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DISSERTATION

ELECTRIC CARS IMPACT IN THE ECONOMIC GROWTH AND THE CO_2: CASE OF EUROPEAN UNION

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Abstract

This dissertation presents an analysis of the impacts of electric vehicles in economic growth and carbon dioxide emissions in the European Union. It was executed a micro panel with annual data from 2008 to 2016, and two models were estimated using the Autoregressive Distributed Lag (ARDL) model. The first one with 26 countries, where the dependent variable is the carbon dioxide emissions, and the second one, with 24 countries, the dependent variable is the gross domestic product, as a proxy for economic growth. The findings in this study suggest that investing in electric vehicles, in the long run, is beneficial to the European Union, economically and environmentally. Increasing the fleet of EVs, improves the quality of air, and increases the GDP.

Keywords: Carbon Dioxide, Electric Vehicles, European Union, Gross Domestic Product

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Resumo

Esta dissertação apresenta uma análise do impacto dos veículos elétricos tanto no crescimento económico, como nas emissões de dióxido de carbono na União Europeia. Realizou-se um micro painel, com dados anuais de 2008 a 2016, em que se estimaram dois modelos utilizando o modelo Autoregressive Distributed Lag (ARDL). O primeiro modelo, com 26 países, tem como variável dependente as emissões de dióxido de carbono, e no segundo, com 24 países, a variável dependente é o produto interno bruto, utilizada como proxy para o crescimento económico. Os resultados deste estudo sugerem que investir em carros elétricos, no longo prazo, é benéfico para a União Europeia, ambientalmente e economicamente. Ao aumentar a frota de veículos elétricos, há uma melhoria na qualidade do ar, e o PIB aumenta.

Palavras-chave: Dióxido de Carbono, Produto Interno Bruto, Veículos Elétricos, União Europeia

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Glossary

AEVs – All Electric Vehicles

ARDL – Autoregressive Distributed Lag

BEVs – Battery-Electric Vehicles

DSM – Demand-Side Management

ECM – Error Correction Mechanism

EU – European Union

EVs – Electric Vehicles

FE – Fixed Effects

FCEVs – Fuel Cell Electric Vehicles

FCHEVs – Fuel Cell Hybrid Electric Vehicles

FHEVs – Full-Hybrids Electric Vehicles

GDP – Gross Domestic Product

GHG – Greenhouse gases

HEVs – Hybrid Electric Vehicles

ICE – Internal combustion engine

PHEVs – Plug-in Hybrids Electric Vehicles

RE – Random Effects

SG – Smart Grid

V2G – Vehicle-to-Grid

I. Introduction

Global warming, caused by the increase of greenhouse gases (GHG) emissions, has been a concern for the whole world, over a few decades. One of the major contributors to this increase is the transport sector, given their dependency on oil. This sector alone is responsible for a large share of carbon dioxide (CO_2) emissions, which is the most prejudicial gas to the environment (Samara, 2016). In addition to this concern, there is also the problem of the depletion of oil, thus being necessary to invest in electric mobility.

Electric vehicles (EVs) have many advantages in comparison to internal combustion ones, especially environmental ones, namely because some types of electric cars do not emit CO_2, which are called All Electric Vehicles (AEVs), and others, the Hybrid ones, produce lower quantities of GHG. Also, these vehicles tend to cost less to consumers due to having more electrical parts (Riesz et al. 2016).

Despite being crucial to invest in electric cars, the electricity to charge the EVs is also generated with oil and coal, so in order to reduce the emissions of prejudicial gases, it is necessary to substitute these extremely pollutant sources with renewable or cleaner sources. Besides this, the increase in the demand of the power grid may become a problem too, and, consequently, the cost of electricity may increase. As Richardson (2013) stated, to overcome these challenges, the introduction of the Smart Grid (SG) might be a solution, given its capability of controlling the vehicle charging in the most advantageous way, not only economically but also in terms of demand of energy. The European Union Commission believes that the investment in this infrastructure is ideal, as its aim is to increase the number of EVs and, therefore, the number of charging points (Niestadt & Bjørnåvold, 2019).

The European Union (EU) has been changing its behaviour in order to achieve lower CO_2 emissions, especially with the growing investment in the electrification of the transport sector. The European governments are also providing benefits to consumers, with the intention of increasing sales of electric vehicles (Piazza, 2020). Despite these improvements, it still is necessary to invest more in electric mobility, and the EU has to change its production of the motor vehicles to the electric ones, to become competitive in the market, and to improve their economy.

