# The impacts of COVID-19 on the energy sector: economics & sustainability

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## Abstract

The COVID-19 pandemic has been developing into one of the most severe challenges that Humankind has faced. The disruption of supply chains, the decrease in industrial productivity, the health crisis, among other factors, have mercilessly created a global crisis. However, the emergency measures adopted by governments, firms, and individuals in response to the threatening virus have driven a series of political, economic, and social changes with the potential to influence a sustainable energy transition. That is what this dissertation aims to analyze, through studying the influence of several independent variables (GDP, Energy Consumption, Oil Prices, Energy Trade Balance, and $CO_2$ emissions) on the behavior of renewable energy consumption (REC), for a panel data formed by five developed countries: Germany, Spain, Portugal, United States of America and Japan. We will apply a time-series Vector Error Correction Model (VECM) supported by stationarity, cointegration, stability, and Granger Causality tests, for two different periods: the first period between 1980 and 2019 (excluding COVID-19) and the second period between 1982 and 2021 (including COVID-19), in order to do a comparative analysis and investigate the impact of the pandemic. The results obtained from the VECM estimations and Granger Causality testing proved that not only the REC can be explained by the independent variables, especially oil prices, $CO_2$ emissions, and energy consumption, that showed a high significance level, but also that there is a relationship, both in the short and in the long run, between variables. We also concluded, through some graphical representations of a deterministic simulation of the model, obtained from the EViews software, that COVID-19 increased the pace of energy transition.

**Keywords:** COVID-19, Energy sector, Energy Impacts, Renewables, Sustainable Energy Transition, Vector Error Correction Model (VECM)

## 1. Introduction

In December 2019 in Wuhan, Hubei province, China, the first cases of what would become one of the greatest pandemics that humanity has ever known were recorded. In just a few months it went from a local outbreak to a worldwide concern that changed not only our routines and habits but, consequently, the economic and political systems (Platto et al., 2020)

Through a more scientific analysis, COVID-19, being a member of the Coronaviridae family, is an RNA virus (nucleic acid) being characterized by its easy propagation and propensity to genetic alterations (mutations). With a higher incidence in mammals, it is responsible for generating mainly respiratory problems and consequently the weakening of the immune system (Platto et al., 2020). In order to stop the spread of the viral situation, certain social measures and restrictions were applied almost immediately: avoid confined areas (for example, elevators), avoid use the of public transport, agglomerations, always keep a distance of 2 meters from other people and use masks; every work and school meeting was converted from physical to virtual through video chat applications (Baghchechi et al., 2020).

The pandemic has led to a dramatic loss of human lives worldwide. From the beginning of 2020 to the of September 2021, 240 million cases were reported, with a respective mortality rate of around 2.2%.

With the set of measures mentioned and many others, such as the quarantine state for most countries, with the disruption of supply chains and reduced labor productivity (Ibn-Mohammed et al., 2021), the majority of the sectors suffered great losses (Madurai Elavarasan et al., 2020):

- The global stock market collapsed by more than 25% in March 2020, as a result of the ongoing lockdown, which might lead to a global economic recession. The COVID-19 pandemic was expected to cost the global economy about $1 trillion in 2020 (Kabir et al., 2020).
- The international oil price fell to its lowest level since 2003 in March 2020, as a result of the combined effect of COVID-19-related demand drop and market issues among Saudi Arabia, the United States, and Russia.

- More than 91 percent of enrolled students have been impacted by the closing of educational institutes worldwide. However, several schools, colleges, and universities have turned to online classes to continue their education, which has affected power structures.
- Since most governments and organizations around the world are focusing their efforts and resources on combating COVID, there is a possibility of delay or reduction in funding of several research activities such as renewable energy projects or initiatives.
- The transportation sector has been severely impacted by COVID-19, with the aviation industry bearing the brunt of the damage. Since the aviation industry was paralyzed, all airport-related services were halted, resulting in a significant drop in electricity demand.
- The use of public transport has been dropped as much as 80% to 90% in major cities in China and in the United States of America (UITP, 2020).
- The strict lockdown halted manufacturing operations due to a shortage of manpower and restricted business due to a travel ban as well. Much of this has indirectly helped in the reduction of emissions from the industrial sector, which has a positive impact on the environment.

So, the pandemic has had a significant impact on many sectors, including agriculture, manufacturing, finance, education, healthcare, sports, tourism, and food. Since the energy industry is a driving force in the economy, it is not immune to these influences (Jiang et al., 2021).

According to International Energy Agency (IEA) statistics and projection data[1], the 2020 energy demand shock was expected to be the largest in the last 70 years. Global energy demand fell by around 6% in 2020 compared to 2019, a drop seven times greater than during the 2009 financial crisis.

COVID-19 has changed the strategic and economic direction of many governments. The magnitude of the epidemic, combined with the government's ability to react to the virus and its economic effects, influences the type and structure of significant economic stimulus initiatives in any given country. These stimulus decisions, in turn, can have an unexpected impact on the speed and trajectory of energy transitions (Dewar et al., 2020).

## 2. Literature Review

### *2.1. COVID-19 impacts*

#### *2.2.1 Socioeconomic domain*

In terms of incidence, the pandemic has shown itself to be transversal to all social segments. However, it is clear that it affects more critically groups with greater social vulnerability, including people living in poverty, with poor hygiene conditions, people with physiological disabilities, the elderly, indigenous peoples and ethnic minorities (Mofijur et al., 2021).

