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Article

Should we be sceptical in the face of calls for degrowth?

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Abstract: In recent years, an 'international' unanimity has been reached as to the importance of collective collaboration to avoid the negative effects of climate change. This requires rethinking the old or traditional development model based on economic growth as the exclusive indicator of wealth. Thus, humanity has an urgent need to adopt a new, more humane and fairer economic model that constitutes an alternative to the models of exponential growth that have dominated in the last two centuries. To do so, humanity is looking to the Degrowth model as a potential concept that aims to reduce wealth from pollutants, seeks more justice (as equity), and the improvement of the capabilities of those who are poor and disadvantaged (in the sense of Amartya Sen and Martha Nussbaum). The purpose of this article is to question this model and whether it actually does improve environmental quality. Additionally, if the response is positive, another question arises: How to finance degrowth especially when we seek other less polluting energy sources whose costs seem to be very high?

Keywords: environment; degrowth; ARIMA
JEL Classification: Q1; Q2; Q3

1. Introduction

For many years there has been a growing call, including from academics, activists, naturalists, and ecologists, for a movement towards Degrowth as the only model that can offer humanity a path to maintaining the ecological balance necessary for sustainability and the viability of the species is the only path that can enable humanity to maintain an ecological balance that allows sustainability and the viability of living species. Before we go further down this path of degrowth, it would be important to define how/why Degrowth might be seen as a sustainable process of lowering the Gross it would be important to define how/why Degrowth is seen as a sustainable process of lowering the Gross Domestic Product (GDP) but without this resulting in a drop in collective well-being. In such an approach—should it be possible to achieve—we can reconcile the trinity: collective and ecological well-being, sustainability, and social equity. Thus, it is a new philosophy—contrary to ordinary capitalist logic which can never conceive of such scenarios of lowering wealth (Schneider et al., 2010, p. 512).

The main objective of this study/investigation/article is to determine whether important social and environmental goals can be achieved in a modern economy without necessarily relying on continued economic expansion, conventionally defined as an increase in real GDP. In particular, we wonder whether it is possible to achieve substantial reductions in greenhouse gas emissions (hereafter carbon emissions) and other environmental pressures and inequalities while controlling the employment situation, all in the context of much slower, if any, economic growth.

At this point, it is important to highlight that Degrowth is the simple result of qualitative changes of life conditions, leading to the rising awareness of the problems that the neoclassical development model has generated during the last two centuries regarding the social welfare of the various developed or developing countries (Amartya Sen, 1986; Club of Rome Report or the Meadows Report, 1972).

Indeed, climate change, polluting emissions, deforestation, poverty, and injustice are all considered as new problems linked to the neoclassical model which attest to its unsustainability, since it is only interested in the productive dimension while turning a blind eye to the costs that humans (present and future generations) must endure in terms of environmental and healthy living degradation.

This line of ideas/thinking converges with the work of the Romanian economist Nicholas Georgescu-Roegen (1971), who highlighted the high level of interdependence between the laws of thermodynamics and those of economics and how this relation can influence the fate of societies (Georgescu-Roegen, 2006). According to the author, material growth, supposed to be the ultimate objective of homoeconomicus, cannot remain/cannot be sustainable over time, because of the irreversibility of the transformation of energy into matter.

Hence, the economy turns out to be a system integrated into the biosphere and therefore it can only be developed by submitting to its laws and constraints: a bioeconomy. Even with recycling, no technique will be able to eliminate the entropic aspects of resource extraction and transformation because industrial societies are giant emitters of polluting and non-renewable energies. At this moment in written history, life is threatened or even corrupted (in the sense of alteration and denaturation). Moreover, the predominant economic model (neoclassical) is subject to accusation and reproach from ethics (as a science of freedom in the sense of Kant) because it lacked decency and propriety. It is a model that looked at false wealth (in the sense of J. J. Rousseau), without thinking about its costs, which turn out to be so detrimental to human life.

What wealth that is measured in terms of added value without worrying about the lack of temporality between immediate production (unsustainable) and intermediate consumption (raw material, wood, animals, fauna, and flora, etc.) seems to leave us with is a problem whose resolution is no longer economic but rather moral and ethical. Neoclassical economics has deceived us because its wealth has in effect brought us back to poverty. This is not a new observation (see Nietzsche in his Will to Power). Its resolution is no longer economic but rather moral and ethical. Just as Immanuel Kant invites the notion of Duty to found mores, we invite him to solve the problem that Homoeconomicus generated because of his irrationality and his ignorance. Neoclassical economics has deceived us because its wealth has brought us back to poverty. This is an old observation (see Nietzsche in his WILL TO POWER).

In recent debates on environmental issues, there is near unanimity that the current capitalist model centred on infinite growth in a finite world is no longer compatible with a viable environment threatened by the recurrence of climate change, water and air pollution, deforestation, and the disappearance of animal and plant species. The trade-off between the desire to pursue the traditional model of growth and the need to protect the environment has led to the emergence of another path, that of Degrowth which proposes to provide solutions to environmental problems outside the framework of economic growth and its classic dogmas. It is at the crossroads of these discussions that our main question arises: What solution can ‘degrowth’ bring to environmental problems and how can it be financed?

Debating the subject of degrowth as a solution to the environmental problems to provide a of clear idea as to what this approach comprises. Thus, we will address the following questions: first, what are the main criticisms addressed by the theory of Degrowth to neoclassical economic growth? second, once Degrowth is elected as an alternative model capable of leading us towards a green and sustainable economy, how can/should it be financed?

2. Literature review

2.1. Definition and objectives of Degrowth

Given the complexity of the concept of Degrowth, it would be important to define it well to avoid any further confusion. And although the definitions are multiple and diversified, we limit them to two of them which we consider to be the more important and exhaustive. The first is that of Bayon (2010) who assumes that the Degrowth is not an academic or scholarly term and that it brings together all the ideas which support for an economy which uses natural resources with reason and releases fewer pollutants for ecological, social and democratic reasons and who are aware that this implies a radical destabilization of the Gross Domestic Product. The second definition is that of Kallis et al. (2010) who converged to the first one. Their main idea is that Degrowth can be Sustainable and well defined from an ecological and economic point of view as a socially sustainable and equitable reduction (and ultimately a stabilization) of resource flows used by society.

Thus, it emerges from these definitions that the main objective of Degrowth as declared during the Conference on economic degrowth for ecological sustainability and social equity (held in Paris in 2008) is to design a more ambitious concept and courageous than that of sustainable development which has not broken with the standard neoclassical model. Thus, the goal of Degrowth is two-dimensional. Firstly, the reduction of the environmental impacts of the global economy to a sustainable level and secondly to ensure a fair distribution both within the same country or between countries. Beyond the idea, there exists a new possibility to save humans through the rational exploitation of natural resources without harming the interests of future generations (the idea of development). Any possible reduction in global wealth can no longer panic governments because in a logic of Degrowth it is necessary to focus economic and ecological policies on the aspect of redistribution which, once maintained with fair justice, then it can maximize the satisfaction of needs humans and the assurance of a good quality of life (the transition to a friendly and participatory society).

2.2. Limits to Degrowth

As already mentioned, Degrowth is much more a philosophy or logic of action than an academic concept which has well-defined and well-circumscribed boundaries.

Being thus, it turns out that Degrowth is a goal that can never be achieved unless collective social consciousness converges towards the establishment of a new social contract based on equitable justice. Degrowth concretizes justice as fairness and puts an end to the utilitarianism which founded the standard neoclassical model. To transition to Degrowth models and converge towards sustainability and environmental sustainability, many constraints must be overcome. In this context Sekulova et al. (2013) and Dittmer (2013) announce significant changes at the economic, political and social levels. However, despite the ambition of the degrowth objectives, constraints are raised in the first conference on the concept of degrowth.

In other words, degrowth requires a transformation of the global economic system, which therefore means rethinking the redistribution policies to be implemented at the national level to enable the reduction and ultimately the eradication of the most total poverty, during that the global economy and unsustainable national economies decline. And as long as degrowth requires a reduction in the size of the economy, GDP, consumption and working hours, distribution and redistribution policies must be carefully designed. However, the realism of the implementation of degrowth is unclear according to certain authors such as (Van den Bergh et al., 2012) who according to them such a lack of clarity can never allow the concept of Degrowth to emerge from marginality and take the place he deserves as a dominant role model.

According to Napari et al. (2023) since the relationship between humans and the environment is complex. This complexity revolves around the boundaries that separate the economic and the environmental. Thus, Degrowth is intended as a limit to the failure of the standard model but which must not affect the quality of life.

Thus, the essential objective of the Degrowth concept/approach is to design an operating model that makes it possible to achieve prosperity without this being conditioned by economic growth, and this in the advanced economies, which makes it possible to reconcile well-being on the one hand with the biophysical balance of the planet on the other.

