consumption, which measures the energy demanded by EU countries. This is non-renewable energy, also known as fossil energy.

The other explanatory variables (**Table 1**), Total Population and arable land, are control variables. Cultivable land takes into account agricultural land in km². This is the part of the territory that is Arab and permanently cultivated. Here it plays the role of agriculture. The total population (POP) is the general population. This includes the working population aged 15 and over. It represents all the people of working age who are available on the labour market. It is made up of the working population with a job and those looking for work (unemployed). It plays an important role in economic growth, as it constitutes the labour force.

Table 1. Summary table of variables.

Variables	Description	Unit of measurement	Sign	Source
Lco₂	The logarithm of CO ₂ Emissions	Metric tonnes	–	WDI 2023
Lgdp	The logarithm of per capita Income	Current USD	+	WDI 2023
Len	The logarithm of Energy Econsumption	Kilotonne	+	WDI 2023
Lpop	The Logarithm Total Population	Million inhabitants	+	WDI 2023
Ltcu	The Logarithm Arable Land	Thousands of hectares	+	WDI 2023

Source: author.

2.2. Descriptive Analysis

The descriptive analysis of the variables is as follows.

According to **Table 2**, the standard deviation shows that the values for Gross Domestic Product (GDP), total population (POP) and arable land (TCU) for the Mano River countries are relatively proportional to the mean value obtained, unlike the variables Carbon Dioxide Emissions (CO₂) and Energy Consumption (EN), whose standard deviations are greater than unity. Similarly, if we consider the coefficient of variation (CV), a criterion that better explains variable dispersion, the coefficients of variation are less than 10% for Gross Domestic Product (GDP), total population (POP) and arable land (TCU), except for those for the variables carbon dioxide emissions (CO₂) and energy consumption (EN) with. The variables are close to the mean value, with the exception of carbon dioxide emissions (CO₂) and energy consumption (EN). We also deduce that our sample is homogeneous in terms of Gross Domestic Product (GDP), total population (POP) and arable land (TCU). Our sample is heterogeneous in terms of carbon dioxide emissions (CO₂) and energy consumption (EN). Overall, the difference

between the maximum and minimum values is also small. Overall, given that the two variables of interest in this work, carbon dioxide emissions (CO₂) and energy consumption (EN), show good dispersion.

Table 2. Descriptives statistics¹.

Variable	Average	Standard deviation	CV ²	Min	Max
Lco2	2.892	4.762	164.644	-2.124	9.122
Lgdp	6.225	0.653	10.494	4.751	7.396
Len	3.968	1.322	33.316	1.542	6.279
Lpop	15.650	0.682	04.363	14.508	16.831
Ltcu	11.134	0.900	08.086	10.123	12.235

Source: author's calculation.

The carbon dioxide emissions (CO₂) cannot be understood without analysing the interaction between population growth, CO₂ emissions and the availability of arable land. According to the [United Nations et al. \(2024\)](#), the world's population rose from 2.5 billion in 1950 to 8.1 billion in 2025, accounting for a significant proportion of the rise in emissions, which increased from 11 GtCO₂ in 1960 to over 37 GtCO₂ in 2023. However, as [Ehrlich \(1968\)](#) points out in *The Population Bomb*, the environmental impact does not depend solely on population size. It also depends on consumption patterns. Thus, according to data from the World Development Indicator, [World Bank \(2022\)](#), a resident of a high-income country emits on average 10 to 15 times more CO₂ than a resident of sub-Saharan Africa.

At the same time, pressure on arable land is mounting. Norman Borlaug, the father of the Green Revolution, had already warned of the need to increase yields in order to feed a growing population without deforestation. [FAO \(2023\)](#) shows that the area of arable land per capita has fallen from 0.45 ha in 1960 to 0.19 ha in 2023. This decline is due to three factors: population growth, urbanisation and soil degradation. However, agriculture and land-use change account for around 22 per cent of global GHG emissions.

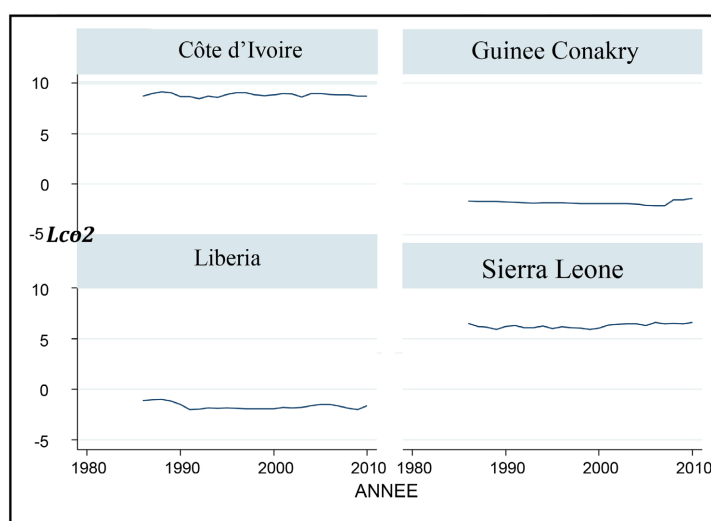
We face a triple constraint highlighted by [Rockström et al., \(2009\)](#) in the concept of Planetary Boundaries: a growing population drives up demand for food. The UN forecasts a global population of 9.7 billion by 2050; less arable land per capita necessitates intensification. The link is therefore clear: population determines the scale of demand, arable land sets the physical limit, and CO₂ measures the impact of our technical choices. As [Sen \(1999\)](#) summarises, development must not come at the expense of sustainability. The challenge is therefore to feed more

¹Cv²: Coefficient of Variation $cv^2 = \frac{\sigma}{m} \times 100$; with σ : Standard deviation and m : the average $0 < cv^2 < 4.99\%$ Excellent; $4.99 < cv^2 < 9.99\%$ very good; $9.9 < cv^2 < 14.99\%$ good.

people, on less land, with lower carbon emissions.

We can therefore say that the sample as a whole is heterogeneous. Consequently, the four countries of Côte d'Ivoire, Guinea Conakry, Liberia and Sierra Leone are heterogeneous as a whole. Thus, there is heterogeneity between the countries in the Mano zone.

Figure 1 shows that carbon (CO_2) emissions show a similar trend over the period 1980 to 2010 in the four Mano River countries. The increase in emissions began in earnest between 1995 and 2010. This can be explained by the fact that these countries began their economic growth in this decade. As the Environmental Kuznets Curve shows, the start of any economic growth process is accompanied by an increase in pollution and environmental degradation, with CO_2 emissions (Grossman & Krueger, 1993).