Another important factor that can contribute positively to the economy is the increase in employment. By decreasing the dependency on oil, and despite diminishing employment in areas related to petroleum, spending on imports will decrease, and other sectors will have to innovate and create jobs, which will enhance the European Union economy (Harrison, 2018).

To achieve the goals defined by the EU's Energy and Climate Change Packages, of CO_2 emissions, and to boost the economy, it is crucial that the population is informed about global warming and, thus, how we are affecting our world. Also, they need to know all the monetary advantages of owning EVs and how positive it can be to the European Union economy. So, the benefits of the electrification of the transport sector, in terms of the environment and economically, must be studied. In this sense, this study aims to answer two central questions: (i) What is the impact of electric vehicles in the CO_2 emissions in the European Union?; and (ii) What is the impact of electric vehicles in the European Union economic growth? To understand these impacts, and answers to these questions, it was executed a micro panel with annual data from 2008 to 2016 and 26 countries of the EU, in the first model, and 24 countries in the second model. These models were estimated by using Autoregressive Distributed Lag (ARDL), a flexible methodology that allows the analysis of variables in the short and long run. This study contributes to the literature related to the adoption of EVs, and its benefits in the economic growth and in the diminishing of CO_2 emissions, which is still scarce. In particular, the benefits of expanding the number of battery-electric and plug-in hybrid electric vehicles circulating in the EU.

The remainder of this dissertation is as it follows: section II presents the literature about electric vehicles and their advantages in the European Union; section III describes the data and methodology used; section IV displays the results of the models, that are then discussed in section V, and finally, section VI presents the conclusions.

II. Literature Review

The creation of nowadays automobiles, that is, cars powered by an internal combustion engine (ICE), is dated back to the XIX century. The use of these vehicles by the population has been increasing significantly throughout these last decades, which indicates that the reliance on this mean of transportation is intensifying. Hereupon, governments all around the world are becoming aware of the problem that internal combustion engine vehicles cause to the atmosphere, the planet and consequently to the humankind (Fontaínhas, 2013).

The invention of electric cars, likewise, goes back to the XIX century. Because ICE vehicles were lighter, had greater autonomy, were cheaper to manufacture, and, as such, purchased at lower prices, in comparison to electric vehicles, their production achieved a higher scale. Besides, electric cars had shorter distance ranges, which led to a lack of progress in the EV field for many years (Sigurðsson, 2010).

Up until now, conventional cars have dominated in relation to the EV, and as previously stated, there has been a rise in the number of vehicles in circulation. The main problem about the expansion of the automobile industry in the world is the increase of emissions of greenhouse gases, mainly the carbon dioxide emissions, representing the ICE based transports, a significant percentage of the total emissions of GHG worldwide.

In order to diminish the air pollution caused by ICE vehicles, cleaner fuels were developed, and also a technology that reduces the toxicity of the emitted gases produced in internal combustion, the fuel catalyst. Although the positive effect created by this device, carbon dioxide emissions did not decrease, being this gas the major cause of the greenhouse effect (Samara, 2016).

The dependency of the transport sector on fossil fuels, as a source of energy, is a growing concern. This sector accounts for a large share of GHG emissions, mainly CO_2. Road transport, as stated in IEA (2016), is accountable for 17% of carbon dioxide emissions, which are the main cause of climate change (Almeida et al. 2018). It also aggravates the air pollution that causes severe health issues. Another problem is the depletion of oil, that, as predicted, can lead to scarcity in the future, so there was a need to invest in renewable energies. Given that electric vehicles are low on carbon and do not depend only on oil, they are the most viable option (Andwari et al. 2017). EVs are typically defined as ultra-low emission vehicles because, even though some types like Hybrid Electric Vehicles (HEVs) can also run on fossil fuels, the EVs run on electricity stored in electric batteries (Butcher et al. 2018).

The fact that 100% electric automobiles do not emit injurious gases, or, when not 100% EV, do not release, at least, the same quantities as conventional cars, is the most valued aspect, but there are also other advantageous features. As Holmberg & Erdemir (2019) refer in their study, electric cars have higher energy efficiency than fossil fuel vehicles due to low thermal losses and low friction, even though the Battery-Electric Vehicles (BEVs) are the most energetically efficient ones, since there is an absence of a reciprocating engine, while other types of electric cars, HEVs, can have both a reciprocating engine and an electric motor. EVs are more silent than ICE vehicles, which also contributes to the reduction of noise pollution, thus, being an important improvement. Electric vehicles have lower maintenance costs than conventional cars, as Riesz et al. (2016) state, this because the components of the EV are mostly electrical, and the quantity of moving parts is much lower, comparing with an ICE car, causing less mechanical wearing, thus needing less maintenance and repairs.

