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 higher 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)

Resumo

A pandemia COVID-19 constituiu um dos acontecimentos mais desafiantes das últimas décadas e, certamente, um dos maiores que a Humanidade, à escala global, enfrentou até aos dias de hoje. A ruptura das cadeias de abastecimento, a queda da produtividade industrial, a crise na saúde, entre outros, deram impiedosamente origem a uma instabilidade a nível global, nos mais diversos setores. Com o objetivo de travar esta grande ameaça, foram adoptadas inúmeras medidas de emergência por governos, empresas e indivíduos, as quais geraram uma série de mudanças políticas, económicas e sociais com grande potencial para influenciar uma transição energética sustentável. É este tópico que esta dissertação pretende analisar, através do estudo da influência de várias variáveis independentes (PIB, Consumo de energia, Preços do petróleo, Balanço comercial de energia e Emissões de CO_2) no comportamento do consumo de energias renováveis (REC), para um painel de dados formado por cinco países do chamado mundo desenvolvido: Alemanha, Espanha, Portugal, Estados Unidos da América e Japão. Aplicaremos um modelo adequado para séries temporais, denominado por Vector Error Correction Model (VECM) e suportado por testes de estacionariedade, cointegração, estabilidade e causalidade, para dois períodos diferentes: o primeiro período entre 1980 e 2019 (logo, excluindo o período pandémico) e o segundo período entre 1982 e 2021 (incluindo o período pandémico), a fim de fazer uma análise comparativa e investigar o impacto da pandemia no setor das energias renováveis. Os resultados obtidos nas estimativas do VECM e no teste de Causalidade permitiram comprovar que não só o REC pode ser explicado pelas variáveis independentes, principalmente pelo preço do petróleo, emissões de CO_2 e consumo de energia, visto que apresentaram maior nível de significância, como, também, que existe uma relação, tanto no curto como no longo prazo, entre as variáveis. Concluímos, também, por meio de algumas representações gráficas de simulações determinísticas do modelo, facultadas pelo software EViews, que o COVID-19 aumentou o ritmo da transição energética, assim contribuindo para o paradigma de um setor energético mais sustentável.

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ADF – Augmented Dickey-Fuller

AIC – Akaike Information Criterion

COP21 – United Nations Climate Change Conference 2015

COVID-19 – Coronavirus Disease 2019

CO_2 – Carbon Dioxide

ECT – Error Correction Term

EEA - European Environmental Agency

EPOV - EU Energy Poverty Observatory

EU – European Union

FDI – Foreign Direct Investment

FPE – Final Prediction Error

GDP – Gross Domestic Product

GHG - Greenhouse Gas

GSI – Greenness of Stimulus Index

HQ – Hannan-Quinn Information Criterion

IEA – International Energy Agency

IMF - International Monetary Fund

MLE – Maximum Likelihood Estimates

NO_2 – Nitrogen

OPEC - Organization of the Petroleum Exporting Countries

QMS – Quantitative Micro Software

REC – Renewable Energy Consumption

RES – Renewable Energy Source

R&D – Research and Development

SC – Schwarz Information Criterion

UNFCCC - United Nations Framework Convention on Climate Change

USA – United States of America

VAR – Vector Autoregressive Model

VECM – Vector Error Correction Model

WHO – World Health Organization

1. Introduction

1.1. Context and Problem Definition

Over the past year, the COVID-19 pandemic has caused an extraordinary global economic and social crisis. Originating from Wuhan, China, cases rapidly spread to Japan, South Korea, Europe and the United States and the rest of the world. From the beginning of 2020 to the end, 84 million cases were reported, with a respective mortality rate of around 2.2%.

In the weeks leading up to the World Health Organization's (WHO) formal pandemic declaration in March 2020, substantive economic indications from various sources suggested that the world was on the verge of an unparalleled watershed in our lifetime, if not in human history (Gopinath, 2020).

More visibly, this pandemic phenomenon has affected countries' social and economic areas in at least the following areas (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.

In detail, 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.

Since the energy sector (electricity, heat, and transportation) is the largest contributor to carbon dioxide emissions, with a share of 73,2% according to Our World In Data[2], we observed, as described above, a substantial reduction in pollutant gas emissions, mainly during lockdown times. By 2020, global carbon dioxide emissions fell by 6.4%, about 2.3 billion tonnes[3].

With no doubt resolving the public health implications of COVID-19 is the top priority, but the essence of the equally crucial economic recovery efforts calls for some important questions as policymakers around the world implement stimulus packages to aid those recovery efforts: “Should these packages focus on avenues to economic recovery and growth by thrusting business as usual into overdrive or could they be targeted towards constructing a more resilient low-carbon circular economy?” (Ibn-Mohammed et al., 2021).

These are some of the questions that we try to evaluate and answer in this Project, regarding energy transition and emerging opportunities in this field. While the positive environmental benefits experienced during the pandemic cannot be explicitly replicated in non-pandemic periods in the future, the motivation and lessons learned have demonstrated the possibility (El Zowalaty et al., 2020). Similar lessons from COVID-19 prompt thoughts and discussions on how to achieve such positive outcomes as part of a more resilient and desirable low-carbon future in a more inclusive, expected, and less disruptive manner (Howarth et al., 2020).

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. And aspects of these stimulus decisions, in turn, can have an unexpected impact on the speed and trajectory of energy transitions (Dewar et al., 2020).

Although Europe, the United States, and Southeast Asia are poised to continue moving in a green direction, some hard-hit countries in Latin America, Africa, and some Asian countries (figure 1), such as India, may be so harshly undermined by COVID-19 that their ability to support energy transitions will be severely hampered (Dewar et al., 2020).

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[1] See https://www.iea.org/reports/global-energy-review-2020 (Accessed on February 2021)
[2] See https://ourworldindata.org/emissions-by-sector (Accessed on February 2021)
[3] See https://www.nature.com/articles/d41586-021-00090-3 (Accessed on February 2021)

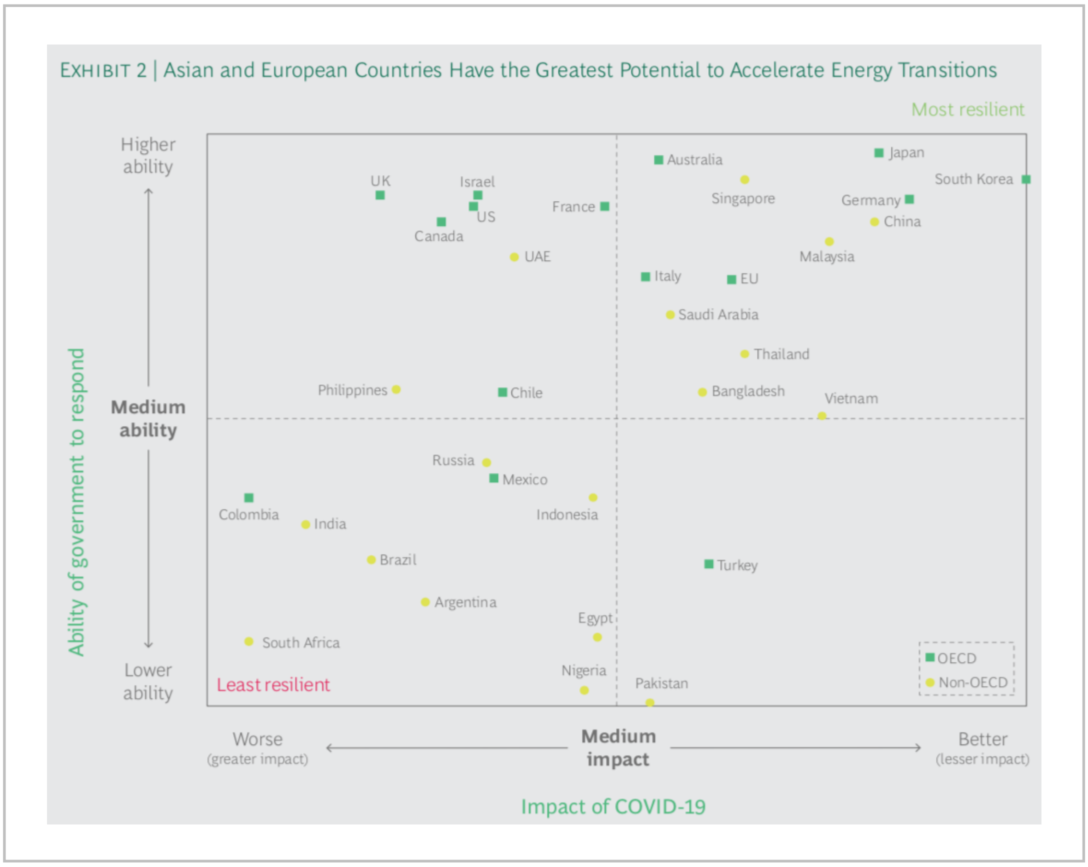

Figure 1 – Potential to accelerate Energy Transitions (Dewar et al., 2020)

There are several variables that can help to explain this situation. First, many leading Asian economies, including China, Japan, South Korea, Malaysia, and Singapore, have experienced relatively few adverse health and economic consequences of the pandemic. As a result, they are well placed to make the significant investments in energy infrastructure needed to promote energy transitions. Second, they stand to benefit the most from shifting to renewable energy generation and electrified energy consumption, especially in transportation. Third, while these Asian countries' stimulus initiatives and economic changes are ostensibly aimed at boosting industrial productivity, they are also likely to hasten energy transitions (Dewar et al., 2020).

Therefore, the main objective of this Dissertation is to investigate how "green" energy sources can progress, taking into account the pandemic situation and its consequences. To this end, topics such as the evolution of the energy sector before the situation of COVID-19 are addressed, to explain its normal functioning, and then the impact of the pandemic on the global economy, with a special focus on the energy sector. The motivation is thus to contribute to the few existing literature (since it is a new topic) by investigating the impact of COVID-19 on the transition to “green” and alternative sources of energy.

To get some quantitative insights on the problem, an econometric model will assess the impact that some variables, that have been affected by this global situation, have on the transition for alternative energy technologies. The analysis will be focused on open economies with a high share of renewables in the energy sector.

1.2. Structure

This Project is structured as follows. After the Introduction, section 2 presents the literature review, divided into three topics and introducing the main concepts for the analysis to be carried out: first, a detailed analysis on the evolution of the energy sector in economic, political, social and environmental terms, highlighting the main milestones and events that contributed to periods of progress or recession in this sector worldwide; second, a description of the pandemic caused by COVID-19, covering different topics; finally, an interconnection of the two previous topics, with an in-depth analysis of the impact of COVID-19 in the energy sector. Section 3 presents the fundamentals of the methodology to be used and, finally, section 4 presents some conclusions. References are placed at the end of the document.

2. Literature Review

2.1. Energy in History

Energy, derived from the Ancient Greek word *ergos*, which means work, is one of the concepts that best defines the evolution of societies over time. Its existence is so essential for human life that, together with water and food, it forms the essential elements for human survival (Caineng et al., 2016).

In scientific terms, and more specifically in a thermodynamic perspective, energy refers to a physical greatness associated with the ability to generate work and to perform any action.

The history of energy production, as many researchers describe it, is divided into 2 periods (Malanima, 2014) (Table 1): *First epoch*, from the birth of the human species until the early modern age, and the *Second epoch*, which has witnessed a fast acceleration in the pace of energy consumption.

First epoch	General periods
Food	Prehistory
Firewood	
Foder (for working animals)	
Water power	Middle Ages
Wind power	
Second epoch	
Coal	Modern Age (Revolução Industrial)
Oil	Contemporary history
Primary electricity	
Natural gas	
Nuclear power	

Table 1 – Distribution of energy sources by periods (Malanima, 2014)

The first era began more than 300,000 years ago. During the long range of ancient times, the human species depended uniquely on its somatic energy, using their muscles to get the basic food supply and to build their shelters.

Even in this period, emerged an art that came to revolutionize the evolution of the sector until today: the art of dominating fire, which is considered by many industries in the sector to be the basis of its operation. This type of extra-somatic energy (which is not generated by the human body) has come to play an important role mainly in the preparation of food, protection and a source of warmth and lighting (Smil, 2004).

In the adjacent periods, several new energy sources have revolutionized the sector's efficiency, from the use of pack animals for agricultural activities to the development of new equipment (mills) dependent on sources, now well known in the field of renewables, such as water and wind (Malanima, 2014).

Already in the *second epoch*, first in England and later in the United States of America and Western Europe, between 1760 and 1850, an era, known to date as Industrial Revolution (Table 2), had come to modernize the manufacturing processes. It contributed to the development and optimization of processes, such as the production of iron, textiles, chemical products, which, previously handcrafted, started to be automated by machines that were built with steam engines, mainly fed with coal (Fremdling, 1996).