The majority of the measures applied by the different countries to avoid the spread of the virus came to affect the development of the global economy. An example was the implementation of a confinement model, which, when possible, forced people to be guided by a telework system ((Jiang et al., 2021), closing the workplaces, resulting in an immediate disruption in supply chains and a reduction in productivity. Several governments also opted to close the borders, both land, air and sea, compromising the normal functioning of the international trade market. The discouragement of social agglomerations and the use of shared services has also created several adversities for the sectors that benefit from these two characteristics. Exemplifying with the areas of the public sector, commerce, culture and especially tourism that had the greatest reduction in its activity ever (Fernandes, 2020; Mofijur et al., 2021), the recorded reduction was around 90% (transportation, accommodation, hospitality services and travel agencies). This is a substantial drop that represents a bad indicator for countries such as Greece, Portugal, Mexico and Spain, where these sectors directly represent more than 15% of the country's GDP (Fernandes, 2020).

It is clear that, with all these conditions, many people saw their incomes being squeezed and got unemployed (Anseel et al., 2021), where around 255 million people lost their full-time jobs due to the pandemic.

#### *2.2.2 Energy domain*

During the lockdown, with limited restrictions imposed by governments, the reduction in many activities, e.g. mobility, economic activity, construction and manufacturing, reduced global energy demand. According to data from July 2020, compared to the same period in 2019, some countries such as France, UK, Italy, Germany, Spain, China and India saw a reduction of electricity demand above 10% during the lockdown[2].

To date, from both macro and micro scales the demand changes are highlighted as follows:

- Short-term demand decreases when lockdowns are enforced (Mofijur et al., 2021), but demand is expected to rebound steadily after relaxing lockdown measure

1 See https://www.iea.org/reports/global-energy-review-2020 (accessed on February 2021)

2 See https://www.iea.org/reports/COVID-19-impact-on-electricity (Accessed on February 2021)

- Industrial and commercial demands decrease while residential demand increases (a maximum of 66% in March of 2020 compared to the previous years) (Madurai Elavarasan et al., 2020), as a result of the lockdown that forced people to spend more time at home than usual.
- Renewable energy demand increases while fossil energy declines
- The energy consumption for producing standard products (i.e. clothes and travel necessities) declines but for producing medical products and personal protective equipment increases (Klemes et al., 2020)
- The consumption of energy on private cars and public buses declines during the lockdown (Sui et al., 2020)
- The peak-time for electricity demand also changes during the week (Abu-rayash & Dincer, 2020)

The COVID-19 outbreak has also exacerbated the problems of energy poverty. With most countries having implemented measures to stop the spread of the virus, they force people to stay at home, and as such many of them have had a double effect:

- Residential consumption raised due to both augmented conventional demand (space heating, hot water, cooking and dishwashing) and new energy demand (as the one related to teleworking).
- The confinement, or the associated measures, provoked a strong contraction in the job market and many people lost their employment, either temporarily or permanently, seeing their income abruptly decline.

This confluence of circumstances plainly aggravates the traditional challenges associated with energy poverty, by making it more difficult to pay energy bills and by exacerbating the discomfort of living in households with inadequate levels of critical energy services. Several governments have included particular provisions in emergency acts enacted during the epidemic to combat COVID-19 induced energy poverty. The most widespread intervention was the postponement of any supply disconnection in case of non-payment[3].

In Africa, the situation is slowly getting worse with the outbreak. As said before, since 2010, the number of Africans without access to electricity has been rapidly reducing. However, the pandemic has put this progress into reverse, with the number of those lacking electricity rising to more than 590 million people in 2020, an increase of 13 million people, or 2%, compared to the last year[4].

There are various underlying causes for this, where the most important of which is a scarcity of available financial resources for governments, the private sector, and individual households. Because of the health crisis, governments' immediate priorities have shifted to purely emergency measures, resulting in a lack of available funding to expand and improve electricity infrastructure. In Uganda, for example, governmental subsidies for the electricity access program have been suspended, while authorities in South Africa have been forced to transfer funds to health and welfare programs and facilities at the expense of expanding rural electrification[7].

### *2.2.3 Oil production and prices*

The COVID-19 pandemic is an unprecedented shock for the global oil industry. Oil prices have crashed due to the sharp drop in oil demand, largely driven by the fall in the global transportation market (Hauser et al., 2020). Several factors that influence the price variation, starting with the demand drop, a consequence of the closure of many businesses and the lockdowns that resulted in oil demand falling from 100 to 73 million barrels per day in April of 2020. Then, the lack of storage space, that with the excess of supply filled some crude storage facilities. This lack of storage and pipeline transmission capacity has driven up the cost of storage. Reducing also, the supply by temporarily plugging off wells is a complex operation with a strong effect on the health of reservoirs, besides being costly.

So, the COVID-19 pandemic proved that the oil market is fragile and volatile. The drop in demand, coupled with an unexpected increase in supply, led to a collapse in crude oil prices and subsequent impacts on prices for refined petroleum products and other downstream items, notably gasoline.

As a result, companies paid traders to take oil off their hands, since this is a cheaper solution for some of them in the long run than closing down production or finding a place to store the product out of the ground in April 2020, the market saw an unforgettable moment in its history: the U.S. benchmark price for crude dropped below zero for the first time[5].