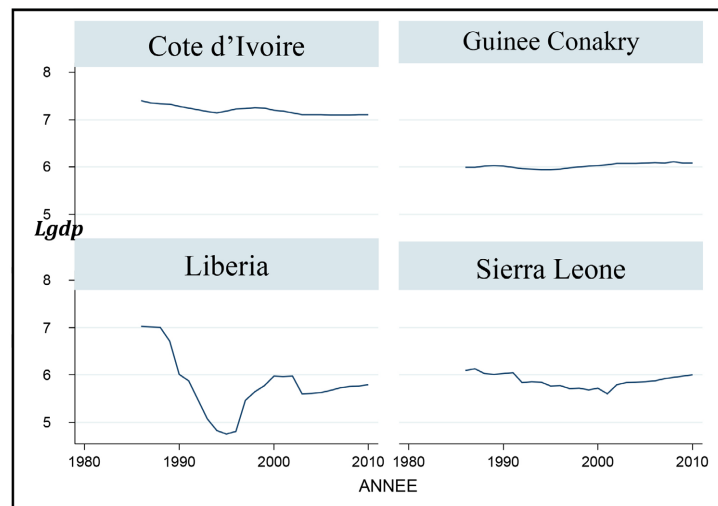
Source: author.

Figure 1. LCO₂'s over the period 1980-2010.

Figure 2 shows a similar trend between three countries in the union: Côte d'Ivoire, Guinea Conakry and Sierra Leone. Gross domestic product (GDP) fell between 1985 and 1990 in Côte d'Ivoire and Guinea Conakry, before rising again until 2010. For Sierra Leone, gross domestic product (GDP) began to fall between 1980 and 2000, before rising until 2010. The figure shows a downward peak for Sierra Leone in 1995. Sierra Leone's gross domestic product (GDP) therefore fell from 1980 to 1995, before rising again until 2010. On the whole, the four countries of the union have seen an increase in their gross domestic product (GDP) since the 1990s, with the exception of Sierra Leone, where GDP growth began in the 2000s. It is clear that this economic growth in GDP is leading to an increase in carbon dioxide (CO_2) emissions.

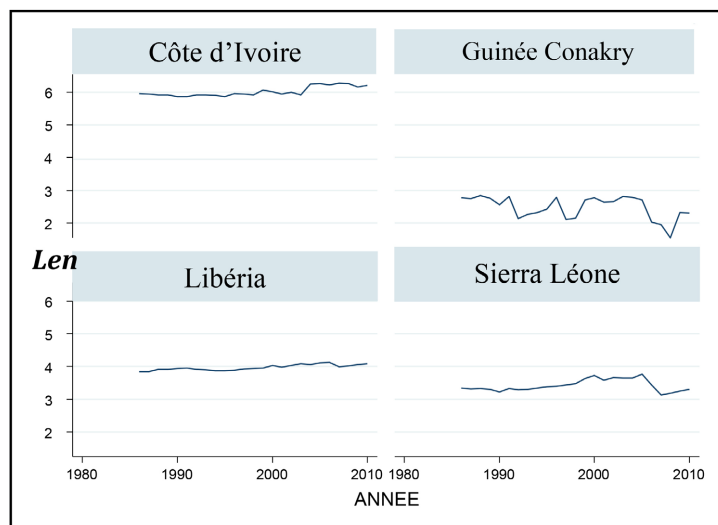
Figure 3 shows a constant upward trend for three countries: Côte d'Ivoire, Liberia and Sierra Leone over the entire study period. Guinea Conakry, on the other hand, shows a sawtooth downward trend over the study period. These trends in

the figure are justified by the quest for economic growth, which is accompanied by an increase in energy consumption. Energy is one of the prerequisites for production. So the first three countries are more advanced than Guinea Conakry.



Source: author.

Figure 2. Lgdp's over the period 1980-2010.



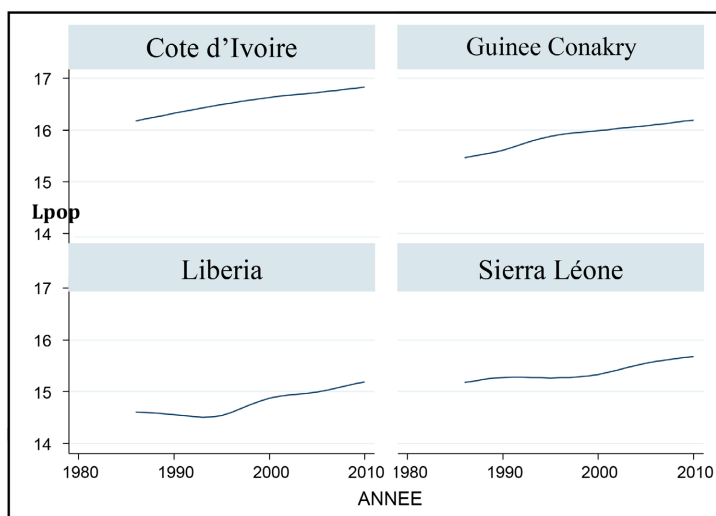
Source: author.

Figure 3. Len's evolution over the period 1980-2010.

In contrast to the previous series, Côte d'Ivoire's **Figure 3** shows an upward trend in population throughout the period from 1980 to 2010, whereas the other three countries show a similar trend, with an increase in population around 2000. This can be explained by the fact that demographic growth is an inescapable fact of life in this region, and one that requires special attention.

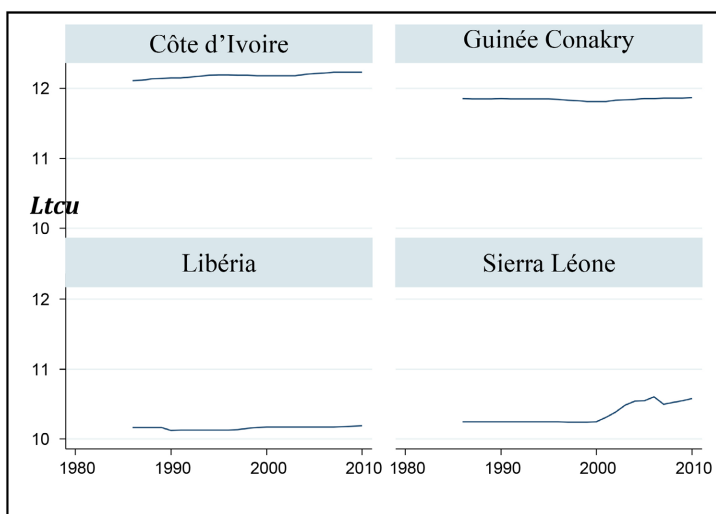
Figure 4 and **Figure 5** also show a constant trend for Sierra Leone from 1985 to 2000, followed by an increase over the entire period from 2000 to 2010. The

other three countries show a constant trend over the entire study period. The trends in this agricultural land series can be explained by the fact that the population of these countries is growing while agricultural land is shrinking, given that they are agricultural countries.