2.3. How to measure Degrowth

Thus, given that the Degrowth concept is relatively recent, few studies have looked at how to measure its potential effectiveness. But the relative scarcity of works is not explained exclusively by the novelty of the concept but rather by the fear, experienced by researchers, of the impossibility of its conversion into reality (at least in the horizon of the short- and medium-term future). One researcher who did carry out such work is Victor (2008; 2009), who tried to use a model designed to make simulations on macroeconomic scenarios of the Canadian economy. The first ‘business as usual’ scenario is a projection of past trends into the future, the second is a ‘selective growth’ scenario in which differential growth rates are applied to parts of the economy based on their direct and indirect greenhouse gas emissions, and the third is that of ‘degrowth’.

Victor (2008) tried to simulate three scenarios for Canada in the long term over a twenty-year period from 2000 to 2020 using the dynamic simulation model ‘Lowgrow’. The simulations of the scenarios were based on estimates by the ordinary least square method of certain functions of production, consumption, investment, public expenditure, and unemployment, as well as that of emissions, in order to make certain forecasts on the evolution of GDP, unemployment, poverty, and CO_2 emissions in the event of normal growth, weak growth, or zero growth.

Jackson (2009) opted for a macroeconomic simulation model that highlights several scenarios for the Canadian economy under different assumptions relating to key macroeconomic, social, and environmental variables. This model took into account different dimensions, mainly the production and consumption processes, the evolution of employment in the ‘real economy’, and the ecological constraints and their evolution in the case of normal, weak, and zero growth.

Daly Herman (2023) showed that the unpredictable laws of thermodynamics and other ethical constraints that currently dictate the speed of economic growth rates cannot continue at the same pace. Indeed, while it is quite true that the economy grows at the physical scale, it is no longer so at the ecosystem level. An economy, if it looks at sustainability and durability, will have to build up constant stocks of objects and people.

3. Methodology

Given the scarcity of research works interested in the forecast of Degrowth scenarios, we will focus on the few researches established by Victor (2008) and Jackson (2009). We have not found in the economic literature any simulation studies of the quality of the environment in a situation of ‘degrowth’. The approach that we will follow in the simulation of growth scenarios (normal, weak, and zero) and its effects on the quality of the environment (which is represented in this study by the quantity of CO_2 emitted), is inspired by the work of these three authors.

First, we are going to forecast CO_2 emissions, gross domestic product (GDP), and energy use in the United States of America for the period 2021–2050. Then we are going to calculate energy intensity (energy consumption/GDP) and CO_2 per unit of energy (CO_2/energy) because reductions in energy intensity (i.e. energy per unit of GDP) and reductions in CO_2 per unit of energy, as a resource or environmental flow relating to an economic activity, can be understood as the combination of two variables: the scale of the economic activity and the intensity of the flow. For example, the greenhouse gas (GHG) emissions of a national economy in a year can be found by multiplying GDP per year (a measure of scale) by GHG/GDP per year (a measure intensity), where GDP is measured in constant 2010 dollars and GHG emissions are measured in tonnes. Since the emissions of these gases also depend on the type of energy used for production, it follows that any target for reducing greenhouse gas emissions must be achieved by reducing energy intensity (energy in tonnes of oil equivalent/GDP in dollars). Finally, we will calculate the CO_2 emissions in the different scenarios (normal growth, ‘business as usual’, low, zero, and negative growth).

3.1. Presentation of the sample

Our study will focus on the case of the United States of America (US), covering the period 2021–2050. This choice was dictated on the one hand by the availability of data and on the other hand by the classification of the US in terms of CO_2 emissions.

This country ranks second after China with 4,744,450 kilotons of CO_2 in 2019 (which represents 12.91% of total global emissions). The data used in the analysis comes mainly from two sources: the official website of the World Bank (WB), and that of the International Energy Agency (IEA).

It is important to note that it has often been assumed that for a sample size below 50 points, convergence and power issues are documented (Hecht and Zitzmann, 2021). If c in this case, sample size recommendations for continuous-time models are to compensate for shorter time series with larger numbers of people and vice versa. However, in our study we retained only one country and this for two essential reasons: Firstly, the absence of reliable and exhaustive information for other countries and secondly that the Degrowth model is more adapted to the case of the USA which has experienced a convergence of its growth for more than twenty years.

3.2. Presentation of variables

GDP: The gross domestic product. Data are in constant 2010 US dollars;

INTENG: Energy intensity is a measure of a country's energy efficiency. It is equal to the quotient of energy consumption to gross domestic product (Energy/GDP)

$INTCO_2$: The amount of CO_2 per unit of energy. It is equal to the quotient of CO_2 emissions to energy uses in a country (CO_2/Energy measured in kg per kg of energy use in oil equivalent):

CO_2: CO_2 emissions in kilotonnes.

To calculate the effects of decline on unemployment, we will estimate:

The conventional Cobb-Douglas production function: Output (GDP) is a positive function of capital employed, labour employed, and time:

$GDP = \beta_0\ K^{\beta 2}\ L^{\beta 3}$

$\ln (GDP) = \beta_0 + \beta_1 \ln K + \beta\ _2 \ln L\ _+ u$

ln = log naturel

T: time expressed on years number

K: capital in millions of constant 2010 dollars

L: workforce employed in thousands

We retain the estimate of the panel with fixed effects. Labour force (ols)

$L = \beta_0 + \beta_1 POP + \beta_2\ GDP + u$

L: workforce employed in thousands

POP: population in millions

GDP: GDP in millions of constant 2010 dollars

u: error term

In this model, the active population is a positive function of the population and the GDP. Population is based on statistical projection for each year from 1990 to 2020.

capacity utilization (ols)

$CU = \beta 0 + \beta 1\ ur + u$

With CU: Utilization Capacity, ur the unemployment rate, and u the error term.

The following equations were estimated using data from 1990 to 2020 from the World Bank website. The estimation method was either ordinary least squares (ols) or two-stage least squares (2sls). The t-statistics for the coefficients are shown below in parentheses and the R-squared value is shown.

3.3. Model specification

We will, in what follows, present and define the different variables that will be introduced into our model. Our main objective is to examine the impact of normal, low, zero or negative growth on the quality of the environment, represented here by the quantity of carbon dioxide emitted and other socioeconomic variables such as unemployment, during the period 2021–2050.

Addressing this question leads us first to use the Autoregressive Integrated Moving Average (ARIMA) method (Box and Jenkins, 1976) for a forecast of GDP, final energy consumption, CO_2 emissions, population, and investment in the United States of America in the longer term during the period 2021–2050. Then we will estimate by ordinary least squares (1) the CO_2 emissions function, (2) the Cobb-Douglas production function, and the work function. Finally, we will simulate different growth scenarios (normal, low, zero and negative) and see the effects on CO_2 emissions and other socio-economic variables such as unemployment.

Previous studies have used various approaches to forecast economic time series. One of the approaches is known as the univariate or autoregressive integrated moving average (ARIMA) forecast model developed by Box and Jenkins (1976). In this model, a time series is expressed in terms of past values of itself (the autoregressive component), in addition to current values, and lagged by a white noise error term (the moving average component). This approach has been widely used by many researchers in forecasting studies. The popularity of this approach stems from the fact that it has proven its ability to accurately predict whether all the conditions for its application are met. Among these studies is that by Kenny et al. (1998) who used the ARIMA model to forecast Irish inflation after outlining the practical and necessary steps, where the results revealed that the predicted values of the consumer price index were in line with the actual values. Also in Ireland, Meyler et al. (1998) forecast inflation for the period using ARIMA models with quarterly data ranging from 1976 to 1998 and illustrated some practical issues with ARIMA time series forecasting

The ARIMA forecast of total primary energy demand appears to be more reliable than the sum of the individual forecasts. In studying monetary policy in China, Dongdong (2010) used monthly CPI data from January 2000 to December 2009. Empirical results showed that the ARIMA model (12, 1, 12) provided a better prediction of monthly CPI in China after 2010, with the hope that the government might formulate an appropriate monetary policy. Kiriakidis and Kargas (2013) used the ARIMA model to forecast Greece’s GDP. The forecast results successfully anticipated the recession that later occurred in the Greek economy. Similarly in Greece, Dritsaki (2015) used an ARIMA (1, 1, 1) model over the period 1980–2013 to forecast the actual GDP of Greece during the period 2015–2017. The statistical results showed that the actual GDP of Greece is improving steadily.

Kharimah et al. (2015) made forecasts of the Consumer Price Index (CPI) of Malaysia using ARIMA models with a data set covering the period from 2009 to 2013, and found that ARIMA (1, 1, 0) proved to be the best model to predict the consumer price index. Wabomba et al. (2016) used data obtained from the Kenya National Bureau of Statistics for the years 1960 to 2012 to model and forecast the Kenyan GDP by applying the ARIMA model. The prediction results showed that the relative and predicted values were within the range of 5% of the actual values, so the prediction power of this model was relatively adequate and effective in modelling the annual Kenyan GDP returns at the time.