	England	Rest of Europe
1800	96	4
1830	79	21
1840	73	27
1850	73	27
1860	65	35
1870	58	42

Table 2 – Share of coal production in England and the rest of Europe 1800-1870 (%), (Malanima, 2014)

With this imbalance increase of the coal as a non-renewable source, new adversities were emerging that until then were practically negligible. The increase in pollution and the consequent degradation of air quality, contributed to the beginning of a period characterized by the deterioration of the planet.

In the last and present period, new sources began to follow the path of coal. In this case, it is the oil that plays the main role. From the Latin *petra*, meaning rock, and *oleum*, meaning oil, petroleum is the most conventional fossil fuel and the number one traded physical commodity in the world (Walters, 2006). It started to be used as a raw material for waterproof building materials, for lighting and lubricants in the 19th century.

Currently, through various chemical and thermodynamic processes (e.g. distillation in refineries), oil is converted into products that have the higher market value such as gasoline, diesel, lubricants, naphtha, among others (Larraz, 2019).

However, the exponential increase in its consumption, through its burning and even through its own extraction, has drastically worsened the state of the planet.

Thus, to try to neutralize this situation, new energy production alternatives started to be developed. These solutions are based on several sources of renewable energy that, as the name implies, come from natural resources that are replenished naturally (Balcioglu & Soyer, 2017).

Although the last two centuries have been marked by the intensive exploitation of fossil fuels, since they are cheaper, these days have shown a contrary image, where the growing investment in the renewable area (Sørensen, 1991), more specifically in solar, water and wind projects, has been notorious for a large part of the governments.

More recently, another source has been gaining its place in this sector due to the European commitment to the decarbonization program: hydrogen, a gaseous, colorless, odorless and insoluble in water chemical element. In scientific terms it is given by the molecular formula of H2. According to several studies already carried out (Singh et al., 2020), hydrogen is considered the “clean fuel” with the greatest potential to replace the fossil fuels currently used.

With this historical framework, marked by some recent troubled periods, in which the degradation of the planet is notable today, contemporary societies have not only been defining and adopting policies, but have also been making major investments in research and development on this sector. The next chapter provides some economic and political insights about the industry.

2.2. Economic importance of the energy sector

From an economic point of view, we could define energy "*as the capacity of performing work, useful for human beings, thanks to changes introduced with some cost or effort in the structure of the matter or its location in space*" (Malanima, 2014).

Since the middle of the 19th century, more specifically in the Industrial Revolution, capitalism began to take root in the energy sector. The intention of reducing the production effort, minimizing and optimizing the available resources, marked what would become the foundation of all companies in the industry until today (Kocka, 2015).

Energy is an unavoidable and powerful force in the economy, so that energy economics is an applied sub-discipline of economics covering all parts of the concept: policy, supply, demand, pricing and investment strategies (Tyner & Herath, 2018). Besides these, it is also essential to define and evaluate the relationship between energy and GDP, including the concept of energy poverty.

2.2.1. Policy analysis

The various problems associated with the energy sector, mainly climate change, resulting from its production, distribution and consumption, have forced not only organizations but also governments to take some action. In this way, policies supported by legislation, international agreements, subsidies, incentives and taxes have been defined in recent decades (Economidou et al., 2020).

In 2015, at the well-known United Nations Conference on Climate Change in Paris (COP21), involving the 195 members of the UNFCCC (United Nations Framework Convention on Climate Change), multiple commitments were defined, establishing the important goal of reducing the global average temperature by 1.5°C (Morgan, 2016).

Two years later, in 2017, during the "Sustainable Development Round Table", a campaign promoted by the United Nations, in order to accelerate the progress of renewable activities, incentives were defined to stimulate the development of clean technologies (Ilham et al., 2019).

However, despite the international efforts, it is up to the sensitivity of each country to define its policies, taking into account two important aspects (Coffey & Andersen, 2011):

- Characteristics of the market
- General state of the economy

Although in Europe each country defines its policies according to its energy market, they generally follow the same standards in terms of reducing CO_2 emissions, aiming at decreasing the planet's average temperature, and increasing energy efficiency. Some key goals for 2030[4] are:

- At least 40% cuts in greenhouse gas emissions, from 1990 levels (EU)
- At least 32% share for renewable energy (EU)
- At least 32.5% improvement in energy efficiency (EU)

Even though most countries in Asia are subject to energy insecurity situations, in general, energy policy objectives do not deviate much from other continents, which is heightened on sustainable development and climate changes matters. Governments are entirely responsible for regulating their energy market in line with their proposed energy policies (Ilham et al., 2019).

In Africa, the scenario is relatively different. Since energy poverty is one of the biggest problems, energy goals focus on the implementation of energy systems for the entire population, with some attention to renewable solutions (Ilham et al., 2019).

A practical example of a policy that has been adopted in recent years in several countries is the implementation of prices on carbon dioxide (CO_2) and other greenhouse gas (GHG) emissions. It is an instrument widely supported by several economists and researchers as it can mitigate climate change. The concept is straightforward: putting a price on carbon internalizes the societal costs associated with the use of fossil fuels and other activities that create GHGs.
There are already some studies that analyze not only the current impact but also the future impact of implementing these taxes. In the case of the united states, the scenario is as follows ((Larsen et al., 2018)):

- In the short and medium-term, a carbon price might result in significant reductions in GHG emissions in the United States. An economy-wide carbon tax set at \$50/ton in 2020 and rising at a real rate of 2% presents emissions reductions of 39 to 47 percent below 2005 levels by 2030 (Figure 2).

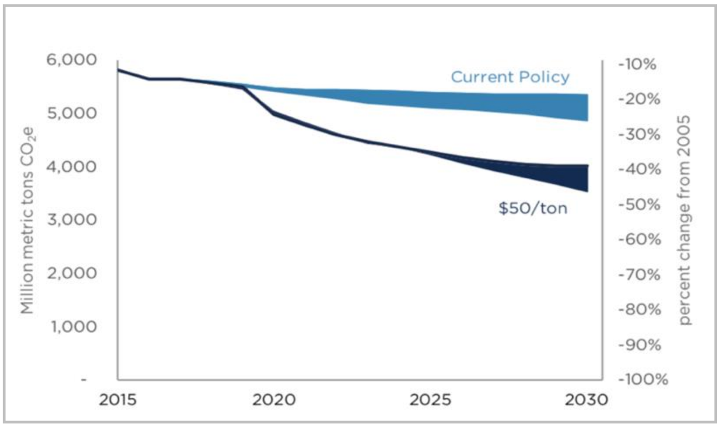

Figure 2 – US net GHG emissions, 2015-2030 (Larsen et al.,2018)

[4] See https://ec.europa.eu/clima/policies/strategies/2030_en (accessed on December 2021)

- A carbon tax leads to significant increases in renewable energy generation and significant decreases in coal generation. Depending on the tax rate scenario, zero-emitting renewable energy accounts for 29 to 41 percent of total US electric power generation in 2030, representing a two to threefold increase over 2015 levels.
- Carbon tax revenue could be substantial, ranging from $617 million to $2.5 trillion during the first ten years, depending on the tax rate and technological progress in the US economy. This revenue could be used for a variety of constructive purposes, such as tax cuts and deficit reduction.

2.2.2. Economic performance (GDP and energy correlation)

Economic growth is an important factor in reducing poverty and generating the resources necessary for human development and environmental protection. It is driven by many factors, including productivity, process and organizational innovations based on technological change. Economists usually measure this concept in terms of gross domestic product (GDP) or related indicators.

Sustainable economic growth requires constant and sufficient availability of energy products, which becomes viable when energy intensity declines (Mahmood & Ahmad, 2018). The concept of energy intensity is used as a measure of energy inefficiency (Sahu & Narayanan, 2009). The higher its value, the higher the prices and costs involved in converting energy into GDP. An improvement in efficiency through the adoption of sustainable production techniques enables a more effective model of production of the final product, through a reduction in energy use (Mahmood & Ahmad, 2018).

Generally, European countries tend to need less energy input to attain any specific growth rate of GDP compared to economically and technologically less developed countries (Mahmood & Ahmad, 2018). According to the European Environmental Agency (EEA), between 2005 and 2017 the region's GDP grew at an average annual rate of 1.7%, while energy consumption decreased at an annual rate of 0.5%. This difference of 1.2 p.p., represents the annual decrease in energy intensity in Europe (EEA, 2019)[5].

[5] See https://www.eea.europa.eu/data-and-maps/indicators/final-energy-consumption-intensity-5/assessment (Accessed on January 2021)

To establish this relationship between energy intensity and economic performance, several models have been developed. Table 3 presents three of these models as examples:

	Model	Description
(1) *"Long-run elasticities in energy consumption and GDP relationship"* (Campo & Sarmiento, 2013)	$GDP_{it} = \alpha_i + \beta_i EC_{it} + \varepsilon_{it}$	i = 1,2,3,…, N countries; t (time) = 1,2,3,…, N; GDP = Gross Domestic Product; EC = energy consumption; β = country-specific slope; ε = term error
(2) *"Conventional neo-classical one-sector aggregate production function"* (Kasperowicz & Štreimikienė, 2016)	$GDP = f\,(K, L, E)$ $GDP_{i,t} = \beta_0 + \sum \beta_{1j} K_{i,t-j} + \sum \beta_{2j} L_{i,t-j} + \sum \beta_{3j} E_{i,t-j} + \mu_{i,t}$	GDP = log of Gross Domestic Product K = log of Gross Fixed Capital E = log of Total Energy Consumption L = log of Total Employment
(3) *"Steady-state growth condition in neoclassical growth model"* (Mahmood & Ahmad, 2018)	$\frac{E(t)}{Y(t)} = h\left(\frac{s}{(g+\delta)}, t\right)$	E(t) / Y(t) = energy intensity; s = saving rate; g = growth rate of labor; δ = depreciation rate

Table 3 – Energy intensity and economic performance correlation models

2.3. COVID-19 pandemic and its impacts

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).

The situation currently experienced is an event relatively similar to that seen in 1918. That year, a viral crisis arose in the USA and quickly spread throughout the world. It became known as Spanish flu (created by the influenza virus) due to the fact that the first studies were carried out in Spain (Tsoucalas et al., 2016). Coinciding with the last year of the first world war, a year of substantial economic, social and political instability, the virus ended up generating a catastrophic situation. About 50 million people, out of a total of 500 million infected, died (approximate figures, given the uncertainty of records at the time) (Tsoucalas et al., 2016).

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 should be converted from physical to virtual through video chat applications (Baghchechi et al., 2020).

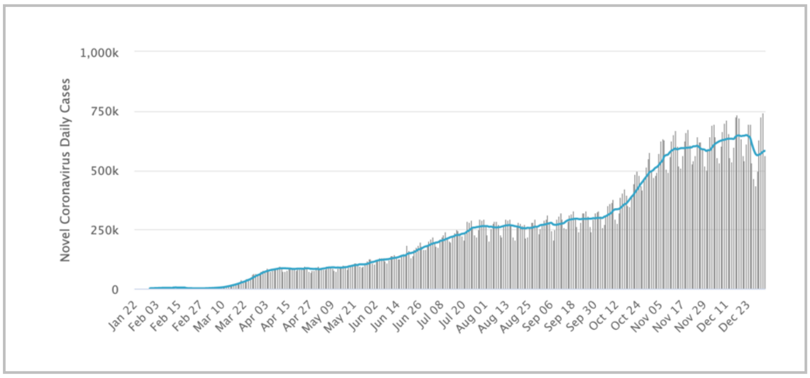

Figure 3 – Evolution of daily new cases worldwide (Source: Worldmeters)

The pandemic has led to a dramatic loss of human lives worldwide. From the beginning of 2020 to the end, 84 million cases were reported (Figure 3), with a respective mortality rate of around 2.2%.

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

COVID-19 has created a new situation for many people. Since the beginning of the last century, as previously mentioned, with the impact of the Spanish flu outbreak, the world has not witnessed a serious viral crisis where, until now, millions of deaths have been registered. The impact it has had on health systems is overwhelming. (Mofijur et al., 2021).

Nevertheless, this is not just a health crisis. Social and economic fields, which are fundamental to a sustainable development, are also being directly affected and in many circumstances, its impact will only be felt later on (Mofijur et al., 2021).

To evaluate the impact of this health crisis in the energy sector, the next topics provide some insights not only about the economic picture but also about the changes in social routines and their consequences in this particular industry.

2.3.1. 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. As mentioned earlier, one of the crucial universal measures was the implementation of a confinement model, which, when possible, forced people to be guided by a telework system (Jiang et al., 2021). As such, workplaces were forced to close, 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). In the coming months, unemployment in Europe can nearly double (Gulseven et al., 2021). This will directly impact the concept of energy poverty since, with the eventual reduction of people's incomes, electricity becomes a larger share in the monthly budget, contracting the financial capacity to have a stable lifestyle.