There are two basic types of EVs, the All Electric Vehicles and the Hybrid Electric Vehicles. Within the first type, AEVs, it is possible to distinguish the BEVs that use a battery as the source of power, wherein electricity is stored. The Fuel Cell Electric Vehicles (FCEVs), that similarly to the BEVs, do not generate tailpipe carbon emissions due to only having an electric engine. Electricity is produced by a blend of hydrogen, stored in a tank, with oxygen from the air. The re-fuelling of hydrogen is done at filling stations and opposingly to BEVs, it does not require plugging the vehicle to the electric grid (Samara, 2016). There are also the Fuel Cell Hybrid Electric Vehicles (FCHEVs) in which there is another energy storage system, such as a battery or an ultracapacitor, to support the fuel cell.

Regarding the second type, the HEVs, they have batteries which are charged primarily by ICE and, also by regenerative braking. They are named as HEVs because they have both an internal combustion engine, powered by fossil fuels, and an electric motor, powered by electricity. There are three types, the Mild-Hybrid EVs, the Full-Hybrids EVs (FHEVs) and the Plug-in Hybrids EVs (PHEVs). The Mild-Hybrid are in fact powered by the ICE, meaning that the features of the electric motor are merely to improve efficiency, in terms of assisting the engine in starting the car, shutting off the motor while the car is stopped, and also in the braking system. Likewise, it is helpful in the task of reducing toxic emissions (Benajes et al. 2019; Solouk et al. 2018). The FHEVs, are subdivided in Series Hybrid EVs, Parallel Hybrid EVs, Series-parallel Hybrid EVs and Complex Hybrid EVs. The PHEVs, in addition to regenerative braking and fossil fuels as sources of energy, the batteries of these automobiles can also be charged by plugging to electricity, identically to the BEVs (Das et al. 2017; Wilberforce et al. 2017).

Despite the growing investment and interest in electric cars, the source of electricity is still a problematic issue. When electricity in power plants is generated using oil, natural gas or coal, the environmental progress made by substituting the conventional cars by EVs can be lost (Ajanovic & Haas, 2016; Almeida et al. 2018). To effectively reduce the GHG emissions and also diminish the dependency of fossil fuels, measures need to be taken in order to produce electricity through renewable, or at least, cleaner sources. As Holmberg and Erdemir (2019) refer, when electrical energy is obtained through biomass, nuclear, wind, hydro or concentrated solar power, the CO_2 emissions are at its lowest levels. Solar photovoltaics and geothermal energy are also viable options, and regardless of emitting a bit more CO_2 than the previously stated alternatives, they are both sustainable and renewable.

Although it is feasible to supply electrical energy issuing small amounts of CO_2, the power grid may require improvements as the number of electric cars rises. It will be observed a higher demand for energy, to charge the vehicles, at peak hours, which could damage the existing power grids (Anastasiadis et al. 2019). This extra demand also affects the costs of electricity, but it is possible to overcome this setback, and it may not be necessary to expand the electrical grid by making controlled charges out of the rush hours (Almeida et al. 2018; Razeghi& Samuelsen, 2016). Despite this, it may be required to shift towards the Smart Grid, that is, an infrastructure that puts together the power system engineering with the information and communication technologies (López et al. 2015). It is, as the European Commission defines, “an electricity network that can intelligently integrate the actions of all users connected to it - generators, consumers and those that do both - in order to efficiently deliver sustainable, economic and secure electricity supplies" (Jenkins et al. 2015, pp. 414). The introduction of SG aims to control the vehicle charging in a more advantageous way, by minimizing the electricity costs, and to charge when the demand is at its lowest or when there's spare capacity, among other measures (Richardson, 2013). The most interesting characteristic of the SG is the Demand-Side Management (DSM), which has as a primary goal to shift energy use to off-peak times, thus Demand Response programmes (DR) ensure that the main objective is fulfilled and control the demand by consumers, by providing information to consumers about electricity prices and the state of the grid, which means that users are aware when there's scarcity of electricity, and can opt by cheaper renewable energy (Gelazanskas & Gamage, 2013).