Abonazel and Abd-Elftah (2019) found that the appropriate statistical model to predict Egypt's GDP is ARIMA (1, 2, 1); this model was used to predict Egypt's GDP until 2026. According to the expected values, the GDP should continue to grow. In another 2019 study of Nigeria based on ARMA, ARIMA and GARCH models, Nyoni and Nathaniel (2019) examined inflation in Nigeria using time series data on inflation rates from the period 1960–2016 and found that the ARMA (1, 0, 2) model is the best model for predicting inflation rates there. Nyoni and Mutongi (2019) used annual CO_2 emissions data in China from 1960 to 2017 to forecast CO_2 emissions for the period 2015–2024 by using the ARIMA model. The results of this study show that there is a projected total annual CO_2 emission of 10,011,297.94 kt in 2024 for China.

After reviewing a few examples of previous studies that managed to arrive at estimates that were close to the true values of the economic variables estimated by the ARIMA model, this study uses the same methodology after modifying it by adding the error variance to the ARIMA regression model to make the model more suitable for forecasting.

3.3.1. Presentation of the ARIMA model

As already noted above, the ARIMA method is, and has been since its formulation in the 1970s, one of the most widely used time series forecasting methods and consists in predicting the future values of a time series by respecting certain aspects of the statistical structure of the observed series. The ARIMA model creates a linear equation that describes and predicts time series data. This equation is generated through three distinct parts which can be described as follows: This equation is generated through three distinct parts, which can be divided as AR-I-MA. Each part is described in what follows below, where AR and I fall within section 'a' and the third is set out in section 'b'.

a) Autoregressive (AR) models:

Autoregressive (AR) models are models in which the value of a variable in a period is related to its values in previous periods. These models are based on autoregressiveness in the sense that equation terms are created from past data points. A process is autoregressive of order *n* when its value yt depends linearly on the previous n values. AR(p) is an autoregressive model with p lags. This model is written:

$$yt = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \varepsilon_t$$

where μ is the constant γ_p is the coefficient of the time-lagged variable t-p, ε_t is a white noise.

I denote integration or differentiation. The differentiation of the original series makes it possible to eliminate the possible non-stationary character. It allows taking into account the overall "trend" of the data.

When a variable yt is not stationary, a common solution is to use a differenced variable, $\Delta yt = yt - y_{t-1}$, for first-order differences.

The variable yt is integrated of order one, denoted $I(1)$, if taking a first difference produces a stationary process.

ARIMA (p, d, q) denotes an ARMA model with p autoregressive lags, q moving average lags and differences of the order of d.

b) Moving Average Models (MA):

Moving Average models MA (q) take into account the possibility of a relationship between a variable and the residuals of previous periods. Error or noise equation terms are based on past data points. This model considers that the variable can be written as a linear combination of the current value of a stochastic process and its previous n values. This model is written:

$$yt = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta i \, \varepsilon_{t-i}$$

where θq is the coefficient of the time-delayed error term t-q. White noise describes the assumption that each item in a series is a random draw from a population with zero mean and constant variance. While all of these three parts constitute the AR-I-MA model, the AR and MA aspects actually derive from stand-alone models that can describe trends in more simplified time series data.

The ARIMA model is almost always represented by ARIMA (p, d, q) where each of the letters corresponds to one of the three parts described above. These three letters represent parameters which are described as follows:

p: determines the number of autoregressive (AR) terms;

d: determines the order of differentiation;

q: determines the number of moving average (MA) terms.

Note: we will therefore apply the autoregressive model only if we notice a “correlation” between the series and a shifted version of itself (autocorrelation).

c) Autoregressive-moving-average model (ARMA)

Autoregressive moving average (ARMA) models combine both autoregressive p terms and q moving average terms, also known as ARMA (p, q).

$$yt = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i}$$

where μ is a constant and γp is the coefficient of the time-lagged variable t-p. θq is the coefficient of the time-delayed error term t-q.

d) Stationarity

Modelling an ARMA (p, q) process requires stationarity. A stationary process has mean and variance that do not change over time and the process has no trends. An AR (1) perturbation process $ut = \rho ut{-}1 + \epsilon t$ is stationary if $|\rho| < 1$ and ϵt is white noise.

3.3.2. ARIMA methodology

The steps followed to define an ARIMA model as outlined by Box and Jenkins are shown in **Figure 1**.

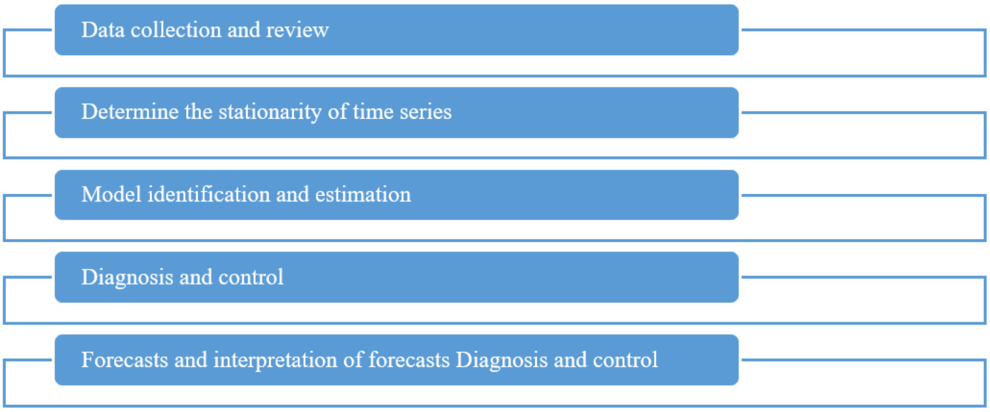

Figure 1. Forecasts and interpretation of forecasts. Diagnosis and control.

Collection of data

This study is based on observations of total annual carbon dioxide emissions, gross domestic product (GDP), and energy use in the United States of America during the period 1990–2020. The data used in the analysis comes mainly from the official website of the World Bank (WB).

Forecast of CO_2, GDP, and Energy variables using ARIMA models

A. Descriptive statistics of the variables:

Table 1 presents the main descriptive statistics of the model variables.

Table 1. Descriptive statistics of the variables.

Variables	**Observations**	**Mean**	**Stand deviation**	**Min**	**Max**
GDP	31	14953.66	3184.54	9794.23	20397
CO_2	31	5244.039	390.4622	4285.89	5776.41
ENERGY	31	2172.983	109.6876	1915.05	2337

Source: Authors' calculations.

B. Stationarity of the CO_2, GDP, Energy, and Population variable:

During the forecast period, that is 2021–2050, the graph given in Appendix shows that the shows that the CO_2 emissions of the US continue to decline. By 2050, they will reach 3730.035 million metric tons. The graph presented in Appendix also shows that during the forecast period, the GDP of the US is constantly increasing. By 2050, the GDP will reach 30,864.71 billion dollars.

To check the stationarity in level and in first difference of the GDP, CO_2, ENERGY, POP and INV variables, we performed the Dickey-Fuller and Phillips-Perron tests. **Table 2** shows the test results.

From **Table 2** we note that in level $Z(t)$ of variables GDP, CO_2, and ENERGY are greater than 0.05 so the series are not stationary hence we will apply first differences and perform unit root tests. In first difference the approximate p-values of MacKinnon $Z(t)$ for the variables GDP, CO_2, ENERGY of the Dickey-Fuller test or the Phillips-Perron test are less than 0.05 which implies that all the three variables are stationary in the first difference. MacKinnon's approximate p-value Z(t) of the variable POP and INV (Investment) is less than 0.05 for the Dickey-Fuller test and for the Phillips-Perron test, so the series are stationary in level.

Table 2. Stationarity at level and in first difference.

Variables	Dickey-Fuller Test			Phillips-Perron Test		
	Stat-stat	**P > *t***	**MacKinnon p-value Z(*t*)**	**St t-stat**	**PP > *t***	**MacKinnon p-value Z(*t*)**
Stationary at level						
GDP	3.12	0.004	0.8532	8.33	0.000	0.6732
CO_2	−0.66	0.515	0.9757	11.18	0.000	0.9906
ENERGY	−1.77	0.089	0.7205	11.51	0.000	0.7354
POP	−11.41	0.000***	0.000	516.51	0.000***	0.000
INV	3.12	0.004**	0.0250	2.00	0.055*	0.0250
Stationarity in first difference						
GDP	−3.84	0.001***	0.0025	2.06	0.0500***	0.0025
CO_2	−4.11	0.000***	0.0009	0.48	0.633***	0.0008
ENERGY	−4.99	0.000***	0.000	0.21	0.000***	0.000
POP	-	-	-	-	-	-
INV	-	-	-	-	-	-

* the test is significant at the level of 10%; ** the test is significant at the level of 5% *** the test is significant at the level of 1%.