From a macroeconomic perspective, there have been several attempts to assess the impact of COVID-19 on GDP. An example is the use of the Envisage model (Figure 4) (Maliszewska et al., 2020), which is a standard computable general equilibrium (CGE) model (Mensbrugghe, 2019).

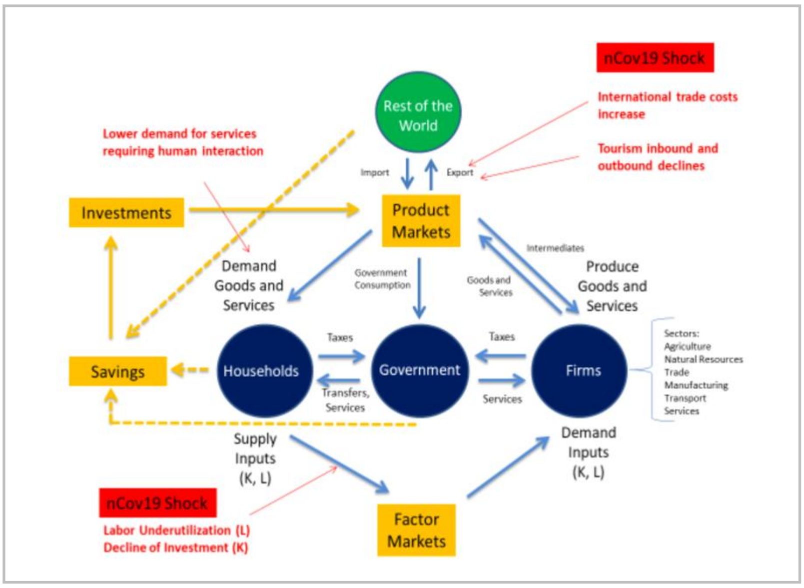

Figure 4 – Implications of the COVID-19 as implemented in the Envisage model (Maliszewska et al., 2020)

There are four sets of shocks evaluated in the strands of the system that are directly affected. The first shock considers the drop in employment, which also means lower demand for capital, as firms need a combination of labor and capital to produce goods and services. The second one addresses the increase in international trade costs of imports and exports, applied across all goods and services, due to the rise in transportation and transaction costs in foreign trade, as a result of increased inspections, reduced operating hours, closed roads, and borders. The third shock studies the drop in international tourism, which generates a typically smaller revenue for countries that depend mainly on this sector. And finally, the fourth shock represents a drop in the demand for services that require close human interaction, such as restaurants, public transports, and so on. The overall impact is measured assuming that all shocks occur simultaneously (Maliszewska et al., 2020).

According to the International Monetary Fund (IMF), the global economy is projected to contract between 3% and 5% in 2020, which is much worse than the 2008 global financial crisis (Mofijur et al., 2021).

2.3.2. 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. The decline in energy demand and consumption tends to expose the energy industry to very vulnerable situations. For example, it caused the bankruptcy of at least 19 energy companies in the United States industry (Jiang et al., 2021).

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 (IEA, 2020)[6].

Figure 5a presents a comparative analysis of the growth rate of total energy demand between 2019 and 2020 for some regions of the planet. The greatest differences are registered for the developed countries.

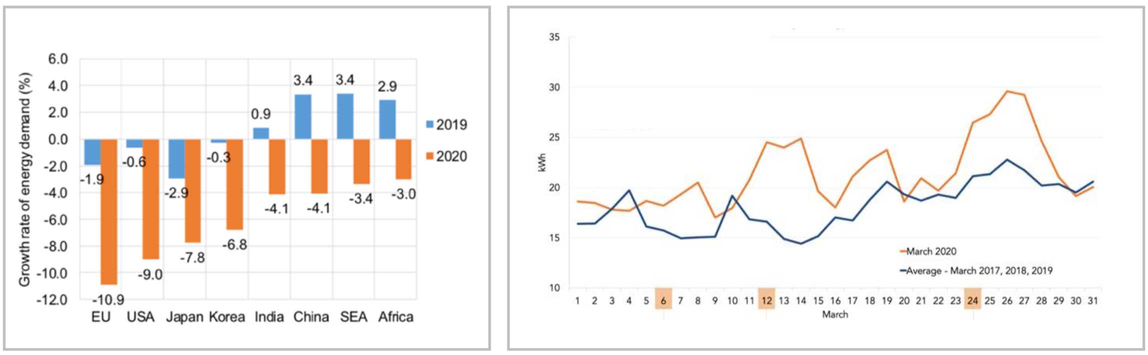

Figure 5 – (a) The year-on-year growth rates of energy demand in 2019 and 2020, SEA = Southeast Asia (Jiang et al., 2021) (b) Daily demand for domestic energy in March 2020, for a sample of 113 households, (Source: https://www.renewableenergyworld.com/2020/04/09/COVID-19-is-changing-residential-electricity-demand/#gref)

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

From a macro-scale, despite the overall drop in energy demand in 2020, the rise in residential energy consumption and medical energy consumption should be contemplated comprehensively to draw a clear conclusion on energy demand (Adeboye et al., 2020). In line with Figure 5b, in March 2020, there was an average demand for domestic energy significantly higher as compared to the average value of the previous three years. For a sample of 113 homes, a maximum increase of 66% was recorded as a result of the lockdown that forced people to spend more time at home than usual (Renewable Energy World, 2020)[7].

To date, from both macro and micro scales the demand changes (Table 4) are highlighted as follows:

Demand changes
- Short-term demand decreases when lockdowns are enforced (Mofijur et al., 2021), but demand is expected to rebound steadily after relaxing lockdown measures (IEA, 2020a)[8]
- Industrial and commercial demands decrease while residential demand increases (Madurai Elavarasan et al., 2020)
- Renewable energy demand increases while fossil energy declines (IEA, 2020b)[9]
- The energy consumption for producing standard products (e.g. 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)

Table 4 – Changes on energy demand

The generalized reduction of electricity in different sectors had an impact on the demand for fossil fuels. Some studies even predict that the coal industry may not recover in the post-pandemic period (Watts & Ambrose, 2020)[10], which is an opportunity to encourage more sustainable solutions.

2.3.3. Energy poverty

Energy poverty it's the conjunction between the two themes discussed above, the economic development of a country and the availability and quality of energy. It is also an extremely important subject to discuss in this project since COVID-19 and the measures applied to combat it, as mentioned before, bring down the financial availability for many people. However, before

[7] See https://www.renewableenergyworld.com/2020/04/09/COVID-19-is-changing-residential-electricity-demand/#gref (Accessed on November 2020)
[8] See https://www.iea.org/reports/COVID-19-impact-on-electricity (Accessed on November 2020)
[9] See https://www.iea.org/reports/global-energy-review-2020 (Accessed on November 2020)
[10] See https://www.theguardian.com/environment/2020/may/17/coal-industry-will-never-recover-after-coronavirus-pandemic-say-experts (Accessed on November 2020)

entering this analysis, it is important to understand the concept and also its evolution before the pandemic situation.

Starting with the definition, it goes through the inability to obtain and deprivation of adequate energy services, like home heating, electrical appliances and mobility (Middlemiss et al., 2019), essential to living a good and fair life (DellaValle, 2019). In most cases, it is not characterized by a lack of energy resources. Actually, the abundance of resources is not identified as a direct indicator of economic growth (Sachs & Warner, 2001).

The vulnerability to energy poverty is not a function that depends only on components associated with people's life circumstances, such as poverty, age, physical disabilities, among others, but rather a complex correlation between social and life circumstances, political climate and availability of infrastructure (Middlemiss et al., 2019).

Although this is a topic for which it nowadays becomes clear the need for intervention in organizational terms, only in December 2016 an initiative was created, the EPOV (EU Energy Poverty Observatory), which aimed to officially incorporate energy poverty in the range of the various policies of the European Union (Simcock et al., 2018).

	Access to electricity (% of population)	GDP per capita (US$)	Electricity consumption (kwh per capita)
United States	100,0	62 297,50	12 154
Germany	100,0	46 445,20	6 306
China	100,0	10 216,60	4 617
Brazil	100,0	8 7171,20	2 830
India	95,2	2 099,60	935
Nigeria	56,5	2 229,90	144
Ethiopia	45,0	855,80	80

Table 5 – Energy and development indicators, 2018 (Source: World Bank)

Close to what might be expected, the analysis of Table 5 is clear. Economic development is associated with access to electrical infrastructures and to an increase in per capita electricity consumption (González-Eguino, 2015).

95% of the 840 million (IRENA, 2019) of people who lack energy systems, including electricity, live in countries spread across Asia and sub-Saharan Africa, where, due to the weak energy distribution system, in most cases, energy barely reaches rural areas (González-Eguino, 2015). A clear example in the concentration of efforts to overcome this problem is the great focus that the 2019 annual energy report (IEA, 2019) attributes to the theme. One of the three chapters of the document presents a detailed analysis of energy development in Africa in recent years, addressing topics such as investments made and obstacles faced.

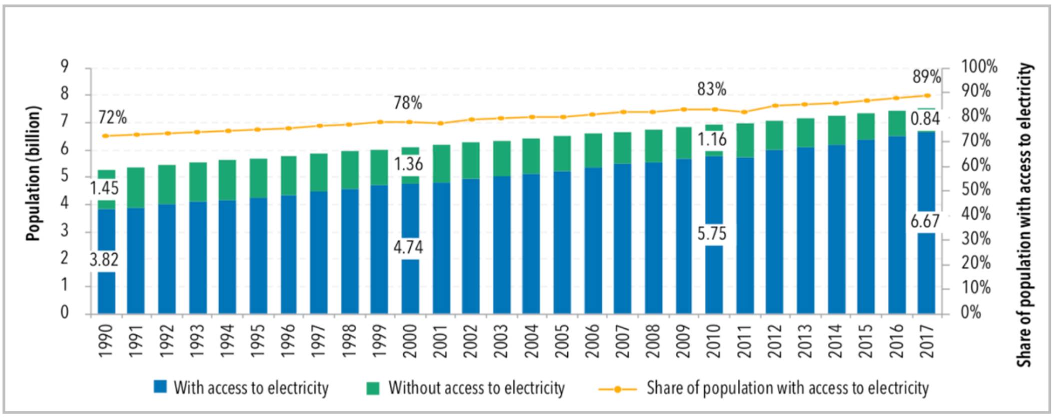

Figure 6 – Gains in electricity access (IRENA, 2019)

According to Figure 6, the rate of sustained electrification has evolved faster than the rate of population growth in the world's underserved areas. Since 2010, global electrification has steadily increased, rising from 83% in 2010 to 89.1% in 2017 (Figure 2) (IRENA, 2019).

Africa ended up being the big picture of these changes, as a result of the focus of international cooperation in the digitalization of communication and financial services that have been critical to the development of mini-grids and solar home systems (IEA, 2019). All this progress has minimized the impact of energy poverty and its consequences on the well-being and quality of life of communities (Table 6).

	Consequences of energy poverty
Health	The use of more accessible fuels such as coal, wood and waste, for heating homes and cooking, contribute negatively to health due to the high pollutant content they emit. **Reference:** Pollutant concentration in these houses varies from 303 to 3000 µg / m³. Extremely high value when compared to that recorded in Europe, 40 µg / m³. Data from the World Health Organization (WHO).
Economy	Affects all production sectors and limits the potential for development.
Environment	Energy poverty and the environment are linked mainly through land use change. The use of biomass as the main source of energy for the poorest people, and its overexploitation, increases deforestation, desertification and land-degradation.

Table 6 – Consequences of energy poverty in different areas (González-Eguino, 2015)

However, the COVID-19 outbreak has 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[11].

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[12].

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[12].

Furthermore, as a result of the pandemic, private enterprises building decentralized energy solutions like solar household systems and mini-grids have faced operational and financial hurdles. The lockdown measures, in several nations like Ethiopia, have disrupted distribution systems and cut sales by 20% in the first half of 2020 compared to the same period last year[12].

Overall, the total number of solar products sold in Africa has dropped by more than 10% in the first half of 2020[12], which is a big drop knowing that these systems are the main solution to these developing communities.

2.3.4. 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).

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

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

However, this topic may be more complex than it seems. 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 (such as in Cushing, Oklahoma, USA, that has filled up 76% of its maximum capacity). This lack of storage and pipeline transmission capacity has driven up the cost of storage.

Reducing supply by temporarily plugging off wells is a complex operation with a strong effect on the health of reservoirs, besides being costly. Thus, operators continue to operate wells at loses (Deloitte, 2020).