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[3] See https://fsr.eui.eu/measures-to-tackle-the-covid-19-outbreak-impact-on-energy-poverty/ (Accessed on August 2021)

[4] See https://www.iea.org/articles/the-covid-19-crisis-is-reversing-progress-on-energy-access-in-africa (Accessed on July 2021)

[5] See https://www.bloomberg.com/news/articles/2020-04-20/negative-prices-for-oil-here-s-what-that- means-quicktake (Accessed on March 2021)

*2.2.4 Energy Transition*

Although the COVID-19 pandemic has had a profound impact on society and the economy, it has also aided in the recovery of some environmental damage. With the implementation of full and partial lockdowns and strict measures by many governments, Greenhouse gas emissions (GHG), nitrogen (NO2), noise pollution, water pollution and the waste on beaches have been reduced significantly (Chakraborty & Maity, 2020; Somani et al., 2020; Zambrano-Monserrate et al., 2020). Such regulations have helped countries reduce their emissions and improving air quality and overall quality of life.
In spite of that, once the restrictions are lifted, economic activity and energy demand are expected to return to normal, as large-scale industrial operations will be resumed, the energy consumption and GHG emissions will increase and will likely exceed the cap set during the lockdown (Wang & Su, 2020).
Due to the growing amount of domestic and medical waste that can be toxic and potentially spread diseases to others if not properly handled, such containments may have negative environmental implications. For example, household waste has grown significantly as a result of the increase in online shopping and home delivery (Zambrano-Monserrate et al., 2020).
Many of these environmental impacts are expected to be short-term. So, it is a crucial time for a long-term plan and sustainable environmental management to be put in place. The COVID-19 pandemic triggered a global response and brought us together to win against the virus. Similarly, in order to defend the planet, the unified efforts of governments and international institutions should be imperative and proactive (Somani et al., 2020).

## 3. Data and Methodology

Before starting data analysis, it is important to understand how we are going to explore this topic. As Covid-19 is a fairly new topic, it is not clear the impact of this shock on the future for energy transition as we have few observations after the pandemic year.
Therefore, for this reason, we decided to run the different econometric procedures for two distinct periods, in order to compare both and present some conclusions:

- First period: between 1980 and 2019 (excluding Covid-19 impact)
- Second period: between 1982 and 2021 (including Covid-19 impact)

### *2.2. Data*

It was used annual data for a set of five countries (Spain, Germany, Portugal, United States and Japan), all of them with open economies that have not only taken an important step in the adoption of renewable solutions in the last decades, but also have ambitious plans for energy transition, to contribute to the reduction of polluting gas emissions and thus satisfy the goals proposed by the Paris Agreement in 2015.
The study explores the interaction among the dependent variable, which is Renewable Energy Consumption (REC) and is measured by the percentage contribution of renewables to total energy generation, and all the independent variables: Crude Oil Prices (Oilprices), in US$; Energy Trade Balance (ETrade), in koe; Energy Consumption per capita (EUse), in kWh; $CO_2$ Emissions per capita ($CO_2$); and Gross Domestic Product per capita (GDP), in constant 2010US$. All of the independent variables were lagged by one year to avoid simultaneity since the present value of the dependent variable depends on the past values of the explanatory variables.
After some failed individual tests for each country, with poor statistical results, it was decided to convert the data sample to a panel data format. Panel data contains more information, greater variability of data, less collinearity between the variables, a higher number of degrees of freedom, and more efficiency in the estimates (Marques et al., 2010).
For REC, EUse, and $CO_2$ data was exported from the World in Data platform, for OilPrices and Etrade was extracted from the Energy International Agency (EIA), and, finally, for GDP was obtained from the World Bank.. However, due to the lack of recent data, that characterizes the post-Covid term in the second period, we had to proceed with interpolation techniques and comparative analysis with similar variables that already have the data for the recent years.
Regarding descriptive statistics, for the first period, the average value of renewable energy consumption was 8.37% of the total energy generated, with a maximum of 29.067% in 2015 in Portugal. Concerning the second period, there was an increase of around 0.7 p.p, regarding the dependent variable, which shows that the changes in the period had a positive mark on the growth of the share of renewable energy consumption, and Its maximum value rose to 29.132% of renewable energy consumption, having been recorded also in Portugal in 2020, which shows the effort made by the government and Portuguese companies in the last decades, a reference in the sustainable green transition.

### *3.2. Methodology*

The main objective of this research was to assess the impact of Covid-19 on the growth of the share of renewable sources in energy generation and the path to an energy transition and, therefore, a model that

explains the behavior of REC through the set of independent variables was applied. All tests and estimations were performed on EViews software.
For both models, it was performed not only the Augmented Dickey-Fuller tests (Unit Root Test), where it was concluded that all variables were stationary in the first order, requiring the application of the first differences method, but also the Pedroni panel cointegration test, which characterized the variables as cointegrated, since for the first period seven, and for the second period nine of the eleven outputs reject the null hypothesis (Table 1), where there is no long-run relationship between variables. According to these results, the best model to apply was the vector error correction model (VECM) in order to evaluate the short-run properties of the series. VECM is a restricted vector autoregressive model (VAR), that adds error correction features to this multi-factor model, designed to use with non-stationary series at level, and known to be cointegrated (Asari et al., 2011).
The regression equation form for VECM is as follows (Equation 1 and 2) (Asari et al., 2011):