4. Forecasts of GDP, CO_2, ENERGY, POP and INV variables using the ARIMA model

In what follows we will make the forecasts using the ARIMA model of the GDP variable.

4.1. Forecasts of GDP, CO_2 variables for the period 2021–2050

4.1.1. Model identification and estimation

First of all, we should determinate p et q for the set of variables GDP, CO_2, ENERGY, POP and INV and second to determine the best model of ARIMA to choose (**Table 3**).

Table 3. Determination of the chosen ARIMA model.

Variable	Best model	p	q	Observations
GDP	ARIMA (1, 1, 0)	3	0	i.e., **Figures A1** and **A2**
CO_2	ARIMA (1, 1, 1)	5	1	i.e., **Figures A3** and **A4**
ENERGY	ARIMA (1, 1, 1)	4	1	i.e., **Figures A5** and **A6**
POP	ARIMA (2, 0, 2)	4	2	i.e., **Figures A7** and **A8**
INV	ARIMA (2, 1, 1)	3	1	i.e., **Figures A9** and **A10**

The ARIMA models are retained are better because the coefficients and the constant of the model are significant, the criterion of information of Akaike (AIC) and the criterion of bayesian information (BIC) are weakest.

From **Table 4,** it appears that the probabilities chi2 are superior to 5%, which implies that residuals of the ARIMA models are stationary (i.e., **Tables A1–A9**).

Table 4. White noise portmanteau test (residual tests).

Variables	Selected model	Q –stat	P > t	Observations
GDP	ARIMA (1, 1, 0)	10.1661	0.6803	Prob chi2 > 0.05
CO_2	ARIMA (1, 1, 1)	9.8248	0.7082	Prob chi2 > 0.05
ENERGY	ARIMA (1, 1, 1)	19.9912	0.0954	Prob chi2 > 0.05
POP	ARIMA (2, 0, 2)	0.6103	1.0000	Prob chi2 > 0.05
INV	ARIMA (2, 1, 1)	12.3812	0.4967	Prob chi2 > 0.05

4.1.2. Forecasts and assessment of forecasts

The forecasts of CO_2 emissions and GDP for all scenarios for the period 2021–2050 is given in **(Table 5)**.

Table 5. Forecasts of CO_2 emissions and GDP for all scenarios for the period 2021–2050.

Year	Forcasted GDP (Low)	Forcasted CO_2 (Low)	Forcasted GDP (gr = 1%)	ForcastedCO_2 (gr = 1%)	Forcasted GDP (gr = 0%)	Forcasted CO_2 (gr = 0%)	Forcasted GDP (gr = −1%)	Forcasted CO_2 (gr = −1%)
2021	20,772.53	4274.847	20,601	4149.265	20,397.01	4111.247	20,193	4073.2
2025	22,178.72	4197.599	21,437.5	3961.27	20,397.01	3783.09	19,397.3	3611.255
2030	23,916.18	4103.774	22,531	3762.962	20,397.01	3432.056	18,446.7	3127.356
2035	25,653.31	4010.362	23,680.3	3591.972	20,397.01	3128.74	17,542.6	2721.473
2040	27,390.45	3916.918	24,888.2	3442.553	20,397.01	2863.717	16,682.8	2377.802
2045	29,127.58	3823.477	26,157.8	3310.721	20,397.01	2630.171	15,865.2	2084.687
2050	30,864.71	3730.035	27,492.1	3193.328	20,397.01	2422.798	15,087.7	1833.099

During the forecast period 2021–2050, the GDP of the US will increase steadily and will reach 30864.71 billion dollars by 2050. During the forecast period, 2021–2050, the results show that the CO_2 emissions of the US continue to decline and by 2050, they will reach 3730.035 million metric tons.

4.1.3. Unemployment forecasts for the different scenarios

To forecast the evolution of unemployment in the US, we first estimate the production function (**Table 6**) and then that of the active population (**Table 7**). The evolution of the active population is based on GDP and population forecasts.

Table 6. Estimation of the production function.

Variables	lnKu	lnL	Constant
	0.42659**	1.757553***	−17.7019***
	(0.17307)	(0.33328)	(1.5075)
R-squared	0.9751		
Prob > F	0.0000		

** significant at the level of 5%; *** significant at the level of 1%.

Table 7. Labour force function estimation.

Variables	POP	GDP	Constant
	0.2371657*** (0.084585)	0.0018421*** (0.0006673)	0.822326*** (0.021567)
R-squared	0.9880		
Prob > F	0.0000		

*** significant at the level of 1%.

4.1.4. Scenario simulation

The simulation of scenarios is based on the forecasts of the variables CO_2, GDP, ENERGY, POP, and INV during the period 2021–2050 using ARIMA models. The scenarios considered are 'business as usual' which is a projection into the future of past trends, growth at a rate equal to 1%, zero growth, and growth at a negative rate equal to −1%.

Of course, the decline is not assumed to continue indefinitely; it is rather a path of transformation aiming at a stable state at a reduced level of economic production. This permanent regime could be defined by a reduced level of use of materials and energy. For present purposes, this reduced level of economic output is defined in terms of gross domestic product and gross domestic product per capita, which is the same when the population is constant. Population is exogenously determined. It is one of the variables that determines consumer spending in the economy. Labour force is estimated based on GDP and population.

'Business as Usual' growth scenario

In the reference scenario illustrated in **Figure 2**, the real GDP of the US is projected to increase by 59.966% from 2021 to 2050, with an average annual growth rate of 1.578%. GDP per capita is expected to increase by 40.091% with a projected average annual growth rate of 1.13%. In the presence of new initiatives to reduce greenhouse gas emissions in the US, carbon dioxide emissions are expected to decline by 12.97% over the same period, reflecting a reduction in the intensity of carbon assumed in the 'Business as Usual' scenario and which can be explained by the adoption of cleaner technologies and the voluntary transition of several sectors of the economy to more ecological economic activity. Indeed, the US has set a goal of becoming a 'net zero carbon emission economy' by 2050. In its primary energy consumption, the share of fossil fuels will become increasingly low while that that of renewable energies will grow more and this is part of the long-term strategy for decarbonization, namely the "United States Mid-Century Strategy for Deep Decarbonization", which aims for a reduction in carbon intensity and low-emission economic development greenhouse gas emissions. The measures undertaken are as follows:

- The increase of three to four times the solar and wind capacity, in parallel with that of the necessary transmission network;
- the elimination of coal production;
- putting an end to the deployment of new oil and gas exploitation sites;
- achieving a proportion of 50% of sales for zero CO_2 emission electric vehicles and electric heat pumps;

- the implementation of strict energy efficiency standards for equipment and buildings.

The unemployment rate is projected to decrease by 11.925% in 2050 compared to its level of 2020 (8.05% in 2020). This can be explained by the high level of the unemployment rate reached in the American economy in 2020 following the crisis caused by the COVID-19 pandemicthis year the GDP growth rate is negative (−3.4%). The evolution of CO_2 emissions, GDP, GDP per capita and unemployment for the 'Business as Usual' scenario during the period 2020–2050 is illustrated in **Figure 2**. The unemployment rate is expected to decrease by 11.925% in 2050 compared to its level in 2020 (8.05% in 2020). This can be explained by the high level of unemployment reached by the US economy in 2020 after the crisis caused by the Covid-19 pandemic, as the GDP growth rate became negative (−3.4%).

Figure 2 shows the evolution of carbon dioxide emissions, GDP, per capita GDP, and unemployment in the business-as-usual scenario over the period 2020–2050.

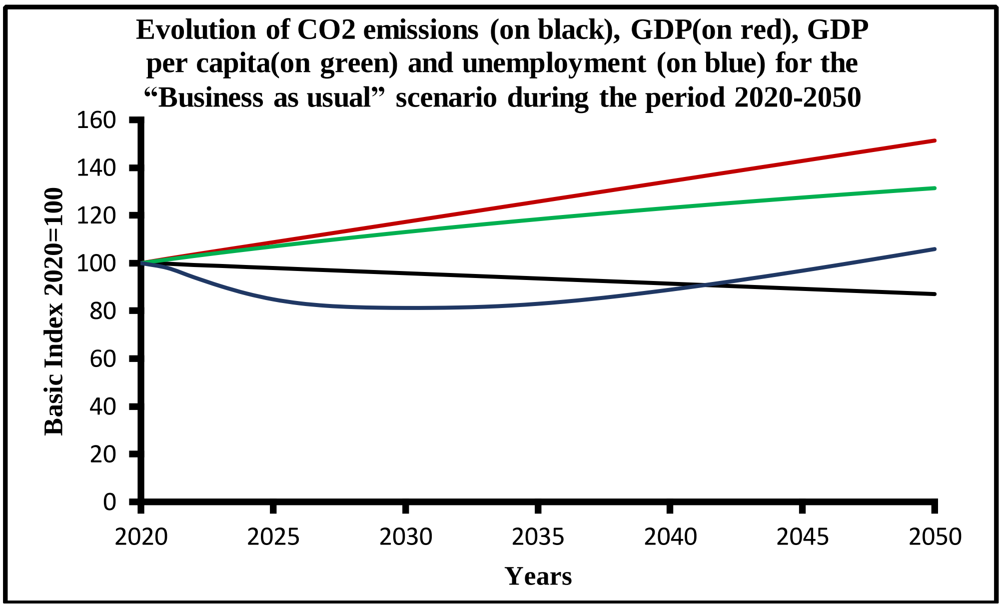

Figure 2. Evolution of CO_2 emissions, GDP, GDP per capita and unemployment for the 'Business as Usual' scenario during the period 2020–2050.