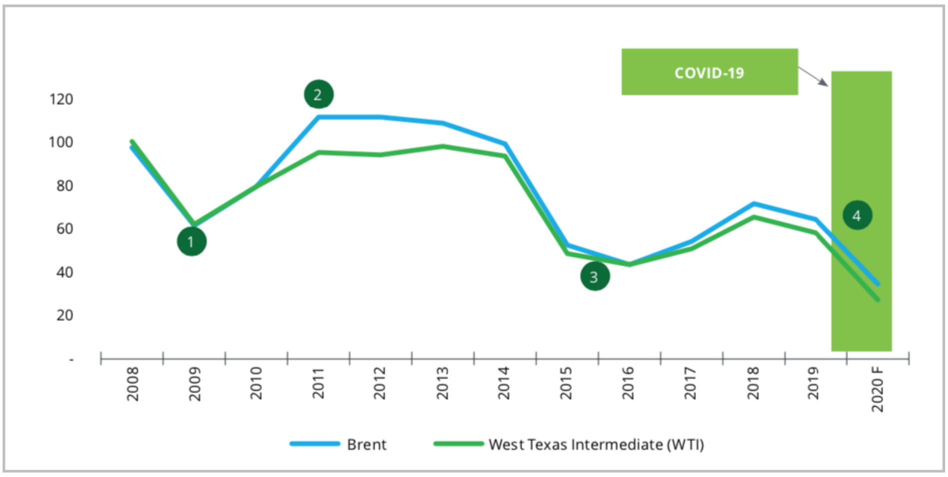


Figure 7 – Average annual crude oil price from 2008 to 2020 ($/bbl), (Delloite, 2020)

1) Global financial crisis (2007-2008): the price of oil decreased dramatically;
2) Libya Civil War (2011): in Libya, oil production has been curtailed. Despite Saudi promises of an increase in production to fight shutdowns, the quality of the product was not at the level required, resulting in high oil prices;
3) Supply glut (2015): the price of crude oil dropped, mainly due to a rise in the supply of non-OPEC oil, mainly shale oil in the US;
4) Russia vs Saudi Arabia war and COVID-19: in 2016, Russia and Saudi Arabia agreed to collaborate to form an informal OPEC+ alliance to control oil prices. However, on 5 March 2020, the OPEC summit agreed on an additional reduction in demand, which Russia opposed; due to an increase of production by OPEC+ and a sharp decline in demand caused by the pandemic, the prices fell.

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 (Tobben, 2020)[13].

The price of electricity followed a similar path. Despite the increase in household consumption, due to the dramatic drop in industrial production, the reduction of fuel costs (oil, coal, and natural gas), and the increase of renewable consumption, the average price in 2020 was significantly lower than in the previous year (EWI, 2020)[14].

As described above, the drastic drop in energy demand and consequently the global drop in oil prices has created a host of new problems for the industry. Some companies are likely to come under growing pressure from investors and other stakeholders to justify how they are implementing decarbonization commitments through their strategies and investment decisions (Sigler, 2020).

2.3.5. Energy investments

The energy sector is complex in terms of investment and, like others, presents a high degree of uncertainty and risk, requiring many economic and sustainability assessments when making decisions. Any investment in exploration ends up being extremely risky. Even in places with a good geological prospect, there is always the possibility of discovering a dry hole (in the case of oil and gas) or no resource deposits (Bhattacharyya, 2011).

According to the International Renewables Energy Agency (IRENA), investment in the energy sector would be around 110 trillion dollars between 2016 and 2050, 35% of which in energy efficiency, 24% in renewables, 23% in electrification and infrastructure, and 18% in fossil fuels (IRENA, 2016).

However, with COVID-19, the picture has changed. The allocation of national and international funds in sectors that directly impact the control of the viral situation, such as health, puts some other sectors in recessionary situations concerning investment (Al-japairai & Mahmood, 2021).

Energy investment declined 18% in 2020, with worrying signals for the development of more secure and sustainable power systems. Renewables investment has been more resilient during the crisis than fossil fuels, but spending on rooftop solar installations by households and businesses has been strongly affected, and final investment decisions in the first quarter of 2020 for new utility-scale wind and solar projects dropped back to the levels of three years ago (IEA, 2020b).

[13] See https://www.bloomberg.com/news/articles/2020-04-20/negative-prices-for-oil-here-s-what-that-means-quicktake (Accessed on March 2021)
[14] See https://www.ewi.uni-koeln.de/en/news/ewi-merit-order-tool-2021/ (Accessed on March 2021)

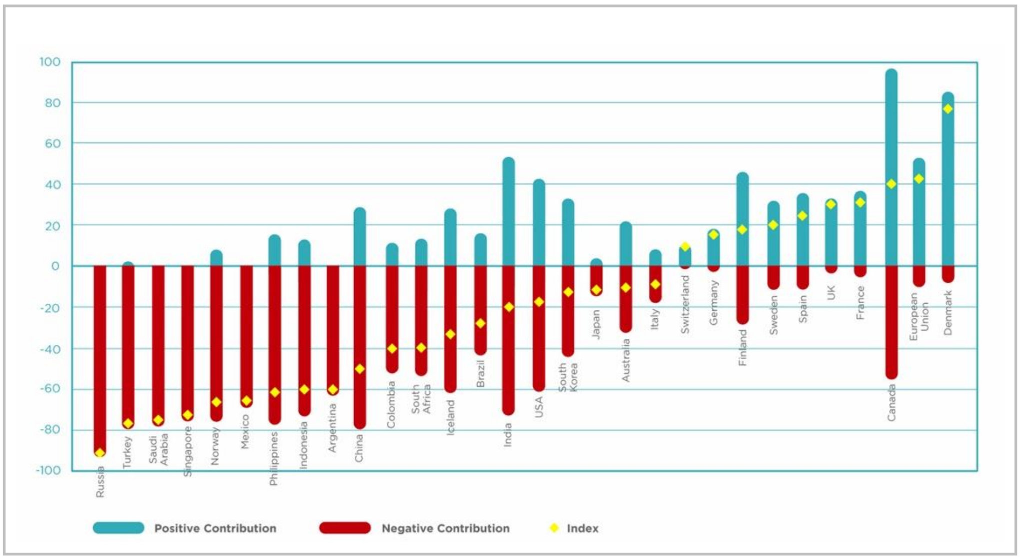


Figure 8 – Greenness of Stimulus Index (GSI) (Vivid Economics & Finance for Biodiversity Initiative, 2021)

According to the GSI (Vivid Economics & Finance for Biodiversity Initiative, 2021), which focuses on combining the volume of stimuli channeled to the five sectors with the greatest impact on reducing emissions (agriculture, energy, industry, transport, and waste) and the global impact on climate and the environment, Europe presents a more optimistic spectrum in its approaches to not only meeting the proposed targets of the Paris Agreement for 2030 but also to boost ambition to achieve carbon neutrality in 2050 (Figure 8).

2.3.6. 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 (NO_2), 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).

However, 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).

Rume and Islam (2020) discuss eight possible strategies for global environmental sustainability:

Firstly, for a (1) *Sustainable industrialization* a transition to less energy-intensive industries, strong energy efficient policies and the use of renewable fuels and technologies is crucial. Furthermore, factories should be designed in a logistical way in order to be placed in specific areas, bearing in mind that the waste from one industry can be used as raw material for another one (Hysa et al., 2020).

Secondly, the (2) *use of renewable energy* can play a decisive role in reducing emissions, such as GHG and consequently the climate change and the ozone layer depletion (Chakraborty & Maity, 2020), by being a substitute of fossil fuels like oil, natural gas and coal (Ellabban et al., 2014).

(3) *Use of green and public transport* contributes to a reduction in emissions. However, for this kind of initiative to become more successful it is important to encourage people to use green and public transports rather than private and fossil fuel-powered vehicles (Rume & Islam, 2020).

(4) *Waste recycling and reuse,* to basically reduce the burning of wastes, the use of raw materials, and environmental pollution by creating circular economies and systems (Hysa et al., 2020).

(5) *Wastewater treatment and reuse*: in order to address the problems of water contamination, all industrial and urban wastewater should be adequately handled prior to discharge (Rume & Islam, 2020).

(6) *Behavioral change in daily life,* to minimize not only the global emissions but also to cut down the carbon footprint per capita. For that, it is important to make society aware of changes in their behavior and way of living (Rume & Islam, 2020).

(7) *Ecological restoration and ecotourism,* promoting periodically shutdown in some touristic areas in order to promote cultural preservation and biodiversity conservation (Rume & Islam, 2020).

(8) *International cooperation,* by defining global measures and environmental goals, through organizations like the United Nations Environment Programme (UN Environment), to fight climate change and the degradation of biodiversity (Rume & Islam, 2020).

Although the impacts of COVID-19 on the global economy are complex and have a negative impact on green energy production, an articulated response could turn this threat into a major opportunity. The recent reduction in oil prices and the unpredictability of the return on investment in fossil fuels could make renewable energy companies much stronger (Hosseini, 2020).

Adopting renewables can in the future provide considerable solutions to the dilemmas of post-COVID-19. Industries can be resurrected by increasing clean energy technology and generating a number of new opportunities for unemployed people (Scott, 2020)[15]. In 2018 the sector employed 11 million people and could expand to more than 84 million in all ranges of renewables by 2050 (Hosseini, 2020).

While the impacts of COVID-19 on the environment are short-term, a united and proposed time-oriented effort based on policies from this strange and new situation can improve environmental sustainability and save the planet from the consequences of global climate change.

[15] See https://www.forbes.com/sites/mikescott/2020/09/30/clean-energy-jobs-will-drive-post-covid-recovery-around-the-world/?sh=3c7897881152 (Accessed on March 2021)

3. Data Characterization

Before starting data analysis, it is important to understand how we are going to explore our subject.

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. This situation will be explained in more detail in “Failed results, limitations and future work” ahead.

Therefore, we decided to run the different econometric procedures for two distinct periods:

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

Since the relationship between variables is non-linear, we cannot go through a multiple linear regression analysis. So, with all the necessary justification, we applied a model that belongs to a class of multiple time series models.

3.1. Variables description

Table 7 presents the shortened variable names. These names are used from this section onwards for the sake of simplicity.

Variable	Definition	Source
REC	Renewable Energy Consumption(%)	World in Data[16]
OilPrices	Crude Oil Prices (US$)	EIA[17]
ETrade	Energy Trade Balance (koe)	EIA[18]
EUse	Energy Consumption per capita (kWh)	World in Data[19]
CO_2	CO_2 Emissions per capita (tonnes)	World in Data[20]
GDP	GDP per capita (constant 2010US$)	World Bank[21]

Table 7 – Dataset definition

The dependent variable, Renewable Energy Consumption (REC), is calculated as the percentage contribution of renewable energies to total energy generation. This variable represents the degree of transition to a renewable energy economy (Sung & Park, 2018).

[16] See https://ourworldindata.org/renewable-energy

[17] See https://www.eia.gov/outlooks/steo/report/prices.php

[18] See https://www.iea.org/data-and-statistics/data-product/world-energy-balances-highlights

[19] See https://ourworldindata.org/grapher/per-capita-energy-use

[20] See https://ourworldindata.org/co2-emissions

[21] See https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

CO_2 is quantified in tons of emissions per capita. These types of gases, so called Greenhouse Gases (GHG), are the primary cause of global warming and climate change and, as a result, it is critical to act in order to limit these types of emissions as soon as possible (Sung & Park, 2018).

GDP, which is the standard measure of the value-added created through the production of goods and services in a country, is quantified in US dollars (constant 2010 US$) per capita. It is a key factor for development, affecting the two previous variables, REC and CO_2.

The variable EUse, which corresponds to energy consumption per capita, is measured in kWh. This variable is directly influenced by several factors, such as economic development sustained by the increase in industrial activity, agriculture, transport and urbanization, as well as the increase in population, thus generating a greater impact on GHG emissions.

Energy Trade Balance (ETrade) is a proxy for a country's reliance on energy imported and is calculated as the difference between energy imports and exports. The importance of this variable stems from the fact that high import dependency should encourage investments in a country's renewable resources, boosting renewables' contribution to the total energy supply (Caruso et al., 2020).

Finally, crude oil prices (OilPrices) are expressed in US dollars and are common to all countries. This variable depends heavily on several factors, such as fluctuations in supply and demand and market speculation (Drachal, 2021), natural disasters, global economic performance and political stability in oil-producing countries. However, it also has great impact on all the energy systems since society is still highly dependent on this resource.

3.2 Data Sources

The analysis covered the period from 1980 to 2021 for five different countries selected according to a Vector Error Correction Model (VECM). VECM belongs to a category of multiple time series models most commonly used for data where the underlying variables have a long-running common stochastic trend, also known as cointegration. The period includes some important events such as the 2007-2008 financial crisis and the subsequent economic recession and, of course, the COVID-19 pandemic. Most of the data sources used were chosen taking into consideration the databases previously employed in the literature. Thus, data for independent variables come from different agencies and organizations, such as the Energy Information Administration (EIA), which is the main agency of the US Federal Statistical System responsible for collecting, evaluating, and disseminating energy information, Our World in Data as well as the World Bank databases.