Source: author.

Figure 4. Lpop's on the period 1980-2010.



Source: author.

Figure 5. Ltcu's on the period 1980-2010.

2.3. Statistical Tests

To better analyse the causal dynamics between non-renewable energy consumption, CO₂ emissions and GDP, the following steps are taken. The preliminary stage of statistical data analysis consists of studying the stationarity of the variables or series in the model. In this case, specific or structural statistical tests are used before tackling the ordinary statistical analysis tests.

2.4. Structural Tests

As part of a panel study, the structure of the panel studied should be determined beforehand using appropriate structural tests. These are the Fisher (1932), Breusch and Pagan (1980) and Hausman (1978) tests. The Fisher test is generally used to highlight the presence of fixed effects (homogeneous panel model); the null hypothesis of the absence of effects is verified; the Breusch-Pagan test verifies the presence of random effects. We therefore test the null hypothesis of the absence of fixed effects against the alternative hypothesis of the presence of random effects. If the p-value resulting from these two tests is less than the critical value (5% or 10%), the null hypothesis is rejected and the alternative hypothesis accepted. In this case, the panel structure is accepted, giving an individual effects model; otherwise, the panel structure is rejected (Hsiao, 1986; Bourbonnais, 2015). If we obtain an individual-effects panel model, the Hausman (1978) test, which is a specification test, allows us to distinguish between a fixed-effects model and a random-effects model. The Hausman test is based on the following hypotheses: H_0 : There is no systematic difference in coefficients and H_1 : There is a difference in coefficients. And for the choice between the two models, fixed effects and random effects, the hypothesis test is as follows:

$$H_0: \beta_{LSDV} - \beta_{MCG} = 0 \Rightarrow \text{the model is a random effects model}$$

$$H_1: \beta_{LSDV} - \beta_{MCG} \neq 0 \Rightarrow \text{the model has fixed effects}$$

The statistic is distributed according to a Chi-square with k degrees of freedom; if the H is greater than the Chi-square with k degrees of freedom for a threshold, we reject the H_0 hypothesis, the LSDV estimator (within) is unbiased, we reject the random effects specification and choose an individual fixed effects model (Bourbonnais, 2015).

2.4.1. Stationarity Tests

The unit root test will be used in this study, as most of the statistical properties of estimation methods apply to stationary series in order to avoid spurious regressions. A series is said to be stationary if its mean and variance generally do not vary over time. Long before this, however, cross-sectional tests of dependence were carried out.

2.4.2. Series Dependency Test

In the study of causality in panel data, one of the important concerns to consider is the interdependence of the different possible cross-sections (countries). First, cross-sectional dependence is examined to decide which unit root test would be appropriate. The Lagrange multiplier (LM) test developed by Breusch and Pagan (1980) is used if T is greater than N , i.e., it applies when the number of cross-sections is small, while the number of time periods is sufficiently large (which is exactly the right point for the dataset used in this paper). Pesaran's (2004) cross-sectional test of dependence (CD) is used when and can be applied to balanced and unbalanced panels. In the literature, several studies conclude that panel data

models are likely to exhibit substantial cross-sectional dependence in errors (De Hoyos & Sarafidis, 2006). Correlations across errors could be due to omitted common effects, spatial effects, or could arise due to the presence of common shocks and unnoticed components that eventually become part of the error term (Robertson & Symons, 2000; Pesaran, 2004; Baltagi, 2005). However, ignoring the cross-sectional dependence of errors (as is commonly done by practitioners) can have serious consequences. It is well known that ignoring cross-sectional dependence can affect the first-order properties (impartiality, uniformity) of standard panel estimators and lead to incorrect statistical inference. The reduction in evaluation efficiency can become so great that, in fact, the pooled least squares estimator can provide little gain over simple-equation ordinary least squares (Phillips & Sul, 2003).

However, the test of Breusch and Pagan (1980) is based on the seemingly unrelated regression equation (SURE) methodology, so it means that it requires previously identified model specifications.

Pesaran (2004: p. 9) proposes an alternative CDD test that does not require a predetermined model and can be applied to a specified set of models. The test statistic for Pesaran's CDD test has the following properties under the null hypothesis of no cross-sectional dependence:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \quad (2)$$

where:

T = number of years.

N = number of individuals (Countries).

$\hat{\rho}_{ij}$ = correlation coefficient of the residuals between individual i and individual j .

In addition, Pesaran's CD test is robust to structural breaks (lag prediction variations in the dataset) (Pesaran, 2004). Time series of energy consumption, GDP and CO₂ emissions in emerging economies, such as the MANO River countries, could be susceptible to structural breaks, as Tamazian and Bhaskara Rao in 2010 showed for the BRICS. On the other hand, disparities within these countries would also benefit economic growth. Consequently, the test of Breusch and Pagan (1980) would be more appropriate for determining the presence of inter-individual dependence. The data used meet the condition test of Breusch and Pagan (1980). The data is expected to suffer from cross-sectional dependence, since MANO countries are likely to have common factors or unnoticed spillover effects due to the common stage of economic development, broadly similar economic indicators and other common features (O'Neill, Wilson, & Stupnytska, 2005).

2.4.3. Panel Unit Root Test

A number of unit root tests (statistical properties that are constant over time) on panel data have been developed in the literature: (Levin et al., 2002; Im, Pesaran, & Shin, 2003; Pesaran, 2007). There are two generations of tests. The generation

of unit root tests based on the cross-sectional hypothesis of independence taking into account cross-sectional dependence and includes the contributions of [Maddala and Wu \(1999\)](#), [Choi \(2001\)](#), [Hadri \(2000\)](#), [Im et al. \(2003\)](#).

The second generation includes contributions from [Bai and Ng \(2004\)](#), [Moon and Perron \(2004\)](#), [Smith et al. \(2004\)](#), [Pesaran \(2007\)](#). This last category of tests shows the diversity of potential correlations in cross-section. In the presence of dependence cuts, “first generation” unit root tests tend to reject the null hypothesis of a unit root excessively. Therefore, in this study, the unit root tests used are those of [Levin, Lin, and Chu \(2002\)](#), and [Im, Pesaran, and Shin \(2003\)](#). The null hypothesis of the [Levin, Lin, and Chu \(LLC\) \(2002\)](#) test states that each series in the panel contains a unit root against the hypothesis that all series are stationary. The test of [Im, Pesaran, and Shin \(IPS\) \(2003\)](#) presents the null hypothesis that all the series are non-stationary against the alternative hypothesis that a fraction of the individual series are stationary. The null hypothesis of these two tests is rejected if the p-value is below the critical value. If the variables are stationary in level, tests of inter- and intra-individual heteroskedasticity, inter-individual correlation and error autocorrelation are performed. Where appropriate, estimates will be used to determine the structure of the panel. The results of these various statistical tests will reveal the appropriate estimation method. In the CIPS panel unit root test proposed by [Pesaran \(2007\)](#), we introduce a panel unit root test based on augmented Dickey-Fuller (ADF) regressions that take the CDD into account. Statistical tests (Dickey-Fuller or cross-sectionally augmented CADF) are then used to calculate the modified version of the first-generation IPS test ([Im et al., 2003](#)), the so-called “cross-sectionally augmented IPS” (CIPS) test.