Scenario 1—business as usual (2020 = 100).

Scenario of low growth at an average annual growth rate of 1%

In this scenario, shown in **Figure 3**, the real GDP of the US is expected to increase by 34.784% from the year 2020 to the year 2050, with an average annual growth rate of 1%, and the GDP per capita is expected to increase during this period by 24.782% or with a projected average annual growth rate of 0.74%. In the presence of new initiatives to reduce greenhouse gas emissions in the US, carbon dioxide (CO_2) emissions are expected to drop by 25.492% over the same period, reflecting a reduction in the intensity of carbon projected in the low growth scenario. The unemployment rate is projected to increase to 8.66% in 2050 from its 2020 level (8.05% in 2020) to rise slowly to 8.747% in 2050.

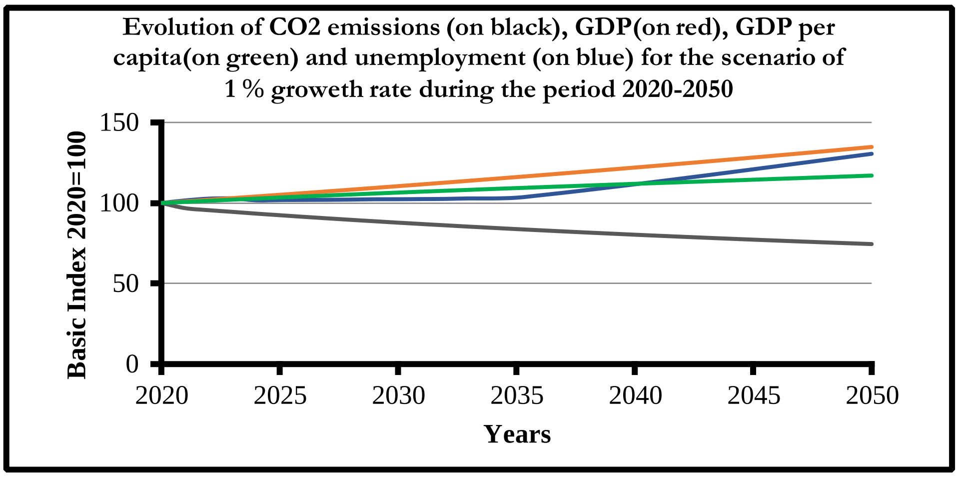

Figure 3. Evolution of CO_2 emissions and GDP, for the 'growth at a rate equal to 1%' scenario during the period 2020–2050.

Scenario 2—from low growth to 1% (2020 = 100).

Zero growth scenario

One such scenario for the United States of America is described in this section. Of course, the decline is not expected to continue indefinitely; rather, it is a path of transformation leading to a steady state and a reduced level of economic output. This state of equilibrium could be defined by a reduced level of material and energy flow. For present purposes, this reduced level of economic output is defined in terms of GDP and GDP per capita, which is the same when the population is constant or slightly increasing. The following assumptions were made to develop a target level of GDP per capita for a zero-growth scenario.

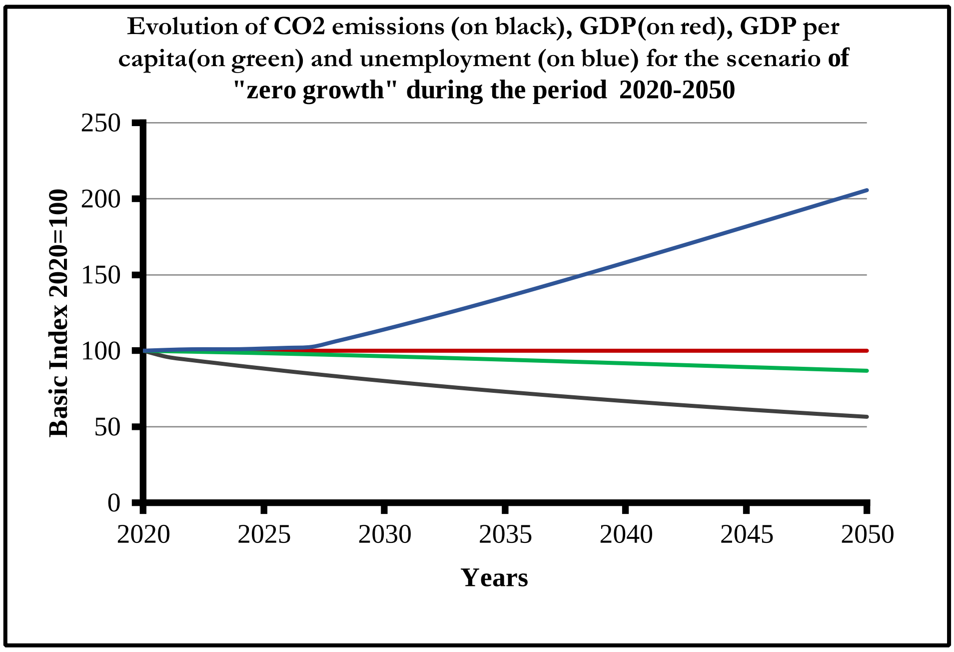

Figure 4. Evolution of CO_2 emissions and GDP, for the 'zero growth' scenario during the period 2020–2050.

Scenario 3—zero growth (2020 = 100).

In an economy showing no growth in total output, as measured by GDP, it is still possible and desirable for some sectors, products, and services to grow, while others remain stable and still others decline. This would be the pattern for the development of an economy in which renewable energy replaces energy from fossil fuels, with or without continued GDP growth. In this scenario, illustrated by **Figure 4**, the growth of the gross domestic product is nil. GDP per capita will experience a slight decrease of 7.419%. The reductions in CO_2 emissions in 2050 will be 43.47% compared to those in 2020 (base year) and the unemployment rate in 2050 will increase by 71.16% compared to compared to that of 2020. In 2050, it will reach a level of 13.78%.

Scenario of negative growth at a growth rate equal to −1%

In this scenario illustrated by **Figure 5** and **Table 8**, the real GDP of the US should fall by 26.03% during the period 2020–2050, with an average annual growth rate of −1%. As a result, GDP per capita is expected to decline by −31.519% with a projected average annual growth rate of −1.254% assuming normal population growth. CO_2 emissions are expected to fall by 57.23% over the same period. The unemployment rate is projected to increase to 140.29% in 2050 from its 2020 level (8.05% in 2020) and will reach 19.34% in 2050. This result is strange and could be illustrate a limitation of the methodology or a proof for the need of political actions to encounter the high employment rate.

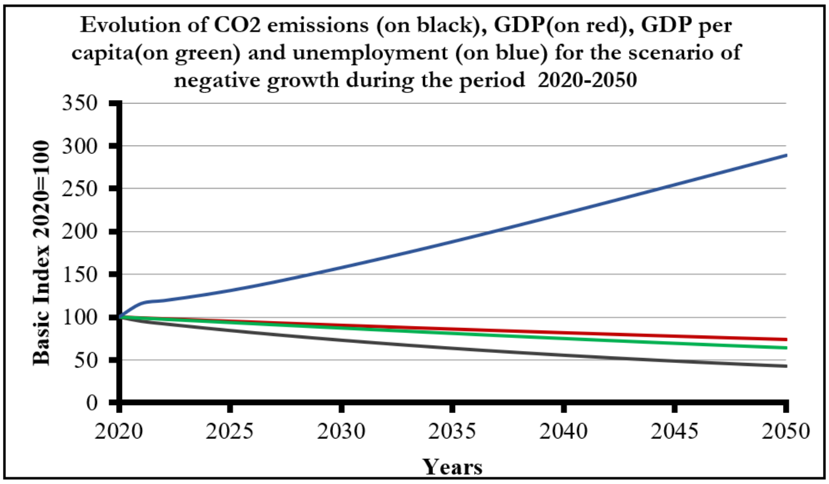

Figure 5. Evolution of CO_2 emissions and GDP, for the ‘negative growth’ scenario during the period 2020–2050.