More specifically, and similar to Opeyemi (2021), for the variables of energy consumption and prices of crude oil, data from “Our World in Data” and the EIA were used. GDP was provided by the World Bank.

Due to a lack of recent data, that characterizes post-Covid in the second period, interpolation techniques and comparative analysis with similar variables that already have the data for these recent years, were used.

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 independent variables. Both one and two-year lags were tested. However, based on the dataset, the results were practically the same regarding the statistical significance with the dependent variable, thus aiding the decision to continue with the one year lag.

After some failed individual tests for each country, which are explained in the section "Failed Results, Limitations and Future Work", 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).

3.3. Country selection

For this analysis, it was initially decided to focus on making comparisons between developed and developing countries. However, as the data for developing countries were not updated, the analysis had to be restricted to developed countries only.

To carry out a more complete analysis of the panorama of developed countries, the focus extended to countries with different behaviors in terms of the evolution of primary energy from renewable resources between the period 1980 and 2019. As can be seen in Figure 9, countries that had a greater growth compared to the world average and countries with growth similar to the average were selected to analyze the reaction of the evolution of renewable energy consumption against different scenarios.

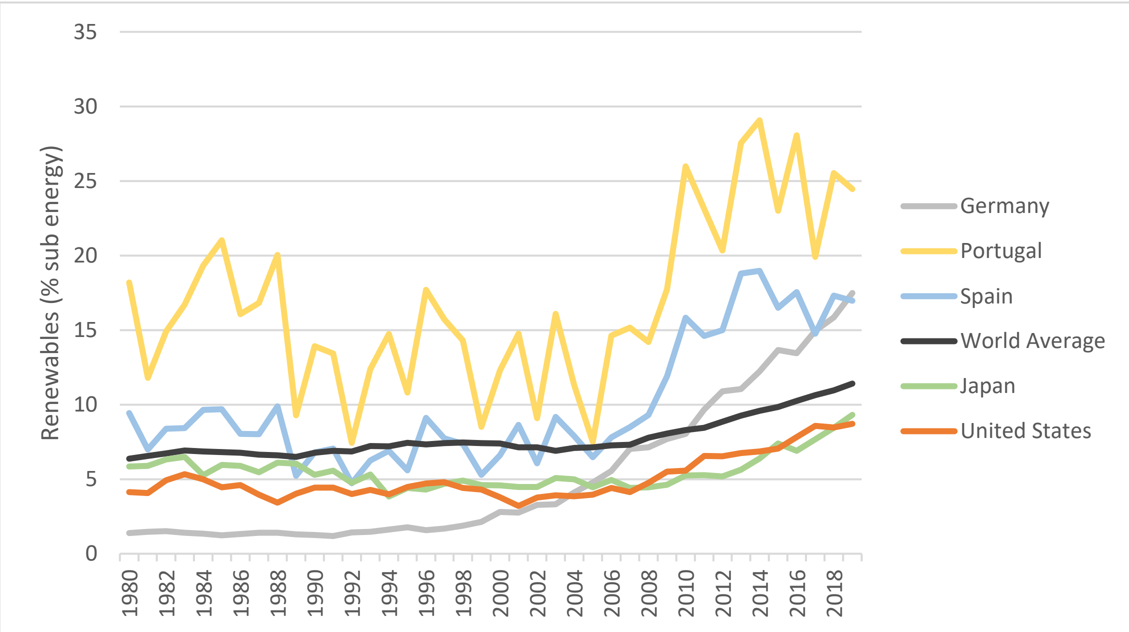


Figure 9 – Evolution of primary energy production from renewable sources between 1980 and 2019 (Source: World in Data)

Table 8 shows the trendlines for each country and for the world average.

Region	Linear regression	Slope
World	y = 0,0956x + 5,7774	0,0956
United States	y = 0,0863x + 3,28	0,0863
Japan	y = 0,0274x + 3,28	0,0274
Germany	y = 0,3752x - 2,5525	0,3752
Portugal	y = 0,2424x + 11,853	0,2424
Spain	y = 0,2535x + 4,7815	0,2535

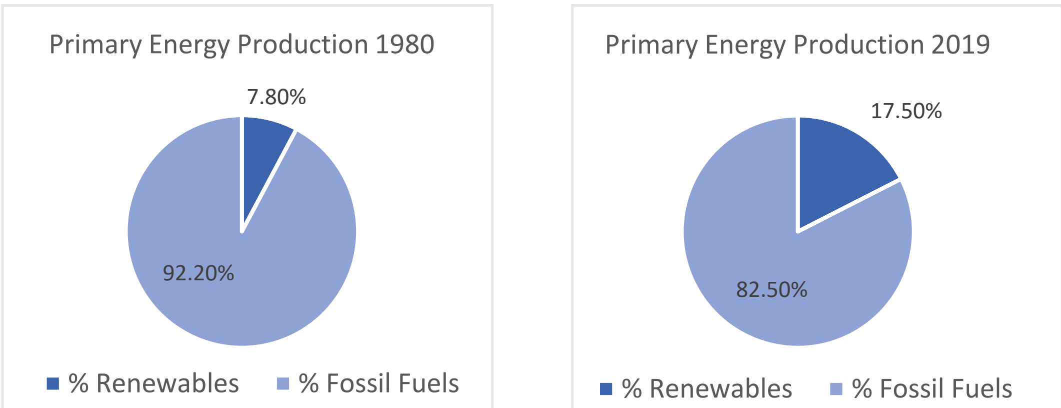
Table 8 – List of trendline equations by country

Based on Figure 9 and Table 8, it was concluded that growth in European countries was more accentuated compared to the United States and Japan.

The results for the European countries arose from the promotion of a set of European Union (EU) directives entitled RES (Renewable Energy Sources) Directives[22] that defined a global European objective of reaching 12% share of gross renewable domestic energy consumption by 2010 and 20% by 2020. Both directives are non-binding, i.e., the EU does not strictly enforce these goals. However, it monitors the progress of member states and, if necessary, proposes mandatory targets for those that do not meet their national goals.

In general, this growth in the share of renewables around the world has been a consequence of the investment made in R&D in the sector and, consequently, the reduction in technology costs[23].

The following Figures (10a and 10b) present the comparison of primary energy production from renewable sources for the cluster of 5 countries that were studied between 1980 and 2019. It increased by 9.7 p.p., twice the growth of the global average, which recorded an increase of 5 p.p.



(a) *(b)*

Figure 10 – Share of energy production by source for the set of five countries in (a) 1980 and (b) 2019

[22] Directive 2001/77/EC, which establishes a group of national targets for the production of renewable energy in each state-member (EPC, 2001) and which was later replaced by Directive 2009/28/EC (Schöpe, 2008)

[23] See https://www.statista.com/statistics/274101/world-renewable-energy-consumption/ (Accessed on July 2021)

3.4 Descriptive analysis

In this section, the main features of our panel data sample are presented and basic statistics provided, according to the variables defined in the previous section for the period 1980 to 2019.

For this basic statistical analysis, the values of the variables are presented in their raw state, without the application of any transformation, as well as the values with the application of differentiation method. This decision is based on the analysis of the stationarity tests that are presented in the next section.

The descriptive statistics of the variables for the first period are presented in Table 9.

Variable	Mean	Std. Dev.	Min	Max	Number of observations
REC	8.366	6.007	1.187	29.067	200
OilPrices	60.322	29.970	19.560	120.500	200
ETrade	219237.191	180631.143	9136.066	736103.400	200
EUse	46872.378	22617.933	12772.003	94561.692	200
CO_2	10.240	5.300	2.573	21.528	200
GDP	32386.478	10796.452	11958.012	54832.980	200
dREC	0.133	2.450	-10.770	8.239	195
dOilPrices	0.137	17.562	- 48.380	49.390	195
dETrade	-1103.430	23185.432	-107934.030	61307.686	195
dEUse	32.591	1375.268	-5038.818	3523.673	195
dCO_2	- 0.034	0.376	-1.615	1.068	195
dGDP	505.835	665.636	-2441.028	2437.773	195

Table 9 – Descriptive Statistics for the period 1980-2019 (d denotes the first difference operator)

For the raw data, the average value of renewable energy consumption is 8.37% of the total energy generated, and the standard deviation is around 6.007. Its minimum (1.187%) refers to the value observed in Germany in 1992 and its maximum (29.067%) in Portugal in 2015.

There was also a reduction in the number of observations as a first difference technique which eliminates five observations in the panel data for each variable and one per country, was applied.

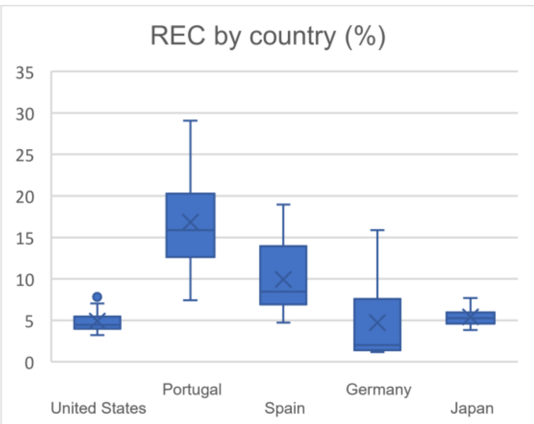
The descriptive statistics of the variables for the second period are presented in Table 10.

Variable	Mean	Std. Dev.	Min	Max	Number of observations
REC	9.050	6.433	1.187	29.132	200
OilPrices	58.667	29.078	19.560	120.500	200
ETrade	215842.756	181474.582	-23380.470	736103.400	200
EUse	46900.669	22091.684	12772.003	93810.546	200
CO_2	10.146	5.181	2.732	21.292	200
GDP	33335.562	10894.217	12288.433	55886.184	200
dREC	0.291	2.335	-10.770	8.239	195
dOilPrices	-1.695	1.136	- 48.380	28.630	195
dETrade	-1347.117	23904.294	-104055.906	61307.686	195
dEUse	48.984	1339.079	-5038.818	3523.673	195
dCO_2	-0.042	0.376	-1.615	1.068	195
dGDP	447.506	807.258	-3755.637	2437.773	195

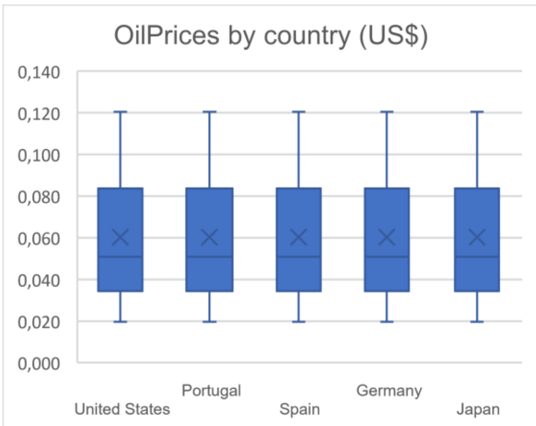
Table 10 – Descriptive Statistics for the period 1982-2021 (d denotes the first difference operator)

Comparing both tables, it was concluded that there was an increase of around 0.7 p.p in the mean of the dependent variable, which shows that the period changes recorded had a positive mark in the growth of the share of renewable energy consumption. Its maximum value rose to 29.132% of renewable energy consumption, compared to the results of the first period, having been recorded 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. The following Figure 11a proves this, since in the last forty years Portugal, the average share of renewable energy consumption was 16.8%, a value higher than that of the other four countries.

The other Figures (11b to 11f) present the mean for each variable and each country included in the panel, between 1980 and 2019, in order to understand the difference between countries and to confirm the reasoning behind the spectrum given above.