Pesaran’s CIPS test is based on the following model:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \hat{y}_{t-1} + d_i \Delta \hat{y}_t + e_{it} \quad (3)$$

The Test statistic is then calculated as follows:

$$\text{CIPS}(N, T) = t\text{-bar} = N^{-1} \sum_{i=1}^N t_i(N, T) \quad (4)$$

In Equation (4), is the Dickey-Fuller cut statistic for each cut derived from Equation (3).

The null hypothesis assumes that all the series are non-stationary, while the alternative hypothesis assumes that part of the series is stationary. It should be noted that the formulation of the null hypothesis and the alternative hypotheses is one of the main drawbacks of panel data unit root tests. While the null hypothesis assumes that the entire series has a unit root, it can be rejected even if only one series is stationary ([Asteriou & Hall, 2015](#)). Therefore, [Hadri’s \(2000\)](#) unit root test is an alternative null hypothesis. It is also performed (on humiliated data) to examine the results to ensure robustness. It is assumed that variables in economics are non-stationary and become stationary at first difference (integrated of order one). If this is the case, there is a possibility that the variables are cointegrated. Consequently, the next stage of the analysis is devoted to cointegration tests.

2.4.4. Cointegration Tests

There are relatively few works comparing the various cointegration tests in terms of size and power. We propose here to summarise the main results of Monte Carlo simulations carried out by [Gutierrez \(2003\)](#). He compares the power of the tests of [Pedroni \(1999\)](#), [Kao \(1999\)](#) and [Larsson et al. \(2001\)](#). He considers various values for the individual dimension N and the temporal dimension T (10, 25, 50 and 100) and also varies the percentage relating to the number of relationships that are cointegrated (from 0 to 100% cointegrating relationships). The results obtained by [Gutierrez \(2003\)](#) can be summarised as follows: The power of all the tests increases with the time dimension, for a fixed value of N . When the time dimension is fixed and low ($T = 10$) and N increases, the Kao tests are more powerful than the Pedroni tests. For the Pedroni tests, the power remains relatively low, even when the individual dimension is equal to 100. The Kao tests dominate the Pedroni tests in terms of power when the time dimension is low, and the Pedroni tests are more powerful than the Kao tests when T increases. Thus, as the sample size increases, the Pedroni tests dominate the Kao tests. Concerning the [Larsson et al. \(2001\)](#) multiple cointegration test, the power and size are close for low values of T . The power of the test tends to increase when the temporal dimension increases, but the Kao and Pedroni tests always remain more powerful. In general, [Gutierrez \(2003\)](#) shows that the power of all the tests tends to increase when N and T increase and when the number of cointegrating relationships within the panel increases. Cointegration tests verify the presence of a long-term relationship between variables. Among the best known types of panel cointegration are the residual-based test ([Kao, 1999](#); [Pedroni, 1999](#)) and the individual combination test ([Maddala & Wu, 1999](#)). In this paper, the [Pedroni \(1999\)](#) cointegration test is performed. Pedroni's approach is robust under heterogeneity of the error term in cross-sections and multiple regressors ([Asteriou & Hall, 2015](#)). Therefore, this test is more appropriate. [Pedroni's \(1999: p. 599\)](#) methodology is based on the following model:

$$y_{i,t} = a_i + \rho_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \dots + \beta_{Mi} x_{Mi,t} + \varepsilon_{i,t} \quad (5)$$

where $m = 1, \dots, M$, is the number of regressors; and are the deterministic components. The test is carried out in four stages. First, Equation (5) is estimated and the, is stored.

Secondly, the original data is differenced for each country and then the residuals are calculated from the differenced regression:

$$\Delta y_{i,t} = \sigma_{1i} \Delta x_{1i,t} + \sigma_{2i} \Delta x_{2i,t} + \dots + \sigma_{Mi} \Delta x_{Mi,t} + \eta_{i,t} \quad (6)$$

The long term variance of and is calculated using the Newey-West kernel estimator.

In conclusion, the autoregressive model is estimated using the error term of the original equation, and then statistical tests (seven statistics) and critical values are calculated to decide on the null hypothesis with no cointegration between the variables. The test statistics are split into two groups: within dimensions and between

dimensions. The alternative hypothesis is that all variables are cointegrated (Pedroni, 2004).

The test is performed for two cases: when CO₂ is the dependent variable (case 1) and when GDP per capita is the dependent variable (case 2).

In addition, the cointegration test of Kao (1999) is performed to check the robustness of the model. To evaluate the cointegration tests, in the event that there is a long-run relationship between the variables, the next stage of the analysis estimates the cointegration ratio. For this (dynamic) purpose, the PMG method (Pesaran, Shin, & Smith, 1999), MG and DFE will be applied. The cointegration equation for the error term is expressed according to Stock and Watson (1993: p. 785) as follows:

$$y_t = X_t' \beta + D_{1t}' \gamma_1 + \sum_{j=-q}^r \Delta X_{t+j}' \delta + v_{1t} \quad (7)$$

One of the positive features of this evaluation method is that it is relatively straightforward and provides an asymptotic distribution of Wald statistics for examining restrictions on cointegrated vectors.

2.4.5. Granger Causality Test: Short- and Long-Term Test

This step makes it possible to determine the source and direction of causality between the variables, after obviously determining the existence of cointegration between the variables. Granger panel causality is determined using the two-stage Engle-Granger causality procedure (Engle & Granger, 1987). To identify the sources of causality and distinguish between short-term and long-term relationships, the group mean method (mg) proposed by Pesaran, Shin, and Smith (2001) and the dynamic fixed effect (dfe) group of mean estimators (Pooled Mean Group, PMG) proposed by Pesaran et al. (1999) are applied. These particular estimators make it possible to deal with an important problem encountered in empirical studies of panel data: the issue of heterogeneity.

The main advantage of PMG is that it allows short-run coefficients, including intercepts, the speed of long-run adjustment to equilibrium values, and variance errors to be heterogeneous country by country, whereas the coefficients of the long-run slope are restricted to be homogeneous across countries. In addition, the PMG estimation technique is robust in estimation and perfect in the choice of lag orders. The basic estimators of PMG, MG or DFE all involve estimating an ARDL model of order (pi, qi). In this case, the dynamic ARDL panel is specified as follows:

$$y_{it} = \sum_{j=1}^p \lambda_{ij} y_{i,t-j} + \sum_{j=0}^q \delta_{ij}^* X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (8)$$

where

$X_{i,t-j}$ represents the vector of explanatory variables.