Scenario 4 from negative growth with growth rate of -1% (2020 = 100).

Table 8. Evolution of GDP, GDP per capita, CO_2 emissions, and unemployment rate in the period 2020–2050.

Evolution of GDP, GDP per capita, CO_2 **emissions and unemployment during the period 2020-2050 (in %)**				
GDP average growth rate	1.578%	1%	0%	−1%
Evolution of GDP in 2050	59.966%	34.784%	0%	−26.03%
Evolution of GDP par habitant in 2050	40.091%	24.782%	−7.419%	−31.52%
Evolution of emessions of CO_2 in 2050	−12.96%	−25.492%	−43.47%	−57.23%
Evolution of the unemployment rate in 2050	−11.925%	8.66%	71.16%	140.29%

Table 9 concludes all possible scenarios already discussed.

Table 9. Results of the different scenarios in 2050.

Variable	**Year 2020**	**Scenario 1 Year 2050**	**Scenario 2 Year 2050**	**Scenario 3 Year 2050**	**Scenario 4 Year 2050**
GDP (in million 2015US$)	19,294,483	30,864,710	27,492,100	203,970,100	15,087,700
GDP per capita (in million 2015US$)	0.058060	0.081337	0.072449	0.053752	0.039760
CO_2 emissions in Kilotonnes	4,285,890	3,730,035	3,193,328	2,422,798	1,833,099
Unemployment rate	8.05%	7.09%	8.747%	13.778%	19.343%

Scenario 1: ‘Business as usual’,
Scenario 2: low growth at an average annual growth rate of 1%,
Scenario 3: zero growth,
Scenario 4: negative growth at a rate equal to −1%.

5. Conclusion

The simulation of scenarios for the period 2021–2050 for the United States of America leads us to the conclusion that any reduction in GDP growth leads to a drop in carbon dioxide emissions and an increase in unemployment. For zero growth, GDP per capita will experience a slight decline by 2050 of 7.419%. Carbon dioxide emissions will decline in 2050 by 43.47% compared to those of the base year 2020, and the unemployment rate in 2050 will increase by 71.16% compared to that of 2020. In 2050 it will reach a level of 13.78%. In conclusion, we can say that any initiative to reduce economic growth in order to act on carbon dioxide emissions requires that accompanying measures must be considered. Two of these measures are ‘standard’. The first is to increase carbon taxes on polluting industrial sectors. This can encourage investment in non-polluting industrial sectors. The second measure that proponents of degrowth propose is to support the underprivileged classes, the poorest and the unemployed in society through programmes that directly redistribute income and provide support for the most important items such as food, clothing, and shelter during the period of growth or little or no growth. The financing of the support programmes will largely be carbon taxes. Without accompaniment and support measures, the slowdown in growth can lead to social tensions and the degrowth project will fail.

So to make the transition to degrowth a success, it would be important to play on several policies. By way of illustration and not exclusion we can cite the following. Firstly, ensure a fair redistribution in the sense of equality which takes into account the most deprived without harming those who are rich. Second, ensure the adoption of ecological regulations that encourage reasoned and balanced exploitation of natural resources that are difficult to reproduce. Also, said regulations must ensure that investments are directed to non- or low-polluting production sectors. Third, governments must finance all efforts seeking the ecological transition through subsidized and reasonable interest rates.

Authors contributions: Conceptualization, IF and MG; methodology, MA and AJ; software, MG; validation, MA, IF and MG; formal analysis, AJ; investigation, IF; resources, MA; data curation, MG; writing—original draft preparation, IF; writing—

review and editing, MA; visualization, AJ; supervision, IF; project administration, IF; funding acquisition, IF. All authors have read and agreed to the published version of the manuscript.

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References

Abonazel, M. R., & Abd-Elftah, A. I. (2019). Forecasting Egyptian GDP using ARIMA models. Reports on Economics and Finance, 5(1), 35–47. https://doi.org/10.12988/ref.2019.81023

Bayon, D. (2010). Poverty, social inequality and market statism (French). Mouvements, 64(4), 71–78. https://doi.org/10.3917/mouv.064.0071

Daly, H. (2023). The Steady-State Economy: Alternatives to Growthmania. The Earthscan Reader in Sustainable Development, 331–342. https://doi.org/10.4324/9781003403432-49

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association, 74(366a), 427–431. https://doi.org/10.1080/01621459.1979.10482531

Dittmer, K. (2013). Local currencies for purposive degrowth? A quality check of some proposals for changing money-as-usual. Journal of Cleaner Production, 54, 3–13. https://doi.org/10.1016/j.jclepro.2013.03.044

Dongdong, W. (2010). The Consumer Price Index Forecast Based on ARIMA Model. 2010 WASE International Conference on Information Engineering. https://doi.org/10.1109/icie.2010.79

Ediger, V. Ş., & Akar, S. (2007). ARIMA forecasting of primary energy demand by fuel in Turkey. Energy Policy, 35(3), 1701–1708. https://doi.org/10.1016/j.enpol.2006.05.009

Jackson, T. (2009). Prosperity without Growth. Routledge. https://doi.org/10.4324/9781849774338

Kenny, G., Meyler, A., & Quinn, T. (1998). Forecasting Irish inflation using ARIMA models (No. 3/RT/98). Central Bank of Ireland.

Kharimah, F., Usman, M., Elfaki, W., & Elfaki, F. A. M. (2015). Time Series Modelling and Forecasting of the Consumer Price Bandar Lampung. Science International (Lahore), 27(5), 4119–4624.

Kiriakidis, M., & Kargas, A. (2013). Greek GDP forecast estimates. Applied Economics Letters, 20(8), 767–772. https://doi.org/10.1080/13504851.2012.744128

Meyler, A., Kenny, G., & Quinn, T. (1998). Forecasting Irish Inflation using ARIMA models. Research and Publications Department, Central Bank of Ireland.

Mills, T. (1990). Time Series Techniques for Economists. Cambridge University Press.

Napari, A., Özcan, R., & Khan, A. U. I. (2023). The language of sustainability: Exploring the implications of metaphors on environmental action and finance. Applied Ecology and Environmental Research, 21(5).

Nyoni, T. (2019). ARIMA modeling and forecasting of Consumer Price Index (CPI) in Germany. MPRA Paper No. 92442.

Nyoni, T., & Nathaniel, S. P. (2019). Modeling Rates of Inflation in Nigeria: An Application of ARMA, ARIMA and GARCH models. Paper No. 91351. Munich University Library.

Nyoni, T., Mutongi, C. (2019). Modeling and forecasting carbon dioxide emissions in China using Autoregressive Integrated Moving Average (ARIMA) models. 2019. MPRA Paper No. 93984.

Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335–346. https://doi.org/10.1093/biomet/75.2.335

Sammy Wabomba, M. (2016). Modeling and Forecasting Kenyan GDP Using Autoregressive Integrated Moving Average (ARIMA) Models. Science Journal of Applied Mathematics and Statistics, 4(2), 64. https://doi.org/10.11648/j.sjams.20160402.18

Schneider, F., Kallis, G., & Martinez-Alier, J. (2010). Crisis or opportunity? Economic degrowth for social equity and ecological sustainability. Introduction to this special issue. Journal of Cleaner Production, 18(6), 511–518. https://doi.org/10.1016/j.jclepro.2010.01.014

Sekulova, F., Kallis, G., Rodríguez-Labajos, B., et al. (2013). Degrowth: from theory to practice. Journal of Cleaner Production, 38, 1–6. https://doi.org/10.1016/j.jclepro.2012.06.022

van den Bergh, J. C. J. M., & Kallis, G. (2012). Growth, A-Growth or Degrowth to Stay within Planetary Boundaries? Journal of Economic Issues, 46(4), 909–920. https://doi.org/10.2753/jei0021-3624460404

Victor, P. A. (2008). Managing without growth: Slower by Design, Not Disaster. Edward Elgar.

Victor, P. A. (2009). Herman Daly and the steady-state economy. Available online: http://www.eoearth.org/article/Herman_Daly_Festschrift:_Herman_Daly_and_the_Steady_State_Economy2009 (accessed on 13 May 2023).

Appendix

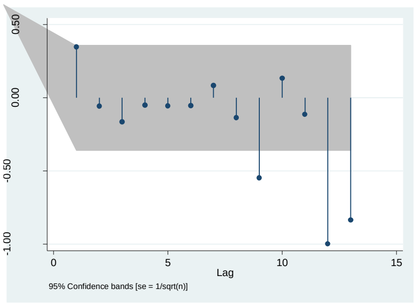


Figure A1. Determination of p from the ARIMA model of the GDP variable.