(a)



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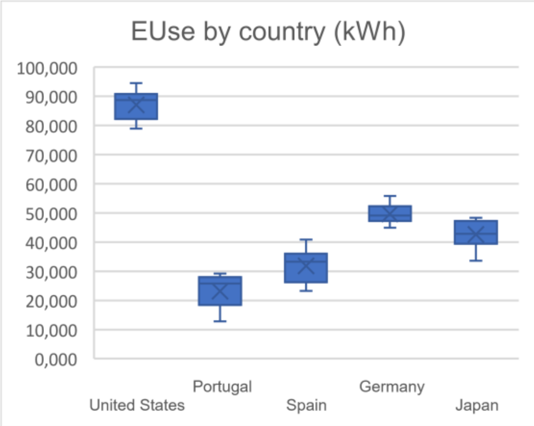

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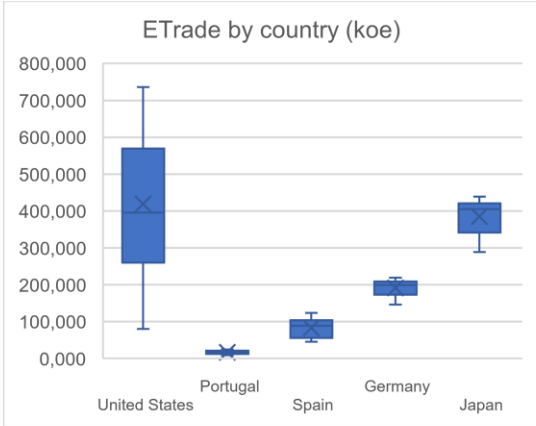
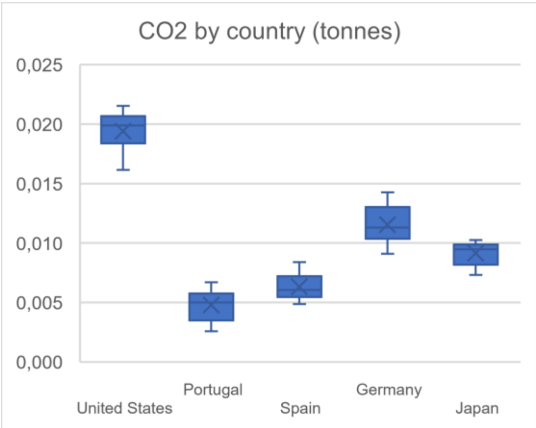
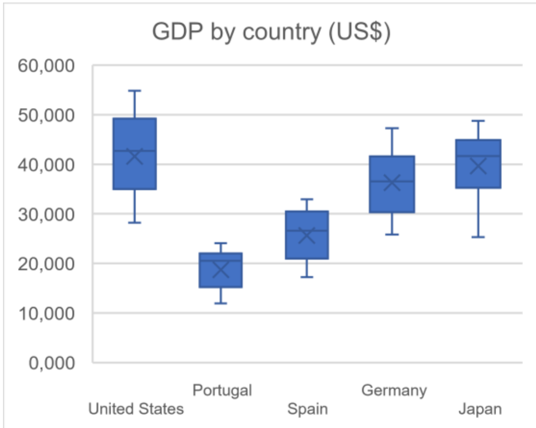


(d)



(e)



(f)

Figure 11 – Variables' characterization for each country (a. REC; b. OilPrices; c. EUse; d. ETrade; e. CO_2; f. GDP)

4. Methodology

This section presents the methodology employed in this dissertation. Time series econometric procedures are used in order to examine the relationship between the growth of our dependent variable, and the behavior of all the independent variables (GDP, CO_2, ETrade, OilPrices, EUse). There are four steps involved in estimating the relationship between the variables. The first step is to test the stationarity of the series or its order of integration, as the series needs to be integrated in the same order. The second step is to examine the presence of a long-run relationship among all variables using the cointegration model proposed by Johansen.

The third step, which depends on the confirmation of cointegration, is to decide which model to use: Vector Autoregressive Model (VAR) or Vector Error Correction Model (VECM). Lastly, some diagnostic tests that examine the validity and reliability of these models are performed. The results of diagnostic tests are analyzed in section 5. For all the tests mentioned above, a 5% significance level was considered, as is the case in many research papers related to this topic (Dinç & Akdoğan, 2019; Sung & Park, 2018).

For the diagnostic tests and analysis, we use EViews, developed by Quantitative Micro Software (QMS) for the Microsoft operating system, which is a modern software that provides sophisticated data analysis, regression, and prediction tools[24]. With its user-friendly and intuitive interface, data can be imported from Excel and then quickly and efficiently create statistical and forecasting equations.

4.1. Unit Root Testing

Variables are sometimes characterized as being non-stationary, which can affect the econometric analysis of time series and panels since the use of non-stationary variables yield spurious results, that is, regressions that tend to accept a false or reject a true relationship of failure regression schemes (Granger, 2007).

This happens when there are similar local trends between variables and will most likely indicate the absence of a relationship:

(i) The coefficient estimate will not converge towards zero
(ii) The t value is very often significant
(iii) R^2 is typically very high

Thus, when the variables of the model are non-stationary, transformation methods such as difference or logarithmic, can be used to circumvent this problem. The first step is to examine the stationarity of the different series using unit root tests. The Augmented Dickey-Fuller (ADF) test is normally used, which employs the following two regression models (Equation 4 and 5) (Guney & Komba, 2016):

(i) $$\Delta Y_t = \beta_1 + \delta Y_{t-1} + \sum_{i=0}^{n} \infty_i \Delta Y_{t-i} + \varepsilon_t \quad \text{(intercept only)} \tag{4}$$

(ii) $$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=0}^{n} \infty_i \Delta Y_{t-i} + \varepsilon_t \quad \text{(intercept and trend)} \tag{5}$$

where Δ = the first difference operator; ΔY_{t-i} = lagged values of the dependent variable; ε_t is a white noise error term; β_1 is a constant; β_2 is a slope coefficient on time trend t; δ is a coefficient of lagged Y_{t-1}.

According to the use of a data panel, there are adequate criteria that are characterized as extensions of the ADF test, to test the stationarity of the variables. The two used were: Fisher Chi-Square which is based on a combination of *p*-values of the test-statistics for a unit root in each cross-sectional unit and for that reason it holds some important advantages such as not requiring balanced data and it is possible to use different lag lengths in the individual ADF

[24] See http://www.eviews.com/help/helpintro.html#page/content/intro-What_is_EViews_3f.html (Accessed on August 2021)

regression; and the Choi Z-Stat develop by In Choi, that proposes a very simple test based on the combination of *p*-values from a unit root test applied to each group in the panel data (Barbieri, 2006).

Table11 and Table 12 show the results of the unit root test for the period between 1980 and 2019 and the period between 1982 and 2021, respectively.

Variables	**Intercept only**		**Intercept and trend**	
	Level statistic (*P-value*)	1st difference statistic (*P-value*)	Level statistic (*P-value*)	1st difference statistic (*P-value*)
REC	1.029 (1.000)	120.894 (0.000)	10.886 (0.367)	131.170 (0.000)
OilPrices	10.269 (0.417)	128.926 (0.000)	4.234 (0.936)	109.007 (0.000)
ETrade	5.475 (0.857)	91.000 (0.000)	1.329 (1.000)	80.167 (0.000)
EUse	5.248 (0.874)	70.083 (0.000)	5.062 (0.887)	92.422 (0.000)
CO_2	4.537 (0.920)	98.376 (0.000)	6.450 (0.776)	84.689 (0.000)
GDP	5.319 (0.869)	68.040 (0.000)	14.171 (0.165)	54.194 (0.000)

Table 11 – Unit Root Test – Augmented Dickey-Fuller Test for the period 1980-2019 (Fisher Chi-Square)

Variables	**Intercept only**		**Intercept and trend**	
	Level statistic (*P-value*)	1st difference statistic (*P-value*)	Level statistic (*P-value*)	1st difference statistic (*P-value*)
REC	3.268 (1.000)	- 8.176 (0.000)	2.071 (0.367)	- 9.081 (0.000)
OilPrices	- 0.813 (0.208)	- 10.204 (0.000)	0.891 (0.813)	- 9.226 (0.000)
ETrade	0.549 (0.708)	- 7.873 (0.000)	3.647 (1.000)	- 7.268 (0.000)
EUse	0.555 (0.711)	- 6.411 (0.000)	2.536 (0.994)	- 8.165 (0.000)
CO_2	0.998 (0.841)	- 8.546 (0.000)	2.314 (1.000)	- 7.728 (0.000)
GDP	1.321 (0.907)	- 6.378 (0.000)	-0.917 (0.180)	- 5.197 (0.000)

Table 12 – Unit Root Test – Augmented Dickey-Fuller Test for the period 1980-2019 (Choi Z-Stat)

The panel unit root tests fail to reject the null hypothesis (H0), so data has a unit root and is non-stationary since its p-value is greater than the statistical significance ($\alpha = 0.05$). For that reason, the first difference method must be applied[25].

For the second period the unit root test results are presented in the following tables (Table 13 and Table 14).

[25] See https://people.duke.edu/~rnau/411diff.htm (Accessed in June 2021)

Variables	Intercept only		Intercept and trend	
	Level statistic (*P-value*)	1st difference statistic (*P-value*)	Level statistic (*P-value*)	1st difference statistic (*P-value*)
REC	0.343 (1.000)	90.913 (0.000)	5.377 (0.865)	173.691 (0.000)
OilPrices	14.559 (0.149)	107.259 (0.000)	10.106 (0.431)	85.376 (0.000)
ETrade	5.906 (0.823)	62.320 (0.000)	0.050 (1.000)	67.215 (0.000)
EUse	7.999 (0.629)	110.823 (0.000)	3.020 (0.981)	116.596 (0.000)
CO_2	3.714 (0.959)	96.767 (0.000)	1.807 (0.998)	90.905 (0.000)
GDP	12.997 (0.224)	49.082 (0.000)	7.104 (0.716)	42.364 (0.000)

Table 13 – Unit Root Test – Augmented Dickey-Fuller Test for the period 1982-2021 (Fisher Chi-Square)

Variables	Intercept only		Intercept and trend	
	Level statistic (*P-value*)	1st difference statistic (*P-value*)	Level statistic (*P-value*)	1st difference statistic (*P-value*)
REC	7.656 (1.000)	- 6.606 (0.000)	4.089 (1.000)	- 12.010 (0.000)
OilPrices	- 1.629 (0.052)	- 9.136 (0.000)	- 0.777 (0.218)	- 7.928 (0.000)
ETrade	0.385 (0.650)	- 5.977 (0.000)	6.236 (1.000)	- 6.352 (0.000)
EUse	0.545 (0.707)	- 9.190 (0.000)	2.758 (0.997)	- 9.422 (0.000)
CO_2	2.311 (0.990)	- 8.467 (0.000)	3.769 (1.000)	- 8.127 (0.000)
GDP	- 0.943 (0.173)	- 4.750 (0.000)	1.282 (0.900)	- 4.042 (0.000)

Table 14 – Unit Root Test – Augmented Dickey-Fuller Test for the period 1982-2021 (Choi Z-Stat)

The results for the second period follow the same reasoning, where all the variables are non-stationary at level and stationary at order one – I(1) – so the first difference technique must also be applied.

4.2. Pedroni Cointegration Test

The long run relationship between variables can be tested through cointegration tests. In this case, since the variables are integrated of order one - I(1) - and the data is presented as a panel, the best option is to follow the Pedroni Cointegration Test (Pedroni, 2004).

Table 15 and Table 16 show the results of the cointegration tests for the first period.

	Statistic	Probability	Weighted Statistic	Probability
Panel v-Statistic	2.251	0.012	0.553	0.290
Panel rho-Statistic	- 1.587	0.056	- 0.285	0.388
Panel PP-Statistic	- 6.767	0.000	- 2.694	0.004
Panel ADF-Statistic	- 6.757	0.000	- 2.920	0.002

Table 15 – Cointegration test – Common Autoregressive coefficients for the period 1980-2019 (with-dimension)

	Statistic	Probability	Weighted Statistic	Probability
Group rho-statistic	- 0.315	0.376	-	-
Group PP-Statistic	- 4.821	0.000	-	-
Group ADF-Statistic	- 4.783	0.000	-	-

Table 16 – Cointegration test – Individual Autoregressive coefficients for the period 1980-2019 (between-dimension)

Seven of the eleven outputs reject the null hypothesis (H0), which is the absence of cointegration, since their p-value is lower than the statistical significance ($\alpha = 0.05$). For this reason, it was concluded that there is a cointegration relationship between the variables.

Table 17 and Table 18 presents the results of the cointegration tests for the second period.

	Statistic	Probability	Weighted Statistic	Probability
Panel v-Statistic	3.082	0.001	1.788	0.037
Panel rho-Statistic	- 5.236	0.000	- 2.502	0.006
Panel PP-Statistic	- 11.026	0.000	- 5.537	0.004
Panel ADF-Statistic	- 5.957	0.000	- 1.666	0.002

Table 17 – Cointegration test – Common Autoregressive coefficients for the period 1982-2021 (with-dimension)

	Statistic	Probability	Weighted Statistic	Probability
Group rho-statistic	- 0.315	0.376	-	-
Group PP-Statistic	- 4.821	0.000	-	-
Group ADF-Statistic	- 4.783	0.000	-	-

Table 18 – Cointegration test – Individual Autoregressive coefficients for the period 1982-2021 (between-dimension)

For the second period, it was concluded that, through the Pedroni Cointegration test, there is also a cointegration relationship between the variables since nine of the eleven outputs reject the null hypothesis (H0).

4.3. Vector Error Correction Model

The main objective of this research is to assess the impact of COVID-19 on the growth of the share of renewable resources in energy generation and the path to energy transition. For that reason, a model that explains the behavior of the share of renewable energy consumption through the set of independent variables, such as Crude Oil Prices, Energy Trade Balance, Energy Consumption per capita, CO_2 Emissions per capita, and GDP per capita, is applied. As already explained, two different periods were considered: one between 1980 and 2019 (pre-Covid) and the other between 1982 and 2021 (including COVID-19). For that purpose, there are some steps that have to be taken.