μ_i , the fixed effect.

λ_{it} , the scalar.

$\delta_{ij}^* (k \times 1)$, the vector coefficient.

To facilitate regression, the following parameters should be used: (see Equation (2) Pesaran et al., 1999).

$$\Delta Y_{it} = \phi_i (Y_{i,t-1} + \theta_i' X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta Y_{i,t-1} + \sum_{j=0}^{p-1} \lambda_{ij}^{r*} \Delta Y_{i,t-j} + \mu_i + \varepsilon_{it} \quad (9)$$

where

$$\begin{aligned} \phi_i &= - \left(- \sum_{j=1}^p \lambda_{ij} \right) \\ \theta_i &= \sum_{j=0}^q \frac{f_{ij}}{(1 - \sum_k \lambda_{jk})}; \\ \lambda_{ij}^* &= - \sum_{m=j+1}^p \lambda_{i,m}; j = 1, 2, \dots, p-1; \\ \delta_{ij}^{r*} &= \sum_{m=j+1}^q \delta_{i,m}; j = 1, 2, \dots, q-1. \end{aligned}$$

ϕ_i Represents the speed of adjustment of the error term correction. The long-term equilibrium relationship can be tested statistically by the significance of ϕ_i . If the null hypothesis $\phi_i = 0$ is accepted, then there would be evidence of long-term equilibrium (i.e., the variables are cointegrated and there is evidence of long-term causality from the independent variable to the dependent variable). The direction of short-term causality can be determined by examining the significance of the coefficients of each explanatory variable, i.e., $\delta_{ij}^{t*} = 0$ Equation (5). In our case we can specify Equation (6) in terms of the variables in Equation (1) as follows:

$$\Delta \text{LCO}_{2it} = \phi_i (Y_{i,t-1} + \theta_i' X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta \text{LCO}_{2i,t-1} + \sum_{j=0}^{p-1} \delta_{ij}^{r*} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (10)$$

Where X is the vector of explanatory variables: in the same way we can specify the equations for the other two variables of interest Lgdp and Len as follows:

$$\Delta \text{Lgdp}_{2it} = \phi_i (Y_{i,t-1} + \theta_i' X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta \text{Lgdp}_{2i,t-1} + \sum_{j=0}^{p-1} \delta_{ij}^{r*} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (11)$$

$$\Delta \text{Len}_{2it} = \phi_i (Y_{i,t-1} + \theta_i' X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta \text{Len}_{2i,t-1} + \sum_{j=0}^{p-1} \delta_{ij}^{r*} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (12)$$

In order to assess the relevance of the results obtained using these methods, we propose to compare them with those obtained using two alternative methods, namely the *Mean Group* (MG) and dynamic fixed effects (DFE). The fundamental difference between these alternative estimators and the PMG lies in the constraints imposed on the coefficients. While the PMG imposes only strict equality of individual long-term coefficients, that of the *mean group* MG imposes no restrictions on either the coefficients or the estimated variances. In other words, it assumes perfect heterogeneity between individuals. The model

is estimated for each individual separately, and the coefficients are unweighted averages over the whole sample. By way of example, the values of the estimator of the adjustment coefficient and the estimator of its variance are given by the following relationships:

$$\begin{cases} \hat{\Phi} = \frac{1}{N} \hat{\Phi}_i & (13) \\ \hat{\Delta}_{\Phi} = \frac{1}{N(N-1)} \sum_{i=1}^N (\hat{\Phi}_i - \hat{\Phi})^2 & (14) \end{cases}$$

Unlike the MG estimator, the dynamic fixed effects method requires perfect homogeneity between the model's coefficients.

3. Results and Interpretation

This part of the study will be devoted to presenting the statistical and econometric results.

3.1. Results of Panel Structural Tests

Several tests can generally be used to determine the structure of a panel. In this particular case, three tests will be used: the Fisher (1932), Breusch & Pagan (1980) and Hausman (1978) tests. Firstly, the Fisher test is used to determine whether the panel has a fixed effect structure, so these assumptions are H_0 : no fixed effect, H_1 : presence of fixed effect. When the p-value is lower than 5%, we reject H_0 , and we accept H_1 . Then the test of Breusch-Pagan determines a random effect panel with the same hypothesis configurations. Then the test of Hausman (1978) is used to arbitrate between the two previous tests with the following hypotheses H_0 : no fixed effect, H_1 : presence of random effect. When the p-value is less than 5%, we reject H_0 , and we accept H_1 . The Hausman test is used under the following assumptions: H_0 : the random-effects (RE) model is valid, in which case the fixed-effects model is rejected; H_1 : the random-effects model is biased, in which case the fixed-effects model is chosen. Thus, if the p-value is less than 0.05, we reject H_0 and select the fixed-effects model; if the p-value is greater than 0.05, we accept H_0 and retain the random-effects model.

Firstly, as Table 3 clearly shows, the p-value associated with the test is less than 5%, then the null hypothesis H_0 is rejected and the alternative hypothesis H_1 is accepted; i.e. there are fixed effects. The random effect will be tested. Next, the null hypothesis of no random effects is accepted since the p-value is well above the 5%. We are dealing with a fixed effect and a random effect. The test of Hausman (1978) will be used to select the appropriate individual effects model. The test allows us to arbitrate between the two effects and make a choice. This also allows us to determine the robustness of the model. Table 3 shows that the p-value of the Hausman test is less than 5 per cent; therefore, the null hypothesis regarding the presence of random effects is rejected, and the alternative hypothesis is accepted. This is therefore a fixed-effects panel.

Table 3. Structural testing of the model.

Various preliminary tests	Probability
Fisher	0.000***
Breusch-Pagan	0.000***
Hausman	0.000***

Source: author's calculation; Significance level at (***) 1%, (**) 5%, (*) 10%.

3.2. Results of the Optimal Number of Delays Test

Table 4 indicates that all variables are delayed by one period.

Table 4. Optimal number of delays Akaike's information criterion and Bayesian information criterion.

Number of delays	AIC					BIC				
	LCO ₂	Lgdp	Len	Lpop	Ltcu	LCO ₂	Lgdp	Len	Lpop	Ltcu
1	-82.61	-125.79	-61.07	-489.12	-472.27	-77.48	-120.85	-55.94	-483.99	-467.15
2	-24.71	-43.38	-28.07	-342.10	-366.90	-19.66	-38.34	-23.03	-337.06	-361.85
3	-3.54	-18.35	-15.52	-259.55	-297.24	1.40	-13.40	-10.57	-254.60	-292.29
4	2.14	-25.33	-11.03	-205.59	-253.03	7.00	-20.47	-6.17	-200.73	-248.17
5	7.71	-41.47	-11.59	-168.38	-222.09	12.48	-36.71	-6.82	-163.62	-217.33

Source: author's calculation.