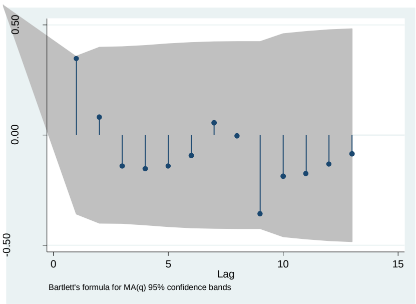


Figure A2. Determination of q from the ARIMA model of the GDP variable.

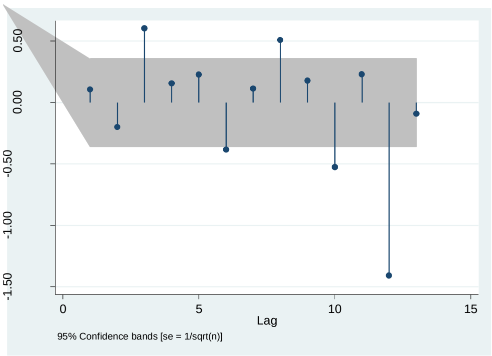


Figure A3. Determination of p from the ARIMA model of the CO_2 variable.

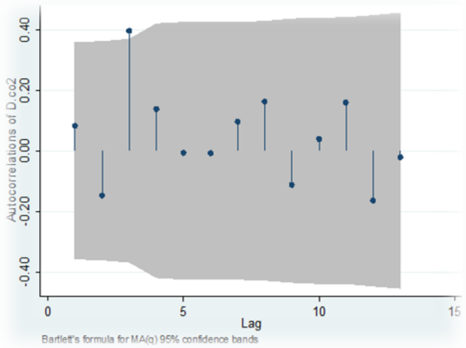


Figure A4. Determination of q from the ARIMA model of the CO_2 variable.

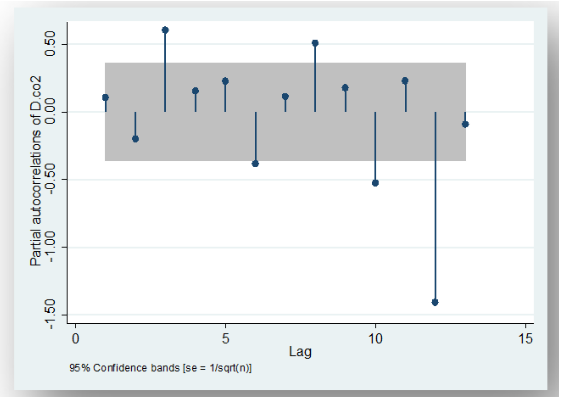


Figure A5. Determination of p from the ARIMA model of the ENERGY variable.

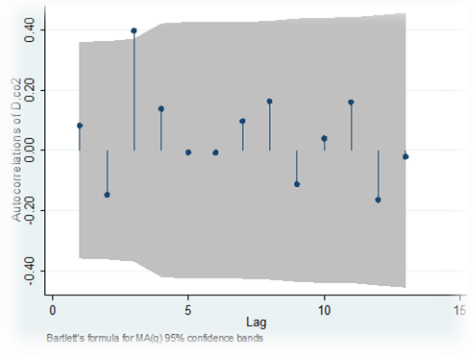


Figure A6: Determination of q from the ARIMA model of the ENERGY variable

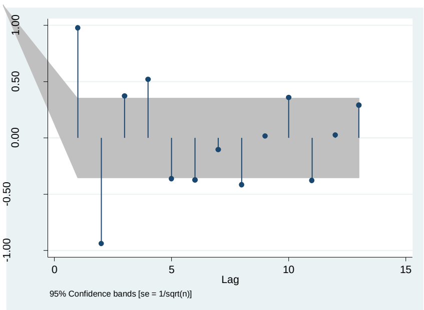


Figure A7. Determination of p ARIMA model of POP variable.

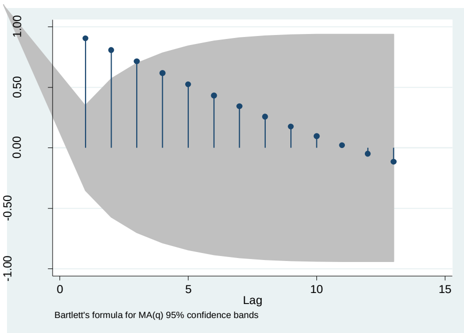


Figure A8. Determination of q ARIMA Model of the variable POP.

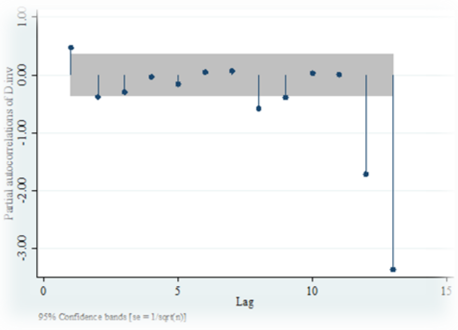


Figure A9. Determination of p ARIMA model of the variable INV.

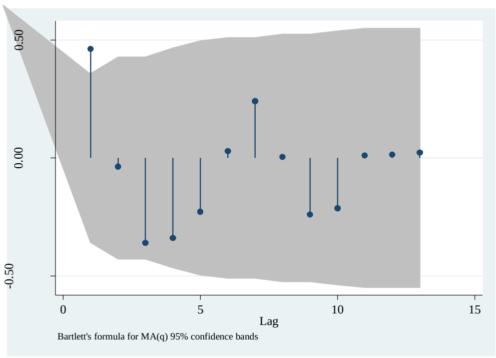


Figure A10. Determination of q ARIMA model of the variable INV.

Estimation of all possible models and identification of the best.

Table A1. Stationarity graphics of the variables CO$_2$, GDP, ENERGIE and population.

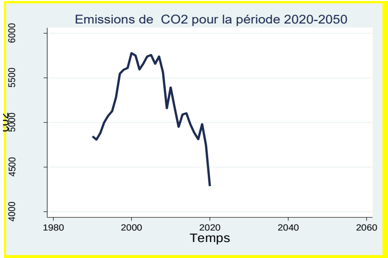
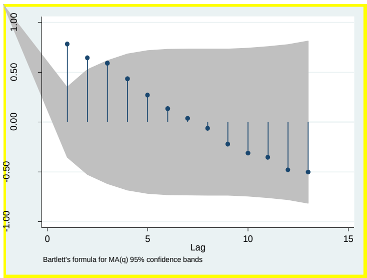
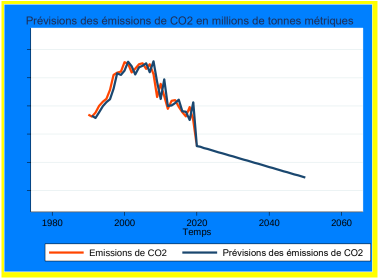
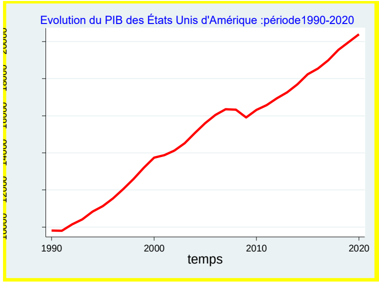
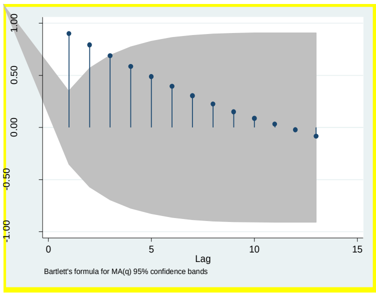
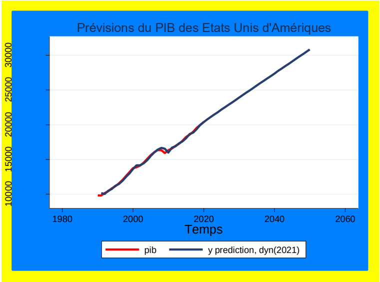
	Graphics analysis	The correlogram	Graphics and forecasts
CO$_2$			
GDP			

Table A1. (*Continued*).