In the majority of the econometric analysis, where the purpose is to explain the behavior of certain variables by other independent variables, it is important to identify all the characteristics of those variables. For example, if it is an integer or non-integer, negative or nonnegative, discrete or continuous variable. Then it is crucial to evaluate the time series by doing statistical tests. All of this to identify which is the more suitable model for the analysis.

For the models developed in this dissertation, and according to the tests made in the previous sections, which show that the data set is stationary at I(1), and that there is a long-run relationship between the variables, the best model to apply is 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 be used with non-stationary series at level, and that is known to be cointegrated (Asari et al., 2011).

Engle & Granger (1987) demonstrated that once a set of variables is detected to be cointegrated, there is always a corresponding error-correction representation, implying that changes in the dependent variable are a function of the level of disequilibrium in the cointegrating relationship.

The regression equation form for VECM is as follows (Equation 6 and 7) (Asari et al., 2011):

$$\Delta Y_t = \alpha_1 + p_1 e_1 + \sum_{i=0}^{n} \beta_i \Delta Y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta X_{t-i} + \sum_{i=0}^{n} \gamma_i Z_{t-i} \quad (6)$$

$$\Delta X_t = \alpha_2 + p_2 e_{i-1} + \sum_{i=0}^{n} \beta_i Y_{t-i} + \sum_{i=0}^{n} \delta_i X_{t-i} + \sum_{i=0}^{n} \gamma_i Z_{t-i} \quad (7)$$

Before the VECM estimation, the last preliminary step was the lag order selection, which is a crucial standard step of the VECM model procedure. (Winker & Maringer, 2005).

The number of lags applied in the model must be chosen carefully: too few lags fail to capture the system's dynamics, resulting in omitted variable bias; too many lags generate a loss of degrees of freedom resulting in over-parameterization (Caruso et al., 2020), a situation in which the model has more parameters than can be estimated from the data[26].

To find the lag length for the model, the optimal VAR on the EViews had to be determined. The results for the first period can be seen in Table 19 and for the second period in Table 20.

Lag	FPE	AIC	SC	HQ
0	1.00e+30	86.105	86.220	86.152
1	9.90e+21	67.674	68.481*	68.002
2	5.28e+21	67.044	68.543	67.653*
3	4.21e+21*	66.823*	69.004	67.602

Table 19 – Lag order selection criteria for the period 1980-2019

Lag	FPE	AIC	SC	HQ
0	1.94e+30	86.766	86.881	86.812
1	2.24e+22	68.488	69.296	68.816
2	1.03e+22	67.709	69.209*	68.318*
3	8.29e+21*	67.490*	69.681	68.380

Table 20 – Lag order selection criteria for the period 1982-2021

[26] See https://www.oxfordreference.com/view/10.1093/oi/authority.20110803100258143 (Accessed in June 2021)

According to the different information criteria, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ), for the first period, the result for the optimal lag is not consensual (the optimal lag length through each criterion is indicated by an asterisk), except for FPE and AIC. For that reason, a model with the factor provided by these two methods was estimated. Thus, the optimal lag length considered was 3 for VAR.

For the second period, the results are different. SC and HQ point towards a lag of 2. However, as the FPE and AIC criteria are usually the most used in research papers that address this type of test with panel data, a lag of 3 for VAR was also considered.

Regarding VECM, its key components include the number of time series, the number of cointegrating relations among the response variables, and the degree of the multivariate autoregressive polynomial composed of first differences of the response series, which is *p – 1* (Sharp, 2010; Sims C. A., 1980). That is, p – 1 is the maximum lag with a nonzero coefficient matrix, being p the optimal lag of the vector autoregression (VAR) model. Accordingly, for VECM an optimal lag length of 2 (that is, 3-1) was chosen.

The following table (Table 21) presents the two different information criteria used.

Lag	Information Criteria definition in VECM(*p-1*) framework
Akaike Information Criterion (AIC)	$AIC^{VEC(p\text{-}1)} = \ln \lvert \sum \rvert + 2\frac{k^2(p-1)}{T}$
Final Prediction Error (FPE)	$\ln(FPE^{VEC(p\text{-}1)}) = \ln \lvert \sum \rvert + kln\frac{(T+k(p-1))}{(T-k(p-1))}$

Table 21 – List of Information Criteria definition (Sharp,2010)

5. Results and Discussion

5.1. Johansen Cointegration Test

The Johansen cointegration test was used for 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 (Johansen & Juselius, 1990).

There are two variants of the Johansen's test: 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) .

The results for the first period are set out in Table 22 and Table 23.

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None*	0.273	110.998	95.754	0.003
At most 1	0.142	53.544	69.819	0.481
At most 2	0.073	25.961	47.856	0.891
At most 3	0.034	12.348	29.797	0.919
At most 4	0.033	6.680	15.494	0.674
At most 5	0.001	0.131	3.841	0.717

Table 22 – Unrestricted Cointegration Rank Test for the period 1980-2019 (Trace)
Trace Test indicates 1 cointegration equation at the 0.05 level
** 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	57.454	40.078	0.000
At most 1	0.142	27.583	33.877	0.233
At most 2	0.073	13.613	27.584	0.848
At most 3	0.034	6.168	21.131	0.979
At most 4	0.033	6.048	14.265	0.607
At most 5	0.001	0.131	3.841	0.717

Table 23 – Unrestricted Cointegration Rank Test for the period 1980-2019 (Maximum Eigenvalue)
Max-eigenvalue Test indicates 1 cointegration equation at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level*

For the second period the outputs are presented in Tables 24 and 25.

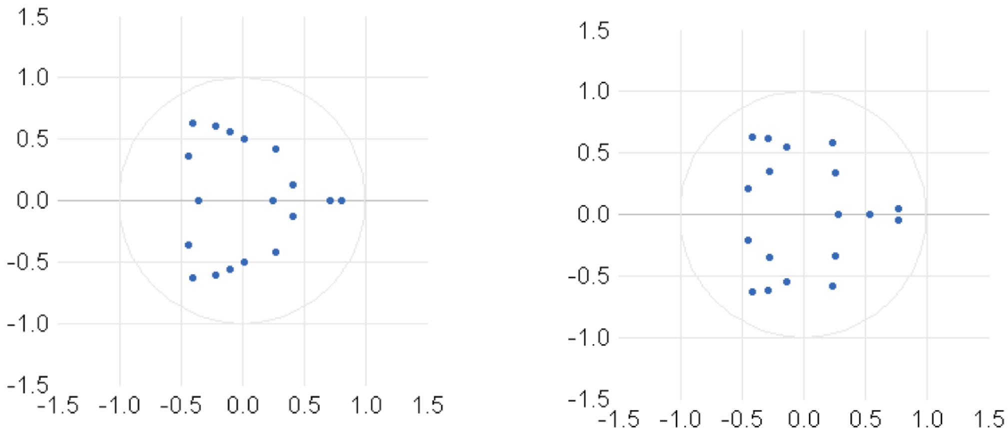
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None*	0.247	110.478	95.754	0.003
At most 1	0.151	59.324	69.819	0.257
At most 2	0.075	29.835	47.856	0.727
At most 3	0.049	15.866	29.797	0.722
At most 4	0.032	6.808	15.494	0.600
At most 5	0.006	0.993	3.841	0.319

Table 24 – Unrestricted Cointegration Rank Test for the period 1982-2021 (Trace)
Trace Test indicates 1 cointegration equation at the 0.05 level
**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*	0.247	51.153	40.078	0.002
At most 1	0.151	29.489	33.877	0.153
At most 2	0.075	13.970	27.584	0.825
At most 3	0.049	9.057	21.131	0.828
At most 4	0.031	5.814	14.265	0.637
At most 5	0.005	0.994	3.841	0.319

Table 25 – Unrestricted Cointegration Rank Test for the period 1982-2021 (Maximum Eigenvalue)
Max-eigenvalue Test indicates 1 cointegration equation at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level*

Both forms determine whether cointegration is present, where the null hypothesis claims the absence of cointegration. According to the results of both periods presented in the tables above, the null hypothesis is rejected by the trace and maximum eigenvalue and there is one cointegration relationship in the models. In other words, it can be said that there is a long-run relationship between the variables.



(a) *(b)*

Figure 12 – Inverse Roots of Autoregressive (AR) Characteristic Polynomial (a) for the period 1980-2019 and (b) for the period 1982-2021

The results from Roots of Characteristic Polynomial (Figures 12a and 12b) 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.

The following normalized Equations 8 and 9 present the long-run relationships between the dependent and independent variables, considering a 5% significance level.

1980 - 2019

$$REC = 3.345OilPrices + 0.001GDP - 0.007EUse - 6.800E\text{-}05ETrade + 31.438CO_2 \quad (8)$$

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

1982 - 2021

$$REC = 3.017OilPrices + 0.004GDP - 0.008EUse - 1.410E\text{-}04ETrade + 38.084CO_2 \quad (9)$$

(t-value = 6.872) (t-value = 2.260) (t-value = 2.667) (t-value = 1.41) (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[27]. 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 10):

$$ECT_{t-1} = [Y_{t-1} - \eta_j X_{t-1} - \xi_m R_{t-1}] \tag{10}$$

In line with the data sample, the error correction term presented itself in the equations below itself (Equation 11 and 12):

1980 - 2019

$$ECT_{t-1} = [1.000\ REC_{t-1} - 0.053\ OilPrices_{t-1} + (3.000E\text{-}04)\ GDP_{t-1} - 0.001\ EUse_{t-1} - (5.690E\text{-}06)\ ETrade_{t-1} + 4.046\ CO2_{t-1} - 0.243] \tag{11}$$

1982 – 2021

$$ECT_{t-1} = [1.000\ REC_{t-1} - 0.019\ OilPrices_{t-1} + (4.710E\text{-}04)\ GDP_{t-1} - (6.270E\text{-}04)\ EUse_{t-1} - (1.370E\text{-}05)\ ETrade_{t-1} + 4.023\ CO2_{t-1} - 0.354] \tag{12}$$

So the VECM equation (Equation 13) established is:

$$D(REC)_t = c + a_1 D(REC)_{t-1} + a_2 D(REC)_{t-2} + b_1 D(OilPrices)_{t-1} + b_2 D(OilPrices)_{t-2} + c_1 D(GDP)_{t-1} + c_2 D(GDP)_{t-2} + d_1 D(EUse)_{t-1} + d_2 D(EUse)_{t-2} + e_1 D(ETrade)_{t-1} + e_2 D(ETrade)_{t-2} + f_1 D(CO2)_{t-1} + f_2 D(CO2)_{t-2} + u_t \tag{13}$$

[27] See https://www.pbl.nl/en/news/2020/long-term-impact-of-covid-19-on-co2-emissions-dependent-on-greenness-of-recovery-packages (Accessed in October 2021)

5.2. VECM Estimations

The VECM test results to the dependent variable REC are provided in Table 26.

	1980 - 2019	1982 - 2021
	D(REC)	D(REC)
ECT(-1)	- 1.480 [-7.562]	-1.449 [-6.396]
D(REC(-1))	0.032 [0.235]	0.018 [0.100]
D(REC(-2))	-0.242 [-2.887]	-0.260 [-2.545]
D(OilPrices(-1))	-0.059 [0.012]	-0.013 [0.011]
D(OilPrices(-2))	-0.033 [-3.583]	0.004 [0.408]
D(GDP(-1))	2.16E-04 [0.751]	1.090E-04 [0.365]
D(GDP(-2))	-9.48E-05 [-0.345]	2.000E-04 [0.715]
D(EUse(-1))	-0.001 [-5.640]	-4.830E-04 [-2.587]
D(EUse(-2))	-4.54E-04 [-2.595]	-2.360E-04 [-1.513]
D(ETrade(-1))	-1.83E-06 [-0.193]	-5.540E-06 [-0.568]
D(ETrade(-2))	4.71E-06 [0.450]	-4.980E-06 [-0.530]
D(CO_2(-1))	4.428 [5.461]	3.100 [3.819]
D(CO_2(-2))	1.711 [2.372]	1.590 [2.670]
C	0.016 [0.100]	0.039 [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 26 – VECM test results (t-statistcs are provided in square brackets)

The first aspect that can be taken from the comparative table (Table 26) 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. In the first period, the ECT (-1) has a higher value, therefore indicating a higher speed of adjustment towards the long-term equilibrium, which may be due to the fact that the pandemic created such a shock in the energy and economic system, altering each country's priorities, 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.

5.3. Granger Causality Test

Next, the short-run relationships among all the variables were investigated. The Granger Causality test was used for this purpose. This test, developed by Clive Granger in 1960, involves examining whether the information provided by the lagged values of one variable allows for a more accurate prediction of another variable's present value[28]. If a variable Granger-Causes the dependent variable, it means that it is useful to predict the dependent variable in the short-run.