The challenges that the power grid may face due to an increase in BEVs and PHEVs in circulation, mainly the problematic of an increase of charges on-peak hours, can have a solution, which to be successfully managed, needs the Smart Grid infrastructure. It is a bidirectional energy exchange system, Vehicle-to-Grid (V2G) technology, in which the electric cars are charged when demand is at its lowest, particularly at night. Moreover, at rush hours, EVs act as distributors of power, by discharging the energy stored in their batteries into the grid. V2G can function as an emergency supply, that is, a backup for renewable resources, as a storage device, and in addition to this, it enhances the performance of a supply grid (Habib et al. 2015).

Even though bidirectional V2G is a potential solution, since the increase of charges and discharges each battery faces, when using this system, a degradation on EV batteries can occur, and their lifespan will be lower than expected (Dubarry et al. 2018; Zheng et al. 2019). Nevertheless, the cost of implementing this system, although it is higher than the cost of employing unidirectional V2G (only from the grid to vehicle), considering that it allows controlling when the charges are made, and thus, levels the peak load, in an economic perspective, is recommended. In particular, this is due to the progress in battery technology, and because it can help the power company reduce electricity costs, consequently decreasing charging costs (Zheng et al. 2019).

The European Union Commission believes that the number of electric cars will rise in the next few years, so the number of recharging points needs to follow this growth, to approximately 2 million recharging points in 2025 (Niestadt & Bjørnåvold, 2019). The EU Commission also supports the idea that these should be capable of not only do its main objective, recharging the batteries but also ought to allow the EVs to discharge their batteries into the grid when necessary (Niestadt & Bjørnåvold, 2019), thus being necessary to invest in the Smart Grid.

The European Union, aware of how dangerous environmental pollution is, has engaged in the task of reducing the GHG emissions, according to the EU's Energy and Climate Change Packages. The aim, by 2030, is to reduce the GHG emissions by 40% and increase the energy efficiency to at least 32,5% and the share of renewable energy sources to 32%, relatively to the levels registered in 1990 (European Commission, 2019). The transport sector, in particular, to reduce the CO_2 emissions, has the goal of decreasing the released grams of CO_2 per km, from 130 to 95, by 2020 (Balsa, 2013).

According to Piazza (2020) in the first quarter of 2020, the electric vehicles market share, in the European Union, reached 6,8%, while in the equivalent period of the previous year registered 2,5%. Both BEV and PHEV contributed to this record. Another improvement is the rising number of electric buses in Europe and the fact that some cities are intending to electrify the majority of their bus fleet (Niestadt & Bjørnåvold, 2019).

There are yet a few barriers to overcome, like the lower offer of EV models and their cost still being higher in comparison to ICEs. There are also some restrictions regarding the electrical network and charging infrastructures (Ajanovic & Haas, 2016). Although it is necessary more investment in these areas, as stated by Piazza (2020), all European Union countries, except for Lithuania, provide stimulus to electric vehicle purchase. Some only offer tax reductions or exemptions while others, additionally to these, offer bonuses or premiums. Also, a few vehicle fabricators in the EU, in the following years, will be switching their production from ICEs to all electric and hybrid vehicles, releasing to the market only new models of these types of cars (Niestadt & Bjørnåvold, 2019).

Changing to electric mobility implies the development of technology, which contributes to the creation of new jobs in the vehicle industry and energy companies (Efe et al. 2018). This might also be verified in less developed areas, where there is a need for building renewable energy plants (Pacesila & Gabriel, 2016).

Another great advantage of electric mobility to the EU countries, since petroleum has to be imported from outside of the EU, is the reduction of oil imports (Petit, 2017). Furthermore, according to the European Climate Foundation, between 2030 and 2050, employment will register a net increase in the services sector, due to this lower spending on oil imports, that subsequently leads to an increase of consumer spending on other areas, enhancing the European economy (Harrison, 2018). Employment in electricity, hydrogen, construction and the majority of manufacturing sectors will also follow a path of growth in this period (Harrison, 2018).

The EU must not neglect the production of EVs. Otherwise, employment in this area will decrease. It is necessary to invest in the manufacturing of these cars, which includes also mining lithium and producing batteries, and it is obviously necessary to train engineers and skilled workers (Petit, 2017). The labour required is less intense than of the ICEs manufacturing, but some countries in Europe are big car producers, so the impact on employment, in the EU, will depend to what extent will companies opt to produce and/or to import (Harrison, 2018).