3.3. Results of Pesaran Dependence Test

Table 5. Dependency test.

Variable	CD	CDw	CDw+	CDw*
Lco2	6.49 (0.000)	2.25 (0.024)		18.16 (0.000)
Lgdp	0.49 (0.625)	3.67 (0.000)		12.84 (0.000)
Len	-1.91 (0.057)	2.05 (0.040)	18.35 (0.000)	5.5e+30 (0.000)
Lpop	10.54 (0.000)	-0.22 (0.829)	25.59 (0.000)	2.6e+28 (0.000)
Ltcu	6.16 (0.000)	-1.14 (0.256)	13.85 (0.000)	3.7e+31 (0.000)

Source: author.

The aim of cross-sectional dependence test (CD test) according to Pesaran's (2004) is to determine whether individuals (countries) are correlated with one another. For example, does a shock in Côte d'Ivoire also affect Guinea? This is tested under the following hypotheses: H0: No cross-sectional dependence (the residuals are independent); H1: Presence of cross-sectional dependence. If the p-value is less than 5 per cent (0.05), H0 is rejected; if the p-value is greater than 5 per cent (0.05), H0 is accepted.

The results of the Pesaran test (Table 5) show that there is a strong correlation between the countries of the Mano region. This could be explained by their sub-regional economic cooperation.

3.4. Results of Stationarity Tests

The appropriate unit root test is that proposed by Pesaran (2007) due to inter-individual dependence. It allows for the correction of correlation between countries or individuals. It is presented under the following two conditions: H1: there is a unit root for all units, so all time series are stationary. H1: at least some of the units are stationary; therefore, it is sufficient for a proportion to be stationary to reject the null hypothesis.

The calculated statistic is compared with the critical value, which is negative. If the CIPS is lower (more negative) than the critical value, H0 is rejected. If the CIPS is higher than the critical value (less negative), then H0 is accepted.

According to Table 6, we can see that the first three variables are level-stationary, whilst the last two are not level-stationary but are stationary at first difference.

As not all variables are level-stationary, we will therefore carry out a cointegration test.

Table 6. Unit root test of CIPS.

	Level	First difference	I(d)
LCO ₂	-2.239	..	I(0)
Lpop	-5.13	..	I(0)
Ltcu	-2.451	..	I(0)
Lgdp	-1.831	-3.482	I(1)
Lcen	-0.696	-4.506	I(1)

Source: author.

3.5. Estimation Results

Variables are not stationary at the original level, some are stationary at the original level and others at the first difference so, it would be advisable to process to a cointegration test. The test chosen for this purpose is that of Pedroni (2004), based on Granger and Hungel.

Two cointegration tests are used to detect the relationship between the variables. These are the cointegration tests by Pedroni (2004) and Cheng and Kao (2004).

3.5.1. Cointegration Tests

Table 7 shows that the two tests carried out, Pedroni (2004) and Cheng and Kao (2004), indicate that the variables are all cointegrated. The two econometric tests conclude that all the variables are highly cointegrated in the four countries. Pedroni considers that the countries are heterogeneous and infers cointegration. Kao, on the other hand, considers that the countries are homogeneous, and also leads to cointegration of the variables in the model. However, the heterogeneity of Pedroni's model is more pronounced than the homogeneity of Kao's because of the significance of Pedroni's tool. It can thus be deduced that the variables are integrated into the four Mano River models, which remain heterogeneous. This confirms the result of heterogeneity between countries shown in the descriptive statistics.

Table 7. Pedroni (2004) and Kao (2004) cointegration tests.

Cointegration test (Pedroni, 2004)	Probability
Dimension within	0.000***
Dimension between	0.000***
Cointegration test (Kao, 1999)	0.000***

Source: author; Significance level at (***) 1%, (**) 5%, (*) 10%.

Table 8. Hausman test for choosing between DFE and MG.

Hausman test for choosing DFE and MG			
Variables	DEF	MG	Difference
Lgdp	0.252	-18.247	18.500
Len	-0.261	0.128	-2.389
Lpop	-0.173	-1.630	1.457
Ltcu	1.690	12.837	-11.146
Probability			0.0823

Source: author's calculation.

The Hausman test (Table 8) allows a choice to be made between the PMG and MG methods and between MG and DFE, with the following test hypotheses Ho: homogeneity of coefficients in the long term and H1: heterogeneity of coefficients in the short term. Table 9 shows that the MG is preferable to the DFE. So the MG method is run next. Nevertheless, the other methods are run to see the variabilities.

Table 9. Estimation's results of MG, PMG DFE.

VAEIALES	PMG		MG		DFE	
	(1) LT	(2) ST	(1) LT	(2) ST	(1) LT	(2) ST
ECT		−0.208 (0.263)		−0.597** (0.245)		0.478*** (0.097)
Δlgdp		2.565* (1.382)		3.153*** (1.534)		0.222 (0.148)
Δlen		−0.056 (0.220)		−0.181* (0.104)		−0.043 (0.090)
Δlpop		−8.095 (7.958)		−19.20 (19.78)		−1.353 (1.181)
Δltcu		1.879 (1.207)		4.105 (3.621)		1.691** (0.550)
Dlgdp	0.943 (0.811)		−18.25*** (19.26)		0.253 (0.113)	
Dlen	0.748*** (0.290)		2.129*** (1.740)		−0.261 (0.182)	
Dlpop	−1.117 (0.682)		−1.631 (1.281)		−0.174 (0.197)	
Dltcu	−2.222 (3.513)		12.84*** (10.51)		1.691*** (0.550)	
Constant		9.482 (11.40)		−87.92* (47.36)		−6.554** (2.716)

Source: author; Respective significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (1); (1) ECT: Long term, (2) ST: Short term.

3.5.2. Tests Results of PMG, MG, DFE

The MG, PMG and DFE tests are used to determine the short- and long-term relationships between the variables.