The results are provided in Table 27.

	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 27 – 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.

5.4. Variance Decomposition

Another technique used to determine the causes of the change in series for the short run is variance decomposition. This analysis not only decomposes the portions of a change in a variable originating from itself and from the other variables, but also gives information about the degree of causality relationships between the variables (Vasco & Mota, 2016).

1980 - 2019							
Period	**S.E**	**D(REC)**	**D(OilPrices)**	**D(GDP)**	**D(EUse)**	**D(ETrade)**	**D(CO_2)**
1	2.112	100.000	0.000	0.000	0.000	0.000	0.000
2	2.252	86.381	1.126	0.395	0.072	0.053	1.975
3	2.362	89.435	2.544	0.853	1.280	0.098	5.790
4	2.713	86.824	5.538	0.702	1.114	0.153	5.670
5	2.742	85.535	5.836	0.797	1.149	0.179	6.504
6	2.863	81.952	6.611	1.244	1.432	0.227	8.535
7	3.001	80.367	8.012	1.166	1.520	0.229	8.706
8	3.032	78.844	8.460	1.282	1.571	0.227	9.616
9	3.136	76.796	9.082	1.470	1.703	0.240	10.710
10	3.218	75.553	9.911	1.458	1.794	0.228	11.057

Table 28 – Variance decomposition for the period 1980-2019

[28] See http://www.scholarpedia.org/article/Granger_causality#Personal_account_by_Clive_Granger (Accessed in September 2021)

According to the results of variance decomposition for the pre-pandemic period presented in Table 28, all the changes obtained in renewable energy consumption in the first period (t=1) are explained by the variable itself, contrary to the last period (t=10), where almost 10% is explained by oil prices and 11% by CO_2 emissions. The other variables have less impact, taking values between a range of 0.2% and 1.8% in the last period.

1982 - 2021							
Period	**S.E**	**D(REC)**	**D(OilPrices)**	**D(GDP)**	**D(EUse)**	**D(ETrade)**	**D(CO_2)**
1	2.110	100.000	0.000	0.000	0.000	0.000	0.000
2	2.346	89.839	0.007	3.455	0.881	0.023	5.795
3	2.407	88.599	1.313	3.282	0.868	0.055	5.883
4	2.671	88.482	1.349	3.167	0.760	0.046	6.197
5	2.720	85.452	1.394	4.385	1.152	0.072	7.544
6	2.780	84.587	1.902	4.315	1.154	0.082	7.959
7	2.892	84.374	1.827	4.272	1.120	0.077	8.331
8	2.937	82.437	1.852	4.878	1.328	0.103	9.300
9	2.992	81.793	2.011	5.001	1.358	0.105	9.724
10	3.067	81.421	1.920	5.064	1.358	0.105	10.134

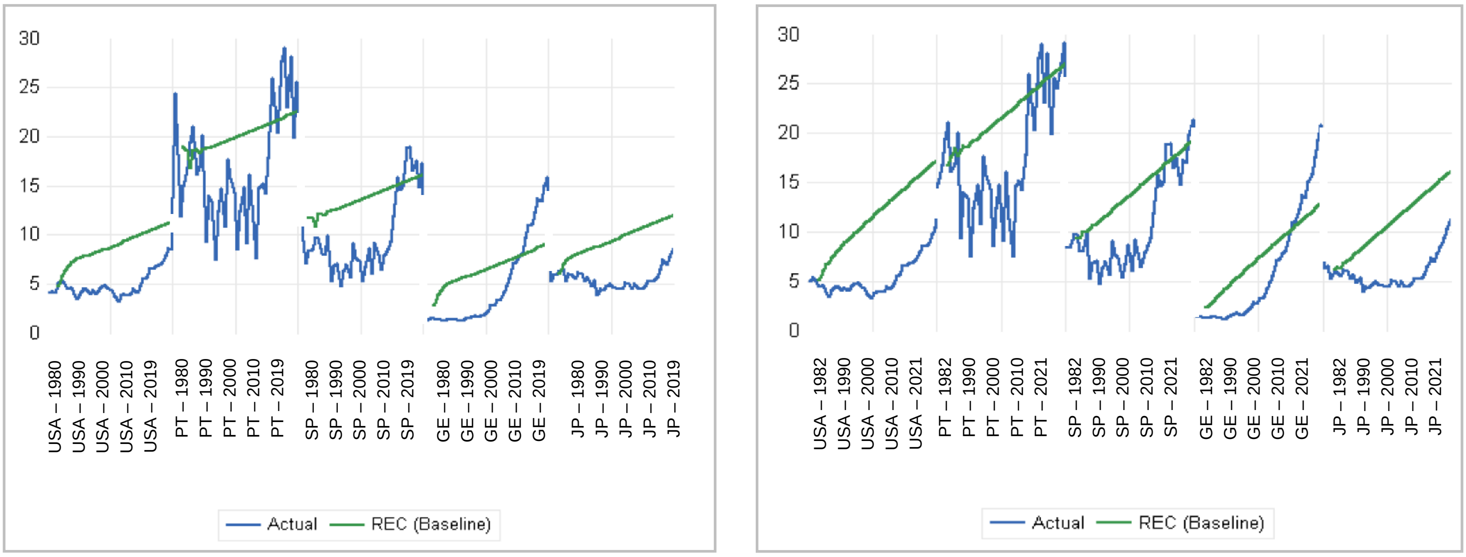
Table 29 – Variance decomposition for the period 1982-2021

When including the pandemic period, despite the fact that in the first period (t=1) all the variations obtained in renewable energy consumption are also explained by the variable itself (Table 29), in the last period (t=10) oil prices explain only 2%, GDP increases its weight to 5% and CO_2 keeps a figure close to 10%. This interesting change in the role of GDP and oil prices is probably related to the pandemic itself.

Overall, it may be concluded that the independent variables have an impact on renewable energy consumption. Therefore, these findings obtained from variance decomposition, except the discrepancy that characterizes GDP, partially support the results of the Granger Causality test for the short-term.

Performing a brief summary of the analysis conducted, we began with the data characterization (descriptive statistics of the panel data), followed by several tests. We employed different tests to define the settings for the Vector Error Correction Model (VECM): the unit root test (Augmented Dickey-Fuller Test) in order to evaluate the stationarity of our variables, the Pedroni cointegration test to study the stability of the time series in the long-run, the optimal lag length, the Johansen cointegration test to find the number of cointegration equations, the Roots of Characteristic Polynomial to investigate the stability of the model. The VECM estimations and Granger Causality allowed to examine the impact of the independent variables on the behavior of the dependent variable.

Finally, to understand not only the evolution and the trend for the future of the dependent variable (Renewable Energy Consumption) 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 13a and 13b).



(a) *(b)*

Figure 13 – Evolution of REC by country for the period of (a) 1980-2019 and (b) 1982-2021

Both Figures (Figures 13a and 13b), corresponding to a graphical representation of a deterministic simulation of the model, are obtained from the EViews software. They present the evolution and trend line of the dependent variable during the two distinct periods by panel data decomposition made directly by the software, where the behavior of each country is presented individually. Thus, according to these representations, we can easily see that the pandemic years, which fall into the second period (1982-2021), added some changes in the behavior of the evolution of renewable energy consumed, proving a greater progression in the energy transition for the analyzed countries since the slopes become more positively accentuated compared to the first period.

5.5. Failed results, Limitations and Future Work

5.5.1. Failed results

Throughout this study, several other models were computed, and different variables were essayed in order to assess the evolution of REC. But in most cases they presented either unsatisfactory results or unfeasibility for application to the models that were shown in this dissertation. Herewith are presented some of the failed experiments:

- **Failed variables** – From the beginning of this project, several variables were incorporated into the model in order to complete and make it more robust. The choice of the tested variables was based on similar research papers where themes on the development and progress of renewable resources in the energy sector and their constraints are addressed. Incorporating variables from different fields was sought: economic, financial, political, environmental and demographic. Some of these variables were: Foreign Direct Investment (FDI), Carbon Taxes, Feed-In-Tariff, R&D and green innovation (by patents), population growth, etc. However, the decision to drop these variables was made both due to unsatisfactory statistical results and, in certain cases, due to lack of available data.

- **Dependent variable** – The first analysis made was with renewable installed capacity (RIC) (million KW) as a dependent variable. However, after some research, it was concluded that, the REC variable, as a percentage of the total energy consumed, would be more appropriate to measure the degree of transition to a renewable energy economy.
- **Country Data** – Before starting the analysis for the panel data, some tests with the purpose of studying individually the behavior of the dependent variable for each country, were performed. Due to the bad statistical results obtained, it was decided to evaluate all this analysis for the group of countries, with different characteristics.
- **OLS model** – Some ordinary least squares models for the group of variables selected were run. However, as all of them were non-stationary, some of the results ended up being spurious.
- **VAR model** – Still with REC as a dependent variable, when performing the Pedroni cointegration test, it was concluded that the variables were not cointegrated and as such did not show any relationship in the long-run. Thus, being stationary in the first order and not cointegrated, the VAR was chosen according to the model's norms. However, after all the tests performed the statistical results were not good, especially the R-Squared, which was very low.

5.5.2. Limitations and Future work

Despite having been the source of limitations related to the lack of recent data for all the variables, the fact that this subject is so recent brought a deep relevance to the dissertation. To deal with the lack of data, some interpolations and some comparative analysis regarding similar variables that already have available data for the most recent years (2019 and 2020) were made. COVID-19 is quite a recent issue, and it is too early to speculate about a transformed, post-Covid world, only making presumptions based on available data. Keeping this work updated as the pandemic keeps spreading could further benefit the trajectory of the analysis in its real terms. Mathematical implications can also be drawn about the future of the renewable energy sector once the world is back to normality.

Taking into consideration a deeper analysis, it would also be interesting to study and compare the results for different sets of countries, presenting different characteristics (e.g. different political systems, developed versus developing countries) in order to understand the contrasting impacts of the pandemic and future approaches for energy transition.

6. Conclusion

The aim of this dissertation was the analysis of the COVID-19 shock's influence in the pathway towards 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 the specific shock caused by the COVID-19 outbreak.

In the literature review, some important historical aspects and concepts that characterize the energy sector were looked at firstly, as well as the main points that described the pandemic that marked the years 2020 and 2021, which has been developing into one of the most severe challenges that Humanity has faced. Some points such as the disruption of supply chains, the drop in industrial productivity, the health crisis, among other factors, have mercilessly affected the current global economy, based and supported mainly on global trade. We have also observed an increase in the unemployment and poverty rates, a drop in GDP, oil prices, and energy consumption, that has resulted in substantial decreases in CO_2 and environmental noise emissions and, as a consequence, a significant reduction in environmental pollution. This was an important step for the dissertation, as the definition of the explanatory variables to be applied in the model based on all the information collected was made and selected for the dependent variable, the renewable energy consumption (REC), and for the independent variables, GDP, crude oil prices, CO_2 emissions, energy trade balance and energy consumption.

One of the main objectives of this study, as stated above, was to understand the impact of COVID-19 on the transition to a green energy sector. However, as this is a fairly recent outbreak, it is unfortunately too early to speculate by making only presumptions based on the available data. Therefore, two identical models with different time periods were developed, one considering the pandemic (between 1982 and 2021) and the other not taking it into consideration (between 1980 and 2020), to be run side by side, enabling the analysis of the impact of the shock on the statistical characteristics of the model.

We went through 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 following step was the data characterization from which analysis of the shock were possible. After some statistical tests for the individual countries, it was decided to construct the data sample using panel data, with the set of the five countries referred above, and using data from different international sources, such as World in Data, Energy Information Administration (EIA) and the World Bank.

Several statistical analysis were performed, considering multiple time series models. A vector error correction model (VECM) that studied the impact of five explanatory variables on the variation of the dependent variable, that characterizes the growth of renewable energy share and intrinsically the path for energy transition, was presented. Considering a lag of one year between the dependent and independent variables, it was concluded that the dependent variable, in both models, is 74% (model without considering COVID-19) and 75% (model considering COVID-19) explained by the explanatory variables. CO_2 emissions, energy consumption, and oil prices are the ones that show significance in explaining 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, led by the technology improvement and consequently by the improvement of energy efficiency, has a positive impact on renewable energy consumption. The price of crude oil shows an unexpected sign, where the negative relation 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). The other two independent variables, GDP and ETrade, proved to be statistically nonsignificant.

The results turned out to be quite interesting since, through the graphical representations provided by the software, it could be observed that the pandemic added some changes in the trend line of the percentage of renewable energy consumed, proving a greater progression in the energy transition by the various countries analyzed.

With this dissertation, it was 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 faced, it is believed that there is further analysis to be conducted, the most obvious of which is the repetition of the analysis with a longer set of post-Covid data.

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