Focusing on becoming market competitive, on adapting to a less pollutant vehicle industry, is not the only important part. People must be educated and informed about the threats of climate change to shift from ICEs to EVs. So, this issue should be addressed in school, and every age range must be instructed the behaviors that contribute to a decrease of CO_2 emissions (Efe et al. 2018). Consumers shall also be enlightened about the advantages of purchasing an electric car, such as lower maintenance costs, the existing incentives that governments provide to EV buyers and lower dependency on fuels (Efe et al. 2018).

III. Data and methodology

The main goal of this work is to analyse the impact of battery-electric and plug-in hybrid electric vehicles in economic growth and the emissions of carbon dioxide emissions in the European Union. This study is executed through a micro panel with annual data from 2008 to 2016 and 26 countries of the EU, in the first model (Model I), and 24 countries in the second model (Model II). Given that the transport sector has always depended a lot on oil, thus contributing to a great quantity of emissions of CO_2 on the EU, it was established the goal of diminishing this impact, by encouraging the population and the industry to increase the integration of renewable energies and so, of the EVs (Efe et al. 2018).

Both the time horizon and countries were chosen regarding the available data for all the variables used and given that electric mobility is recent, and an area in development, there is still little data. Hereupon, in the first model, in which the dependent variable is the carbon dioxide emissions, the countries are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Poland, Portugal, Romania, Slovenia, Spain, Sweden and the United Kingdom. In the other model, the dependent variable is the GDP in constant LCU (Y), a proxy for economic growth, which is done very often in literature, as Neves et al. (2017) stated. In this one there were only two countries, previously listed, that did not comply with the criterion of availability of data, Cyprus and France, thus, not taking part in the study of this second model.

It was used STATA 14.2 to execute the econometric analysis. **Table 1** displays the names, definition, and the sources of the raw variables.

Table 1. Variables description

Variable	Definition	Source
CO2	Carbon dioxide emissions (million tonnes)	BP Statistical Review of World Energy
OIL	Crude oil prices ($)	BP Statistical Review of World Energy
V	Number of BEV registrations + Number of PHEV registrations	EAFO
EMP	The employment rate (active population from 20 to 64 years)	Eurostat
FC	Final consumption of electricity in the transport sector (GWh)	Eurostat
R	Electricity generation from renewable energies (GWh)	IRENA
Y	GDP in constant LCU	World Bank
I	Gross Fixed Capital Formation in constant LCU	World Bank
PD	Population density (people per sq. km of land area)	World Bank
P	The total population in the number of persons	World Bank

Notes: EAFO, European Alternative Fuels Observatory; IRENA, International Renewable Energy Agency

In both models, despite having different dependent variables, CO_2 and Y, in the first and in the second model, respectively, the number of BEV added to the number of PHEV registrations (V), is the control variable.

In Model I, there are three explanatory variables. The crude oil prices (OIL), which is relevant to understand if the economic factor does fasten the change to electric mobility, and therefore, as intended, speeds the diminish of CO_2 emissions. Zaghdoudi (2017) proved that an increase in oil prices, in the long run, negatively affects the CO_2 emissions. The second one was the population density (PD), that, as stated by Gudipudi et al. (2016), by increasing the population density, there will be a reduction of CO_2 emissions in-building and on-road transportation sectors. The third one was the electricity generation from renewable energies (R), that in both the transportation and electric sectors, using renewable energies decreases the CO_2 emissions, as confirmed by Richardson (2013).

In Model II, there were also used three explanatory variables. The gross fixed capital formation (I), as a proxy of investment in electric mobility. In a study for 13 countries in Eurasia, Apergis & Payne (2010) confirmed that an increase in the gross fixed capital formation affects the economic growth positively. The final consumption of electricity of the transport sector (FC), that, as explained by Neves et al. (2017), affects the economic growth negatively, and, at last the employment rate (EMP). This last one shows the social class of people (Almeida et al. 2018), and thus, their capacity to invest.

Given that the number of BEV registrations added to the number of PHEV registrations presented many zeros in their data, it was necessary to add one to all variables in order to perform the econometric analysis. The next step was to extract the variable of the population (P) from World Bank and divide, in each model, the variables by the P to transform them in per capita, in order to eliminate distortions caused by the population variations. The variable population density (people per sq. km of land area) (PD), present in Model I, was the only one that did not suffer this alteration.