Two of the estimates, MG and DEF, confirm the existence of a long-term relationship between the variables under consideration, since all their error-correction parameters (adjustment coefficients) are significantly negative at the 5% and 10% thresholds. Furthermore, the nature of the data tends to confirm the choice of our econometric model. Indeed, the hypothesis of homogeneity of the coefficients in the long term is supported by the Hausman test. This allows a choice to

be made between the PMG and MG estimators by testing the null hypothesis of a non-systematic difference between the model's coefficients. In addition, it also serves as a criterion for choosing between the MG and DFE estimators, in particular by testing the null hypothesis of a recurring minimal endogeneity bias in dynamic fixed effects models (Baltagi et al., 2000). Furthermore, the relative scarcity of similar studies makes it difficult to attempt to compare the results obtained. According to the group means (GM) method, the results show that in the short term: There is a positive correlation between gdp (GDP) and CO₂ emissions. Contrary to the positive relationship expected in the long term, the short-term coefficients associated with energy consumption (en) and CO₂ emissions are negative and significant. This result, far from being anomalous, reflects the immediate adjustment costs linked to energy shocks and environmental externalities. In the short term, the rise in energy consumption reflects price effects and inefficiencies in the production system rather than an increase in output. Similarly, the rise in emissions generates regulatory and health costs that weigh on economic activity. This short-term negative effect is offset in the long term, in line with the dynamics of the Error Correction Model.

3.5.3. Granger Causality Test

The null hypothesis assumes no Granger causality between the choice variables. If the p-value of the Chi-squared statistic is less than the significance level, the null hypothesis is rejected at the corresponding significance level. The presence of causality is examined for combinations of two variables.

In the short term, the empirical evidence points to the presence of a bidirectional causality between Gross Domestic Product (GDP) and CO₂ emissions; subsequently, a unidirectional causality from energy consumption (EN) to CO₂ emissions emerged (Table 10).

This indicates that economic growth and energy consumption have a negative effect on the environment in the Mano River countries. The long-term results show the existence of a unidirectional causal link from Gross Domestic Product (GDP) to CO₂ emissions. Economic growth has a negative effect on CO₂ emissions in the long term. This confirms the positive and linear nature of the growth-environment relationship in the Mano zone countries.

The causality expressed in the short term is from energy consumption (en) to gross domestic product (gdp), while the causal link in the long term is from gross domestic product (gdp) to CO₂ emissions. This indicates that energy consumption drives economic growth in the short term by polluting the environment, and in the long term can improve the environment when the energy consumed is of high quality. There is therefore a pressing need to develop more concrete strategies for energy cooperation and to exploit the high levels of complementarity and interdependence between the different countries, taking into account the specific characteristics of each country in the region. The results also show that there are no uniform causal links between the variables for each country, confirming the heterogeneity of the countries in the region.

Table 10. Results of the granger causality test I.

Null hypothesis	F-statistics	Probability
Lgdp does not cause according to Granger LCO ₂	1.750	0.179
LCO ₂ does not cause according to Granger Lgdp	2.374*	0.099
Len does not cause according to Granger LCO ₂	0.6404	0.529
LCO ₂ does not cause according to Granger Len	1.011	0.368
Lpop does not cause according to Granger LCO ₂	0.675	0.511
LCO ₂ does not cause according to Granger Lpop	0.374	0.688
Ltcu does not cause according to Granger LCO ₂	0.231	0.793
LCO ₂ does not cause according to Granger Ltcu	1.232	0.296
Len does not cause according to Granger Lgdp	2.01326	0.139
Lgdp does not cause according to Granger LEN	0.064	0.937
Lpop does not cause according to Granger Lgdp	18.807***	0.000
Lgdp does not cause according to Granger Lpop	8.5877***	0.000
Ltcu does not cause according to Granger Lgdp	4.514***	0.013
Lgdp does not cause according to Granger Ltcu	0.709	0.494
Lpop does not cause according to Granger Len	0.154	0.856
Len does not cause according to Granger Lpop	0.347	0.707
Ltcu does not cause according to Granger Len	0.090	0.913
Len does not cause according to Granger Ltcu	0.541	0.583
Ltcu does not cause according to Granger Lpop	1.780	0.174
Lpop does not cause according to Granger Ltcu	3.568**	0.032

Source: author; Significance threshold (***) 1%, (**) 5%, (*) 10%.

4. Conclusion and Recommendations

The aim of this study is to investigate the cointegration and causal relationship between carbon emissions (CO₂), energy use (en), and economic growth (GDP) in the Mano River countries, by performing a panel analysis from 1986 to 2010. The statistical techniques used in this study allow us to better distinguish between short- and long-term causality, and to take account of possible homogeneity or heterogeneity. The cointegration and causality analysis found several interesting results that will inform decision-makers in the implementation of future policies to promote environmental conservation combined with macroeconomic policy in the Mano countries. Firstly, the results indicate that in the short term there is a

bidirectional causality between Gross Domestic Product (GDP) and CO₂ emissions. There is also a hypothesis of unidirectional causality between energy consumption and gross domestic product (GDP). This result is consistent with the study conducted by Cowan et al. (2014) for India. Thus, energy is the key determinant of growth and vice versa. A likely economic policy implication of this result is that Mano River countries should consider energy efficiency to reduce consumption of non-renewable energy and increase technical development and investment in cleaner energy production. The continued causality between energy consumption and Gross Domestic Product (GDP) confirms that energy saving policies will have a detrimental effect on real output in the short term. The effects of energy consumption on CO₂ emissions confirm the negative impact of non-renewable energy on the quality of the environment.

This indicates that economic growth and energy consumption are having a negative effect on the quality of the environment in the Mano River countries. So it is important to limit this type of energy, which pollutes more, and to turn to an alternative energy that pollutes less. The move is therefore towards substituting the consumption of non-renewable energy for the consumption of renewable energy. Secondly, over the long term, there appears to be a bidirectional causal relationship between Gross Domestic Product (GDP) and CO₂ emissions. This result implies that the energy-saving policy can be implemented without affecting the true yield in the long term. On the other hand, there is a causal relationship between arable land and gross domestic product (GDP). This result confirms that growth in the Mano River countries is strongly based on agriculture. It would therefore be a good idea for these countries to invest more in the agricultural sector using new, modern processes. There is a pressing need to develop more concrete strategies for energy cooperation and to exploit the high levels of complementarity and interdependence between the various countries, taking into account the specific characteristics of each country in the region. Based on the results of this study, the overall recommendation is to give priority to increasing energy efficiency through technological development and the use of cleaner production resources in order to significantly increase Gross Domestic Product (GDP). This is an ambitious vision, which will require intelligent solutions to complex techniques, including high-voltage interconnection and integration of renewable energy (solar and wind power, etc.)

Author Contributions

Eby Moro. J.-P: Abstract, Introduction, Interpretation of Results, Conclusion, Bibliography, Document Formatting. Koffi Mouroufié. V: Methodology, Statistical and Econometric Analyses. Angaman Kadio. V. R: Literature Review. Aka Brou. E.: Guidance, Reading, and Correction.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendices

Table A1. UNITARY ROOT TEST in first difference EViews.