$$\Delta Y_t = \alpha_1 + p_1 e_1 + \sum_{i=0}^{n} \beta_i \Delta Y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta X_{t-i} + \sum_{i=0}^{n} \gamma_i Z_{t-i} \quad (1)$$

$$\Delta X_t = \alpha_2 + p_2 e_{i-1} + \sum_{i=0}^{n} \beta_i Y_{t-i} + \sum_{i=0}^{n} \delta_i X_{t-i} + \sum_{i=0}^{n} \gamma_i Z_{t-i} \quad (2)$$

| | Statistic | Probability | Weighted Statistic | Probability |
|---|---|---|---|---|
| **Panel v-Statistic** | 2.251<br>**3.082** | 0.012<br>**0.001** | 0.553<br>**1.788** | 0.290<br>**0.037** |
| **Panel rho-Statistic** | - 1.587<br>**- 5.236** | 0.056<br>**0.000** | - 0.285<br>**- 2.502** | 0.388<br>**0.006** |
| **Panel PP-Statistic** | - 6.767<br>**- 11.026** | 0.000<br>**0.000** | - 2.694<br>**- 5.537** | 0.004<br>**0.004** |
| **Panel ADF-Statistic** | - 6.757<br>**- 5.957** | 0.000<br>**0.000** | - 2.920<br>**- 1.666** | 0.002<br>**0.002** |
| **Group rho-statistic** | - 0.315<br>**- 0.315** | 0.376<br>**0.376** | -<br>**-** | -<br>**-** |
| **Group PP-Statistic** | - 4.821<br>**- 4.821** | 0.000<br>**0.000** | -<br>**-** | -<br>**-** |
| **Group ADF-Statistic** | - 4.783<br>**- 4.783** | 0.000<br>**0.000** | -<br>**-** | -<br>**-** |

*Table 1 – Pedroni cointegration test for the period 1980-2019 and 1982-2021* ***(in bold)***

The last preliminary step was the lag order selection, which is a crucial standard step of the VECM model procedure (Winker & Maringer, 2005). The results for both periods are presented in Table 2.

| Lag | FPE | AIC | SC | HQ |
|---|---|---|---|---|
| **0** | 1.00e+30<br>**1.94e+30** | 86.105<br>**86.766** | 86.220<br>**86.881** | 86.152<br>**86.812** |
| **1** | 9.90e+21<br>**2.24e+22** | 67.674<br>**68.488** | 68.481*<br>**69.296** | 68.002<br>**68.816** |
| **2** | 5.28e+21<br>**1.03e+22** | 67.044<br>**67.709** | 68.543<br>**69.209*** | 67.653*<br>**68.318*** |
| **3** | 4.21e+21*<br>**8.29e+21*** | 66.823*<br>**67.490*** | 69.004<br>**69.681** | 67.602<br>**68.380** |

*Table 2 – Lag order selection criteria for the period 1980-2019 and 1982-2021* ***(in bold)***

## 4. Results and Discussion

The Johansen cointegration test was used for the cointegration analysis. More specifically, the validity of a cointegrating relationship is evaluated by employing a maximum likelihood estimates (MLE) approach, a probabilistic framework for automatically finding the probability distribution and parameters that best describe the observed data. There are two variants of Johansen's tests: one that utilizes a trace (from linear algebra), and the other that employs the maximum eigenvalue technique (an eigenvalue is a particular scalar) (Johansen & Juselius, 1990). Both tests indicates one cointegration equation at the 0.05 level (Tables 3 and 4).

| Hypothesized No. of CE(s) | Eigenvalue | Trace Statistic | 0.05 Critical Value | Prob. |
|---|---|---|---|---|
| **None*** | 0.273<br>**0.247** | 110.998<br>**110.478** | 95.754<br>**95.754** | 0.003<br>**0.003** |
| **At most 1** | 0.142<br>**0.151** | 53.544<br>**59.324** | 69.819<br>**69.819** | 0.481<br>**0.257** |
| **At most 2** | 0.073<br>**0.075** | 25.961<br>**29.835** | 47.856<br>**47.856** | 0.891<br>**0.727** |
| **At most 3** | 0.034<br>**0.049** | 12.348<br>**15.866** | 29.797<br>**29.797** | 0.919<br>**0.722** |
| **At most 4** | 0.033<br>**0.032** | 6.680<br>**6.808** | 15.494<br>**15.494** | 0.674<br>**0.600** |
| **At most 5** | 0.001<br>**0.006** | 0.131<br>**0.993** | 3.841<br>**3.841** | 0.717<br>**0.319** |

*Table 3 – Unrestricted Cointegration Rank Test (Trace) for the period 1980-2019 and 1982-2021* ***(in bold)***
**denotes rejection of the hypothesis at the 0.05 level*

| Hypothesized No. of CE(s) | Eigenvalue | Max-Eigen Statistic | 0.05 Critical Value | Prob. |
|---|---|---|---|---|
| **None*** | 0.273<br>**0.247** | 57.454<br>**51.153** | 40.078<br>**40.078** | 0.000<br>**0.002** |
| **At most 1** | 0.142<br>**0.151** | 27.583<br>**29.489** | 33.877<br>**33.877** | 0.233<br>**0.233** |
| **At most 2** | 0.073<br>**0.075** | 13.613<br>**13.970** | 27.584<br>**27.584** | 0.848<br>**0.848** |
| **At most 3** | 0.034<br>**0.049** | 6.168<br>**9.057** | 21.131<br>**21.131** | 0.979<br>**0.979** |
| **At most 4** | 0.033<br>**0.031** | 6.048<br>**5.814** | 14.265<br>**14.265** | 0.607<br>**0.607** |
| **At most 5** | 0.001<br>**0.005** | 0.131<br>**0.994** | 3.841<br>**3.841** | 0.717<br>**0.717** |