It was used the Autoregressive Distributed Lag (ARDL) Model to do the empirical analysis of the study since it is a more flexible model as a result of supporting both levels of integration, I(0) and I(1), and ensuring robustness to endogenous variables. It also allows analysing the impact of the battery-electric and plug-in hybrid electric vehicles in the economic growth and in the emissions of carbon dioxide, both in the short and long run. The ARDL model specifications of the model I (Eq. 1) and model II (Eq. 2) in which "L" means natural logarithms, are:

$$LCO2_{it} = \alpha_{1i} + \delta_{1i}TREND + \beta_{1i1}LCO2_{it-1} + \beta_{1i2}LV_{it} + \beta_{1i3}LV_{it-1} + \beta_{1i4}LR_{it} + \beta_{1i5}LR_{it-1} + \beta_{1i6}LPD_{it} + \beta_{1i7}LPD_{it-1} + \beta_{1i8}LOIL_{it} + \beta_{1i9}LOIL_{1t-1} + \mu_{1it} \quad (1)$$

$$LPIB_{it} = \alpha_{2i} + \delta_{2i}TREND + \beta_{2i1}LPIB_{it-1} + \beta_{2i2}LV_{it} + \beta_{2i3}LV_{it-1} + \beta_{2i4}LFC_{it} + \beta_{2i5}LFC_{it-1} + \beta_{2i6}LI_{it} + \beta_{2i7}LI_{it-1} + \beta_{2i8}LEMP_{it} + \beta_{2i9}LEMP_{it-1} + \mu_{2it} \quad (2)$$

To capture the dynamic relationship between variables, the model I (Eq. 1) and model II (Eq. 2) were re-parameterised to equations (3) and (4), respectively, in which "D" means first differences:

$$DLCO2_{it} = \alpha_{3i} + \delta_{3i}TREND + \beta_{3i1}DLV_{it} + \beta_{3i2}DLR_{it} + \beta_{3i3}DLPD_{it} + \beta_{3i4}DLOIL_{it} + \gamma_{3i1}LCO2_{it-1} + \gamma_{3i2}LV_{it-1} + \gamma_{3i3}LR_{it-1} + \gamma_{3i4}LPD_{it-1} + \gamma_{3i5}LOIL_{1t-1} + \mu_{3it} \quad (3)$$

$$DLPIB_{it} = \alpha_{4i} + \delta_{4i}TREND + \beta_{4i1}DLV_{it} + \beta_{4i2}DLFC_{it} + \beta_{4i3}DLI_{it} + \beta_{4i4}DLEMP_{it} + \gamma_{4i1}LPIB_{it-1} + \gamma_{4i2}LV_{it-1} + \gamma_{4i3}LFC_{it-1} + \gamma_{4i4}LI_{it-1} + \gamma_{4i5}LEMP_{it-1} + \mu_{4it} \quad (4)$$

In the remainder of the dissertation, models I and II refer to equations (3) and (4), respectively.

Table 2 and **Table 3** present the descriptive statistics of the variables, given it is important to understand the characteristics of the series, and the results from the cross-sectional dependence (CD) test, of Model I and Model II, respectively. Because cross-sectional dependence implies that countries are interdependent, and thus they have an impact on each other's results, it is crucial to verify if the variables exhibit this property in data panel studies, as stated by Marques & Caetano (2020). When this is true, it is necessary to correct this issue. Otherwise, the results might be skewed (De Hoyos & Sarafidis, 2006; Marques & Caetano, 2020). As shown in the CD test, in Model I, the variables that do not present cross-sectional dependence are LPD and DLPD.

Table 2. Model I: Descriptive statistics and cross-sectional dependence

Variables	Descriptive statistics					Cross-section dependence (CD)		
	Obs	**Mean**	**St. Dev.**	**Min.**	**Max.**	**CD-test**	**Corr**	**Abs (corr)**
LCO2	234	-11.80182	0.4349748	-12.56653	-10.55061	31.94***	0.591	0.663
LV	234	-11.56328	3.245883	-17.89774	-5.024171	48.68***	0.900	0.900
LR	234	-6.779626	0.9924016	-11.12133	-4.560747	32.87***	0.608	0.622
LPD	234	4.620068	0.7758306	2.916908	6.227525	-0.41	-0.007	0.839
LOIL	234	-11.60351	1.363406	-14.42574	-8.437622	53.93***	0.997	0.997
DLCO2	208	-0.0231378	0.0587674	-0.1519938	0.1953392	19.49***	0.382	0.474
DLV	208	0.8551987	1.119791	-0.0185184	7.646468	7.83***	0.154	0.367
DLR	208	0.0943756	0.1973083	-0.5605984	1.009111	3.44***	0.068	0.341
DLPD	208	0.0015928	0.0081247	-0.0278132	0.0239048	-0.18	-0.003	0.436
DLOIL	208	-0.1000394	0.3038485	-0.6506672	0.3551617	50.99***	1.000	1.000