1: LCO ₂					
Panel unit root test: Summary					
Series: D (LCO ₂)					
Date: 05/29/18		Time: 10:35			
Sample: 1986 2010					
Exogenous variables: Individual effects					
Automatic selection of maximum lags					
Automatic lag length selection based on SIC: 0 to 2					
Newey-West automatic bandwidth selection and Bartlett kernel					
Method	Statistic	Prob.**	Cross-sections	Obs	
Null: Unit root (assumes common unit root process)					
Levin, Lin & Chu t*	-5.85672	0.0000	4	89	
Null: Unit root (assumes individual unit root process)					
Im, Pesaran and Shin W-stat	-7.71505	0.0000	4	89	
ADF - Fisher Chi-square	61.1422	0.0000	4	89	
PP - Fisher Chi-square	58.2840	0.0000	4	92	
**Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.					
2: LGDP					
Panel unit root test: Summary					
Series: D(LGDP)					
Date: 05/29/18		Time: 10:39			
Sample: 1986 2010					
Exogenous variables: Individual effects					
Automatic selection of maximum lags					
Automatic lag length selection based on SIC: 0 to 3					
Newey-West automatic bandwidth selection and Bartlett kernel					
Method	Statistic	Prob.**	Cross-sections	Obs	
Null: Unit root (assumes common unit root process)					
Levin, Lin & Chu t*	-5.07866	0.0000	4	89	
Null: Unit root (assumes individual unit root process)					
Im, Pesaran and Shin W-stat	-5.01449	0.0000	4	89	
ADF - Fisher Chi-square	39.0595	0.0000	4	89	
PP - Fisher Chi-square	34.6233	0.0000	4	92	
**Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.					

Continued**3: LEN**

Panel unit root test: Summary

Series: D(LEN)

Date: 05/29/18 Time: 11:12

Sample: 1986 2010

Exogenous variables: Individual effects

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0

Newey-West automatic bandwidth selection and Bartlett kernel

Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-9.77151	0.0000	4	92
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.50579	0.0000	4	92
ADF - Fisher Chi-square	66.8434	0.0000	4	92
PP - Fisher Chi-square	70.8800	0.0000	4	92

**Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

4: POP

Panel unit root test: Summary

Series: D(LPOP)

Date: 05/29/18 Time: 11:14

Sample: 1986 2010

Exogenous variables: Individual effects

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 3

Newey-West automatic bandwidth selection and Bartlett kernel

Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.49618	0.0673	4	80
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.36417	0.0863	4	80
ADF - Fisher Chi-square	11.3752	0.1813	4	80
PP - Fisher Chi-square	4.69275	0.7899	4	92

**Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Continued**5: TCU**

Panel unit root test: Summary

Series: D(LTCU)

Date: 05/29/18 Time: 11:15

Sample: 1986 2010

Exogenous variables: Individual effects

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0

Newey-West automatic bandwidth selection and Bartlett kernel

Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.77389	0.0001	4	92
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.95878	0.0000	4	92
ADF - Fisher Chi-square	29.6646	0.0002	4	92
PP - Fisher Chi-square	29.6086	0.0002	4	92

**Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Table A2. Estimation results with Eviews without differentiation with Method (FMOLS).

Dependent Variable: LCO2

Method: Panel Fully Modified Least Squares (FMOLS)

Date: 05/29/18 Time: 11:39

Sample (adjusted): 1987 2010

Periods included: 24

Cross-sections included: 4

Total panel (balanced) observations: 96

Panel method: Grouped estimation

Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP	0.882142	0.280895	3.140468	0.0023
LEN	-0.012198	0.310437	-0.039294	0.9687
LPOP	-0.220130	0.183894	-1.197050	0.2344
LTCU	0.069174	0.289883	0.238627	0.8119
R-squared	0.107650	Mean dependent var		2.883404
Adjusted R-squared	0.078552	S.D. dependent var		4.770430
S.E. of regression	4.579235	Sum squared resid		1929.185
Long-run variance	0.029227			

Table A3. Results of the granger causality test II.

Null Hypothesis:	Obs	F-Statistique	Prob.
Lgdp does not Granger Cause LCO ₂	92	1.75062	0.1797
LCO ₂ does not Granger Cause Lgdp		2.37426*	0.0991
Len does not Granger Cause LCO ₂	92	0.64049	0.5295
LCO ₂ does not Granger Cause Len		1.01129	0.3680
Lpop does not Granger Cause LCO ₂	92	0.67593	0.5113
LCO ₂ does not Granger Cause Lpop		0.37480	0.6885
Ltcu does not Granger Cause LCO ₂	92	0.23177	0.7936
LCO ₂ does not Granger Cause Ltcu		1.23231	0.2967
Len does not Granger Cause Lgdp	92	2.01326	0.1397
Lgdp does not Granger Cause Len		0.0643	0.9377
Lpop does not Granger Cause Lgdp	92	18.8072***	0.0000
Lgdp does not Granger Cause Lpop		8.58778***	0.0004
Ltcu does not Granger Cause Lgdp	92	4.51434***	0.0136
Lgdp does not Granger Cause Ltcu		0.70990	0.4945
Lpop does not Granger Cause Len	92	0.15486	0.8568
Len does not Granger Cause Lpop		0.34706	0.7077
Ltcu does not Granger Cause Len	92	0.09078	0.9133
Len does not Granger Cause Ltcu		0.54141	0.5839
Ltcu does not Granger Cause Lpop	92	1.78042	0.1747
Lpop does not Granger Cause Ltcu		3.56858**	0.0324

Table A4. Preliminary test table.

Fisher's exact test (Fixed-effects (within) regression)	
F test that all $u_i=0$: F (3, 92) = 6342.90	Prob > F = 0.0000***
Breusch-Pagan test (Random-effects GLS regression)	
Prob > chibar2 = 1.0000	chibar2 (01) = 0.000***
Test of Hausman (1978)	
$\chi^2(4) = (b-B)'[(V_b - V_B)^{-1}](b-B)$	Prob > χ^2 = 0.0000***

Table A5. Stationarity test.

	CD	CDw	CDw	CD*
LCO ₂	6.58 (0.000)	-1.25 (0.210)	14.86 (0.000)	2.1e+30 (0.000)
Lpop	10.35 (0.000)	-0.20 (0.843)	25.15 (0.000)	1.2e+26 (0.000)

Continued

Ltcu	6.09 (0.000)	0.36 (0.720)	15.22 (0.000)	1.5e+31 (0.000)
Lgdp	0.35 (0.728)	-2.76 (0.006)	6.79 (0.000)	9.2e+29 (0.000)
Lcenr	-1.84 (0.066)	-0.55 (0.585)	15.62 (0.000)	2.9e+30 (0.000)

Table A6. Unit root test CIPS of Pesaran (2007).

	Level	Difference	I(d)
LCO ₂	-2.239	..	I(0)
Lpop	-5.13	..	I(0)
Ltcu	-2.451	..	I(0)
Lgdp	-1.831	-3.482	I(1)
Lcenr	-0.696	-4.506	I(1)