*Table 4 – Unrestricted Cointegration Rank Test (Maximum Eigenvalue) for the period 1980-2019 and 1982-2021* ***(in bold)***
**denotes rejection of the hypothesis at the 0.05 level*

The results from Roots of Characteristic Polynomial (Figure 1a and 1b) above, which is also a model checking test, shows that the VECM models satisfies stability conditions since all the roots lie inside the unit circle.

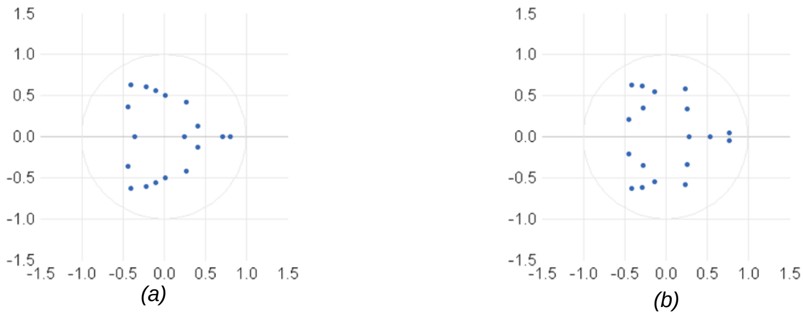


*Figure 1 – Inverse Roots of Autoregressive (AR) Characteristic Polynomial (a) for the period 1980-2019; (b) for the period 1982-2021*

The following normalized Equations 3 and 4 present the long-run relationships between the dependent and independent variables, considering a 5% significance level:

**1980 - 2019:** $REC = 3.345OilPrices + 0.001GDP – 0.007EUse – 6.800E\text{-}05ETrade + 31.438CO_2$

($t$-value = 7.761) ($t$-value = 0.500) ($t$-value = 2.333) ($t$-value = 0.680) ($t$-value = 2.174) (3)

**1982 – 2021:** $REC = 3.017OilPrices + 0.004GDP – 0.008EUse – 1.410E\text{-}04ETrade + 38.084CO_2$ (4)

($t$-value = 6.872) ($t$-value = 0.260) ($t$-value = 2.667) ($t$-value = 0.1410) ($t$-value = 2.695)

For both periods considered, the impact of oil prices and per capita $CO_2$ emissions on renewable energy consumption is positive in the long run. Nevertheless, as probably expected, the oil prices' impact is stronger before the pandemic than in the period up to 2021, possibly due to the slowdown or even lockdown of economic activity and consequent lower need of fossil fuel utilization; accordingly, the GDP impact is significant (and positive) only in the long-run relationship including the pandemic. On the other hand, the impact of $CO_2$ is stronger in the sample which includes the period of the pandemic, a result in line with the fact that COVID-19 is eventually considered a turning point towards a more sustainable energy sector, where $CO_2$ emissions are increasingly seen as a critical factor for governments to develop "green" recovery packages and strategies. Energy use impacts negatively renewable energy consumption, implying that total energy consumption decreases in the long-run (Dinç & Akdoğan, 2019) through the increase of energy efficiency. Finally, energy trade balance is nonsignificant.
The long-run relationship between the variables allows the development of VECM, which obviously incorporates the error correction term derived from the cointegration regressions and is thus targeted at determining the source of causality.
The error correction term (ECT) is given in the form of the following equation (Equation 5):

$$ECT_{t-1} = [Y_{t-1} - \eta_j X_{t-1} - \xi_m R_{t-1}] \tag{5}$$

In line with the data sample, we ended up with the error correction term presented in the equations below (Equations 6 and 7):

**1980 – 2019:** $ECT_{t-1} = [1.000\ REC_{t-1} - 0.053\ OilPrices_{t-1} + (3.000E\text{-}04)\ GDP_{t-1} - 0.001\ EUse_{t-1} - (5.690E\text{-}06)\ ETrade_{t-1} + 4.046\ CO2_{t-1} - 0.243]$ (6)

**1982 - 2021:** $ECT_{t-1} = [1.000\ REC_{t-1} - 0.019\ OilPrices_{t-1} + (4.710E\text{-}04)\ GDP_{t-1} - (6.270E\text{-}04)\ EUse_{t-1} - (1.370E\text{-}05)\ ETrade_{t-1} + 4.023\ CO2_{t-1} - 0.354]$ (7)

So the VECM equation (Equation 8) established is:

$$D(REC)_t = c + a_1D(REC)_{t-1} + a_2D(REC)_{t-2} + b_1D(OilPrices)_{t-1} + b_2D(OilPrices)_{t-2} + c_1D(GDP)_{t-1} + c_2D(GDP)_{t-2} + d_1D(EUse)_{t-1} + d_2D(EUse)_{t-2} + e_1D(ETrade)_{t-1} + e_2D(ETrade)_{t-2} + f_1D(CO2)_{t-1} + f_2D(CO2)_{t-2} + u_t \tag{8}$$