Notes: The CD test has N(0,1) distribution under the H_0: cross-section independence. ***, ** and * denote statistical significance levels at 1%, 5% and 10% level, respectively. It was used the Stata commands *sum* and *xtcd*, respectively, to achieve the results of the descriptive statistics and the test of cross-section dependence.

In Model II, according to the CD test, all variables present cross-sectional dependence, with the exception of LEMP.

Table 3. Model II: Descriptive statistics and cross-sectional dependence

Variables	Descriptive statistics					Cross-sectional dependence (CD)		
	Obs	Mean	St. Dev.	Min.	Max.	CD-test	Corr	Abs (corr)
LY	216	10.6696	1.360142	9.053898	14.95522	22.77***	0.457	0.597
LV	216	-11.64313	3.296959	-17.89774	-5.024171	44.88***	0.901	0.901
LFC	216	-9.412444	0.8283597	-11.63361	-7.783885	6.57***	0.132	0.465
LI	216	9.111893	1.390852	7.294758	13.44777	17.23***	0.346	0.491
LEMP	216	-11.66314	1.253765	-13.82912	-8.800431	1.14	0.023	0.683
DLY	192	0.0055299	0.0402839	-0.157354	0.214633	32.82***	0.698	0.704
DLV	192	0.8860064	1.153663	-0.0185184	7.646468	8.02***	0.171	0.363
DLFC	192	-0.0085726	0.100714	-0.7283115	0.3749723	5.45***	0.116	0.316
DLI	192	-0.0160074	0.1150779	-0.4815969	0.4037457	24.09***	0.513	0.529
DLEMP	192	0.0016784	0.0118494	-0.0313921	0.0379753	4.26***	0.091	0.367

Notes: The CD test has N(0,1) distribution under the H_0: cross-section independence. ***, ** and * denote statistical significance levels at 1%, 5% and 10%, respectively. To achieve the results of the descriptive statistics and of the test of cross-section dependence, it was used the Stata commands *sum* and *xtcd*, respectively.

Tables 4 and **5** show the correlation matrices and the Variance Inflation Factor (VIF), of Model I and Model II, respectively. The correlation matrix informs about the correlation between variables, while the VIF statistics are used to check if there is multicollinearity. In the model I there are no high correlations between variables.

Table 4. Correlation matrices and VIF statistics for Model I

	LCO2	LV	LR	LPD	LOIL		DLCO2	DLV	DLR	DLPD	DLOIL
LCO2	1.0000					**DLCO2**	1.0000				
LV	0.1166	1.0000				**DLV**	-0.0214	1.0000			
LR	-0.1711	0.3806	1.0000			**DLR**	-0.1753	-0.1008	1.0000		
LPD	0.2860	0.0707	-0.3416	1.0000		**DLPD**	-0.2272	0.0516	0.0479	1.0000	
LOIL	0.2889	-0.0541	-0.1457	-0.3650	1.000	**DLOIL**	0.0787	0.1878	0.0308	-0.0864	1.0000
VIF		1.25	1.56	1.51	1.29	**VIF**		1.05	1.02	1.02	1.05
Mean VIF			1.41			**Mean VIF**			1.03		

In model II there is a high correlation between LI and LY, and also among, DLI and DLY. However, since the presence of high correlation is with the dependent variable, it does not represent a problem. Regarding the VIF and mean VIF, for both models, since they exhibit low values, it indicates that multicollinearity is not a concern to the estimation.