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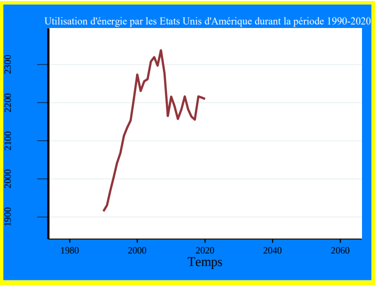
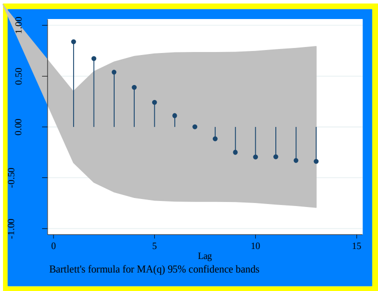
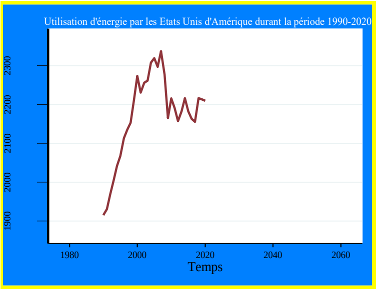
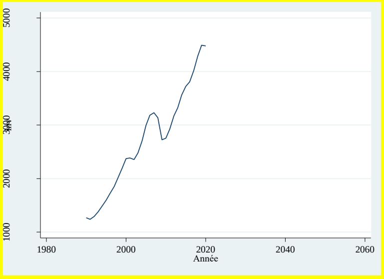
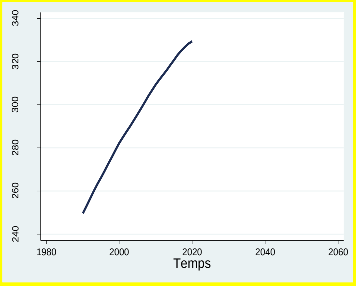
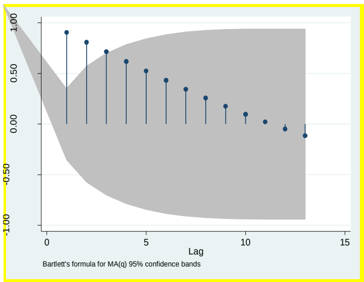
<tr><td>Energy</td><td> </td><td> </td><td> </td></tr>
<tr><td>Investment</td><td> </td><td></td><td></td></tr>
<tr><td>Population</td><td> </td><td> </td><td></td></tr>
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Table A2. Results of estimated models of the variable GDP.

Variable GDP	Model A Arima (1, 1, 0)	Model B Arima (2, 1, 0)	Model C Arima (3, 1, 0)
Constant	347.4265*** (75.693)	347.9944*** (73.088)	348.8107*** (65.900)
AR			
AR (1)	0.3743325*** (0.12307)	0.3981672*** (0.1623181)	0.3803524** (0.1597983)
AR (2)	-	−0.0609249 (0.2560898)	0.0111812 (0.3040291)
AR (3)	-	-	−0.1727292 (0.3752106)

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

Table A3. Identification of the best model of the variable GDP.

Criteria	Model A	Model B	Model C	Choice of the best
	Arima (1,1,0)	**Arima (2,1,0)**	**Arima (3,1,0)**	**A is the best**
Constant coefficients, AR et MA	2/2	2/3	2/4	A
Sigma^2	193.7884	193.4464	190.3903	C
Log likelihood	−200.6468	−200.5939	-200.1682	C
Akaike information criterion (AIC)	407.2936	409.1878	410.3363	A
Bayesian information criterion (BIC)	411.4972	414.7926	417.3423	A

Table A4. Results of estimated models of the variable CO_2.

Variable CO_2	**Model A** **Arima (1, 1, 1)**	**Model B** **Arima (2, 1, 1)**	**Model C** **Arima (3, 1, 1)**	**Model D** **Arima (4, 1, 1)**	**Model E** **Arima (5, 1, 1)**
Constant	−18.6883 (37.76444)	15.05705 (31.78968)	24.05485 (75.27994)	−23.99676 (77.08608)	−22.64628 (86.26908)
AR AR (1)	−0.5946813** (0.2806151)	−0.590955** (0.2608665)	0.3129212 (0.4386938)	0.3242594 (2.06774)	−0.4615466 (0.6757128)
AR (2)	-	−0.259251 (0.300945)	−0.2092743 (0.183609)	−0.2108694 (0.275284)	−0.2732202 (0.251975)
AR (3)	-	-	0.5725835 (0.3082018)	0.5751041 (0.5231869)	0.4736158 (0.3681716)
AR (4)	-	-	-	−0.0069173 (1.246645)	0.3792763 (0.4544768)
AR (5)	-	-	-	-	0.2994086 (0.310064)
MA MA (1)	0.9189135*** (0.1998329)	1.257264*** (0.3481436)	−0.2463355 (0.4907517)	−0.257053 (2.04292)	0.5321013 (0.6567057)

* indicates significance at the 10% level; **indicates significance at the 5% level; *** indicates significance at the 1% level.

Table A5. Identification of the best ARIMA model of the variable CO_2.

Criteria	**Model A**	**Model B**	**Model C**	**Model E**	**Model F**	**The best**
	Arima (1, 1, 1)	**Arima (2, 1, 1)**	**Arima (3, 1, 1)**	**Arima (4, 1, 1)**	**Arima (5, 1, 1)**	**A is the best**
Constant Coefficients, AR and MA	2/3	2/4	0/5	0/6	0/7	A
$Sigma^2$	158.2202	123.4585	144.3373	144.3504	138.978	B
Log likelihood	−194.8438	−194.2428	−192.3297	−192.3296	−191.3971	E
Akaike information criterion (AIC)	397.6876	398.4855	396.6594	398.6592	398.7943	C
Bayesian information criterion (BIC)	403.2924	405.4915	405.0666	408.4676	410.0038	A

Table A6. Estimation of all possible models and identification of the best for the variable Energy.

Criteria	**Model A**	**Model B**	**Model C**	**Model D**	**The best**
	Arima (1, 1, 1) **Sans constante**	**Arima (2, 1, 1)** **Sans constante**	**Arima (3, 1, 1)** **Sans constante**	**Arima (4, 1, 1)** **Sans constante**	**A is the best**
Constant Coefficients, AR and MA	2/2	0/3	0/4	0/5	A
$Sigma^2$	39.70734	39.85454	36.99589	36.99559	E
Log likelihood	−153.0764	−153.1658	−151.1629	−151.1628	E
Akaike information criterion (AIC)	312.1528	314.3316	312.3259	314.3256	A
Bayesian information criterion (BIC)	316.3564	319.9364	319.3319	322.7328	A

Estimation of all possible models and identification of the best for the variable population.

Table A7. Resultats of estmated ARIMA models of the variable population.

Variable POP	**Model A Arima(1,0,1)**	**Model B Arima(2,0,1)**	**Model C Arima(3,0,1)**	**Model D Arima(4,0,1)**	**Model E Arima(1,0,2)**	**Model F Arima(2,0,2)**	**Model G Arima(3,0,2)**	**Model H Arima(4,0,2)**
Constant	289.42 *** (39.74232)	265.78*** (22.149)	-	270.942*** (22.530)	288.42*** (27.60955)	274.54*** (27.609)	271.37*** (24.257)	270.87*** (23.513)
AR AR (1)	0.997 *** (0.02759)	1.9949*** (22.1497)		1.703 *** (0.459655)	0.9974*** (0.0265)	1.9899*** (0.01402)	1.3469*** (0.174181)	1.5170*** (0.3589)
AR (2)	-	−0.9975*** (0.00431)	-	0.0088637 (0.915881)	-	−0.9933*** (0.0134)	0.2912805 (0.3482)	0.0148143 (0.53523)
AR (3)	-	-	-	−1.14359 (0.66915)	-		-0.643266 (0.174425)	−0.598365 (0.547479)
AR (4)	-	-	-	0.4281261 (0.28433)	-		-	0.062224 (0.366805)
MA	-	-	-		-		-	
MA (1)	-	-	-	0.5626136 (0.55595)	1.765955 *** (0.0888922)	0.73238*** (0.2522)	1.229383 (0.119913)	0.89179*** (0.276406)
MA (2)	-	-	-		0.9999998 -	1.33867*** (0.441147)	1.000006 -	0.70819*** (0.248062)

Table A8. The choice of the best ARIMA model.

Criteria	**A**	**B**	**C**	**D**	**E**
	Arima(1,0,1)	**Arima(2,0,1)**	**Arima(3,0,1)**	**Arima(4,0,1)**	**Arima(1,0,2)**
Constant Coefficients, AR and MA	2/3	3/4	-	2/6	3/4
Sigma^2	1.397669	0.1452985	-	0.1345191	0.0027253
Log likelihood	−59.43783	7.190644	-	9.328213	131.6098
Akaike information criterion (AIC)	124.8757	−4.381287	-	−4.656426	−255.2196
Bayesian information criterion (BIC)	129.1776	2.788649	-	5.381484	−249.4836

Table A9. The choice of the best ARIMA model.

Criteria	**F**	**G**	**H**	**The best**
	Arima(2,0,2)	**Arima(3,0,2)**	**Arima(4,0,2)**	**F is the best**
Constant Coefficients, AR and MA	5/5	4/6	4/7	F
Sigma^2	0.0003242	0.0004121	0.000412	F
Log likelihood	187.0891	187.6975	187.7056	H
Akaike information criterion (AIC)	−362.1781	−361.395	−359.4111	F
Bayesian information criterion (BIC)	−353.5742	−351.3571	−347.9392	F