The first aspect that can be extracted from the comparative table of VECM estimations (Table 5) between the two periods is that the error correction term (ECT (-1)), which shows the size of the past imbalance, in both cases is not only negative, as it should be to converge in the long term, but also statistically significant. However, the weight differs. For the first period model, the ECT (-1) has a higher value and therefore indicates a higher speed of adjustment of any disequilibrium towards a long-run equilibrium state, which may be due to the fact that the pandemic created such a shock in the energy and economic system that, by including this period, it caused the speed of adjustment to decrease, either by the increase of adjustment costs or by the fact that the recovery of the system depends on something completely exogenous which made the system more inefficient, staying longer in an unbalanced state.
According to the results, it is possible to draw some conclusions regarding the relationship between the dependent and the explanatory variables. First, as mentioned before, an increase in $CO_2$ emissions seems to generate an increase in REC. As expected, this means that growing $CO_2$ emissions is one motivation to make renewable energy investments (Bayar et al., 2021), that tend to promote a progression towards an energy transition system. Secondly, there is a negative relationship between energy consumption per capita (EUse) and the dependent variable. If EUse decreases, due, for instance, to technology improvement and consequently the improvement of energy efficiency, REC seems to increase. Finally, regarding the variable oil prices, as was observed, a positive long-term relationship in the cointegration equation (Equation 8 and 9) and as, theoretically, an increase of crude oil prices should increase the growth of renewable energy consumption as an alternative source, a positive relationship was expected. However, the results from VECM estimations (Table 26) present a negative relationship, which may be due to the fact that the renewable energy sector economy has become increasingly competitive in recent years, allowing renewables to compete successfully with oil even while oil prices fluctuate around recent low levels (Kyritsis & Serletis, 2017; Tambari & Failler, 2020). The other two independent variables, GDP and ETrade, proved to be statistically nonsignificant for the two models.
Both models present some good statistical results, including the R-Squared (0.740 for the first period and 0.750 for the second period). Comparing one with the other, despite small variations and contrary to what might be expected, it was concluded that the model that includes the pandemic period is better at explaining the behavior of the dependent variable used. This can happen because there is only one of forty observations in the data sample, characterized by the Covid impact. Possible future research, with greater coverage of post-Covid data, may lead to different conclusions.

| | 1980 - 2019 | 1982 - 2021 |
|---|---|---|
| | D(REC) | D(REC) |
| **ECT(-1)** | - 1.480<br>[-7.562] | -1.449<br>[-6.396] |
| **D(REC(-1))** | 0.032<br>[0.235] | 0.018<br>[0.100] |
| **D(REC(-2))** | -0.242<br>[-2.887] | -0.260<br>[-2.545] |
| **D(OilPrices(-1))** | -0.059<br>[0.012] | -0.013<br>[0.011] |
| **D(OilPrices(-2))** | -0.033<br>[-3.583] | 0.004<br>[0.408] |
| **D(GDP(-1))** | 2.16E-04<br>[0.751] | 1.090E-04<br>[0.365] |
| **D(GDP(-2))** | -9.48E-05<br>[-0.345] | 2.000E-04<br>[0.715] |
| **D(EUse(-1))** | -0.001<br>[-5.640] | -4.830E-04<br>[-2.587] |
| **D(EUse(-2))** | -4.54E-04<br>[-2.595] | -2.360E-04<br>[-1.513] |
| **D(ETrade(-1))** | -1.83E-06<br>[-0.193] | -5.540E-06<br>[-0.568] |
| **D(ETrade(-2))** | 4.71E-06<br>[0.450] | -4.980E-06<br>[-0.530] |
| **D($CO_2$(-1))** | 4.428<br>[5.461] | 3.100<br>[3.819] |
| **D($CO_2$(-2))** | 1.711<br>[2.372] | 1.590<br>[2.670] |
| **C** | 0.016<br>[0.100] | 0.039<br>[0.244] |
| **R-Squared** | 0.740 | 0.750 |
| **Adj. R-Squared** | 0.720 | 0.730 |
| **F-Statistic** | 36.430 | 38.000 |
| **Akaike AIC** | 4.414 | 4.404 |
| **Schwarz SC** | 4.662 | 4.653 |

*Table 5 – VECM test results (t-statistcs are provided in the square brackets)*

Next, the short run relationships among all the variables were investigated. The Granger Causality test was used for this purpose, and the results are provided in Table 6. If a variable Granger-Causes the dependent variable, it means that is useful to predict the dependent variable in the short run.

| | 1980 - 2019 | | 1982 - 2021 | |
|---|---|---|---|---|
| | Chi-sq | Prob. | Chi-sq | Prob. |
| **D(OilPrices)** | 27.788 | 0.000 | 2.928 | 0.231 |
| **D(GDP)** | 0.830 | 0.660 | 0.546 | 0.761 |
| **D(EUse)** | 32.912 | 0.000 | 6.760 | 0.034 |
| **D(ETrade)** | 0.287 | 0.867 | 0.502 | 0.778 |
| **D($CO_2$)** | 31.308 | 0.000 | 15.608 | 0.000 |
| **All** | **53.624** | **0.000** | **20.888** | **0.0219** |

*Table 6 – The Granger Causality test for the dependent variable (REC)*

For the first period, only the OilPrices, EUse, and $CO_2$ Granger-Cause REC, since their p values are below the 5% significance level. For the second period, only EUse and $CO_2$ Granger-Cause REC. Through this test, it was concluded that, for both periods, the global p-values reject the null hypothesis (where there is no Granger Causality), and thus the dependent variable is explained in the short run by the combination of the independent variables.

Finally, to understand not only the evolution and the trend for the future of the dependent variable (rec) but also the impact that the years of COVID-19 pandemic had in this progress, it is important to have a visual perspective, as provided by the following figures (Figure 2a and 2b).

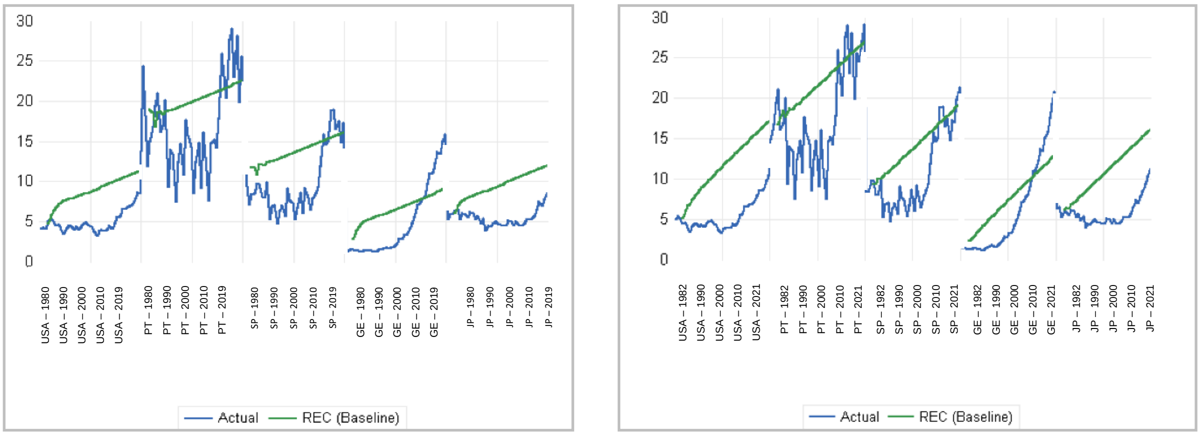


*Figure 2 – Evolution of REC by country for the period (a) of 1980-2019 and (b) of 1982-2021*

According to these graphical representations of a deterministic simulation of the model, obtained from the EViews software, we can easily see that the pandemic years, which fall into the second period (1982-2021), aggregate some changes in the trend of the share of renewable energy consumed, proving a greater progression in the energy transition for the analyzed countries since the slopes are more positively accentuated, compared to the first period.

## 5. Conclusions

The aim of this dissertation was the study and analysis of Covid-19 shock and its influence in the pathway toward transformation of the global energy sector from fossil-based to zero-carbon.
The concept of energy transition has gained considerable attention in recent decades due to the deterioration of planet Earth. Therefore, the decarbonization of the energy sector requires urgent actions on a global scale and, while a global energy transition is underway, other actions are needed to reduce carbon emissions and mitigate the effects of climate change. One solution that is being adopted by most countries around the world is the implementation of renewable solutions and energy efficiency measures that can potentially help achieve 90% of the required carbon reductions.
The growth of renewable energy is a result of the combination of several critical factors, depending on the country and its characteristics, and in specific shocks as the Covid-19 outbreak.
We performed several statistical analyses, considering a multiple time series models. For these analyses, we presented a vector error correction model (VECM) that studied the impact of five explanatory variables on the variation of one response variable that characterizes the growth of renewable energy share and intrinsically the path for the energy transition. From our results and by considering a lag of one year between the dependent and independent variables, we concluded that the response variable, in both models, is 74% (model without considering Covid-19) and 75% (model considering Covid-19) explained by the explanatory variables, despite some of them have a higher significance degree when evaluating the model compared to others. $CO_2$ emissions, energy consumption, and oil prices are the ones that have a higher share of the impact of the behavior of the dependent variable. According to the results, an increase in $CO_2$ tends to promote a progression towards an energy transition system, while a drop in energy consumption, by the hand of technology improvement and consequently by the improvement of energy efficiency, has a positive impact on the renewable energy consumption. For the price of crude oil, the variable shows the opposite effect regarding the theoretically expected relationship. The other two independent variables, GDP and ETrade, proved to be statistically insignificant for the models.
Despite being too early to speculate about a transformed, post-Covid world, only making presumptions based on available data, the results turned out to be quite interesting since, through the representations provided by the software, we could observe that the pandemic added some changes in the futuristic trend of the percentage of renewable energy consumed, proving a greater progression in the energy transition by the various countries analyzed.
With this dissertation, we had hoped to introduce the effects of the Covid-19 pandemic on the growth of green alternative energy solutions by analyzing economic, social, and environmental factors.
However, considering the limitations of our data and models, we believe there are further analyses to be conducted. Our suggestion for further investigation is to perform a more detailed analysis with a greater set of post-Covid data.

## References


Abu-rayash, A., & Dincer, I. (2020). Analysis of the electricity demand trends amidst the COVID-19 coronavirus pandemic. Energy Research & Social Science, 68, 1–3.

Anseel, F., Antonakis, J., Bamberger, P. A., & Bapuji, H. (2021). Supplemental Material for COVID-19 and the Workplace: Implications, Issues, and Insights for Future Research and Action. American Psychologist, June, 13–15.

Asari, F. F. A. H., Baharuddin, N. S., Jusoh, N., Mohamad, Z., Shamsudin, N., & Jusoff, K. (2011). A Vector Error Correction Model ( VECM ) Approach in Explaining the Relationship Between Interest Rate and Inflation Towards Exchange Rate Volatility in Malaysia. World Applied Sciences Journal, 12, 49–56.

Baghchechi, M., Jaipaul, N., & Jacob, S. E. (2020). The rise and evolution of COVID-19. International Journal of Women's Dermatology, 6(4), 248–254.

Chakraborty, I., & Maity, P. (2020). COVID-19 outbreak: Migration, effects on society, global environment and prevention. Science of the Total Environment, 728, 3–6.

Dewar, A., Alkadiri, R., Fitz, R., & Webster, J. (2020). How COVID-19 is changing the pace of energy transitions (pp. 1–5).

Dinç, D. T., & Akdoğan, E. C. (2019). Renewable energy production, energy consumption and sustainable economic growth in Turkey: A VECM approach. Sustainability (Switzerland), 11(5), 1–10.

Fernandes, N. (2020). Economic effects of coronavirus outbreak ( COVID-19 ) on the world economy. SSRN Electronic Journal, ISSN 1556-5068, Elsevier BV, 12–14.

Hauser, P., Anke, C., Gutierrez Lopez, J., Möst, D., Scharf, H., Schönheit, D., & Schreiber, S. (2020). Comparison to the 2008 Financial Crisis. IAEE Energy Forum, Covid-19 Issue 2020, 2–7.

Jiang, P., Fan, Y. Van, & Klemeš, J. J. (2021). Impacts of COVID-19 on energy demand and consumption: Challenges, lessons and emerging opportunities. Applied Energy, 285(December 2020), 1–7.

Johansen, S., & Juselius, K. (1990). Maximum Likelihood Estimation and Inference on Cointegration — With Applications To the Demand for Money. Oxford Bulletin of Economics and Statistics, 52(2), 169–210.

Kabir, M., Afzal, M. S., Khan, A., & Ahmed, H. (2020). COVID-19 pandemic and economic cost; impact on forcibly displaced people. Travel Medicine and Infectious Disease, 35(April), 1.

Klemes, J. J., Fan, Y. Van, & Jiang, P. (2020). The energy and environmental footprints of COVID-19 fighting measures e PPE, disinfection, supply chains. Energy, 211(January), 1–4.

Kyritsis, E., & Serletis, A. (2017). Oil Prices and the Renewable Energy Sector (pp. 3–16).

Madurai Elavarasan, R., Shafiullah, G. M., Raju, K., Mudgal, V., Arif, M. T., Jamal, T., Subramanian, S., Sriraja Balaguru, V. S., Reddy, K. S., & Subramaniam, U. (2020). COVID-19: Impact analysis and recommendations for power sector operation. Applied Energy, 279, 1–8.

Marques, A. C., Fuinhas, J. A., & Pires Manso, J. R. (2010). Motivations driving renewable energy in European countries: A panel data approach. Energy Policy, 38(11), 6877–6885.

Mofijur, M., Fattah, I. M. R., Alam, M. A., Islam, A. B. M. S., Ong, H. C., Rahman, S. M. A., Najafi, G., Ahmed, S. F., Uddin, M. A., & Mahlia, T. M. I. (2021). Impact of COVID-19 on the social, economic, environmental and energy domains: Lessons learnt from a global pandemic. Sustainable Production and Consumption, 26, 343–359.

Platto, S., Wang, Y., Zhou, J., & Carafoli, E. (2020). History of the COVID-19 pandemic: Origin, explosion, worldwide spreading. Biochemical and Biophysical Research Communications, 538, 2.

Somani, M., Srivastava, A. N., Gummadivalli, S. K., & Sharma, A. (2020). Indirect implications of COVID-19 towards sustainable environment: An investigation in Indian context. Bioresource Technology Reports, 11, 2–8.

Sui, Y., Zhang, H., Shang, W., Sun, R., Wang, C., Ji, J., Song, X., & Shao, F. (2020). Mining urban sustainable performance: Spatio-temporal emission potential changes of urban transit buses in post-COVID-19 future. Applied Energy, 280, 1–3.

Tambari, I., & Failler, P. (2020). Determining if oil prices significantly affect renewable energy investment in african countries with energy security concerns. Energies, 13(24), 1–21.

UITP. (2020). Public Transport Authorities and Covid-19. 1–4.

Wang, Q., & Su, M. (2020). A preliminary assessment of the impact of COVID-19 on environment – A case study of China. Science of the Total Environment, 728, 1–3.

Winker, P., & Maringer, D. (2005). Optimal lag structure selection in VEC-models. IFAC Proceedings Volumes (IFAC-PapersOnline), 16, 89–94.

Zambrano-Monserrate, M. A., Ruano, M. A., & Sanchez-Alcalde, L. (2020). Indirect effects of COVID-19 on the environment. Science of the Total Environment, 728, 1–4.