Table 5. Correlation matrices and VIF statistics for Model II

	LY	LV	LFC	LI	LEMP		DLY	DLV	DLFC	DLI	DLEMP
LY	1.000					**DLY**	1.0000				
LV	0.1194	1.0000				**DLV**	0.0831	1.0000			
LFC	0.3846	0.2040	1.0000			**DLFC**	0.0869	0.1309	1.0000		
LI	0.9912	0.0979	0.4036	1.0000		**DLI**	0.8034	0.1388	0.0715	1.0000	
LEMP	-0.0223	0.1038	-0.1453	-0.0030	1.0000	**DLEMP**	0.1529	0.0475	0.0141	0.0937	1.0000
VIF		1.06	1.28	1.20	1.05	**VIF**		1.04	1.02	1.03	1.01
Mean VIF			1.15			**Mean VIF**			1.02		

Given that the variables LPD and DLPD, in Model I, and variable LEMP, in Model II, do not present cross-section dependence, it was executed the 1st generation panel unit root test. **Table 6** and **Table 7** display the results of Maddala and Wu test, for Model I and Modell II, respectively. As it can be observed, from **Table 6**, the variables LPD and DLPD are I(0).

Due to the fact that the Maddala & Wu (1999) test considers that variables present cross-sectional independence, the remaining variables, of both models, that present cross-sectional dependence, need to be analysed with a second-generation panel unit root test, the cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007).

Table 6. Maddala and Wu Panel Unit Root test (MW) for Model I

	MW (Zt-bar)	
	Without trend	**With trend**
LCO2	77.140**	47.034
LV	92.563***	31.338
LR	160.496***	96.442***
LPD	227.211***	234.029***
LOIL	8.669	1.800
DLCO2	220.029***	212.429***
DLV	116.784***	115.596***
DLR	177.137***	116.934***
DLPD	258.034***	181.304***
DLOIL	74.943**	250.384***

Notes: ***, **, * denote statistical significance levels at 1%, 5% and 10%, respectively. Maddala and Wu (1999) Panel Unit Root test (MW) assumes cross-sectional independence and H_0: series is I(1). The Stata command *multipurt* was used to compute this test.

Table 7. Maddala and Wu Panel Unit Root test (MW) for Model II

	MW (Zt-bar)	
	Without trend	**With trend**
LY	69.320**	343.189***
LV	92.533***	29.041
LFC	78.424***	24.244
LI	187.369***	341.371***
LEMP	67.330**	45.705
DLY	557.894***	382.658***
DLV	113.342***	114.810***
DLFC	129.790***	130.772***
DLI	358.043***	175.482***
DLEMP	110.591***	104.032***

Notes: ***, **, * denote statistical significance levels at 1%, 5% and 10%, respectively. Maddala and Wu (1999) Panel Unit Root test (MW) assumes cross-sectional independence and H_0: series is I(1). The Stata command *multipurt* was used to compute this test.

Table 8 and **Table 9** present the 2nd generation unit root test, for Model I and Model II, respectively, because most variables present cross-section dependence, and the Maddala and Wu test turns to be inefficient in this case.

Table 8. Panel Unit Root test (CIPS) for Model I

	CIPS (Zt-bar)	
	Without trend	**With trend**
LCO2	-1.084	1.080
LV	-5.701***	-2.479***
LR	-2.044**	0.799
LPD	-1.882**	0.199
LOIL	2.638	1.918
DLCO2	-2.543***	-2.237**
DLV	-6.624***	-4.333***
DLR	-2.535***	-1.545**
DLPD	-1.548**	2.594
DLOIL	-0.425	2.493

Notes: ***, **, * denote statistical significance levels at 1%, 5% and 10%, respectively. Pesaran (2007) Panel Unit Root test (CIPS) assumes that cross-sectional dependence is in the form of a single unobserved common factor and H_0: series is I(1). The Stata command *multipurt* was used to compute this test.

Table 9. Panel Unit Root test (CIPS) for Model II

	CIPS (Zt-bar)	
	Without trend	**With trend**
LY	0.043	-1.637**
LV	-4.370***	-2.020**
LFC	-0.439	1.111
LI	-1.778	-0.080
LEMP	1.397	2.069
DLY	-2.533***	-1.939**
DLV	-6.039***	-3.968***
DLFC	-2.116**	-2.405***
DLI	-2.046**	-1.501**
DLEMP	-0.721	0.153

Notes: ***, **, * denote statistical significance levels at 1%, 5% and 10%, respectively. Pesaran (2007) Panel Unit Root test (CIPS) assumes that cross-sectional dependence is in the form of a single unobserved common factor and H_0: series is I(1). The Stata command *multipurt* was used to compute this test.

Provided the results of the CIPS tests, for both models, and even though there might be a suggestion that the variables EMP and PD might not be in the borderline of level I(0) or the level I(1), in this study, it is being used a micro panel. Given that the period is of 8 years, and the number of countries is much higher than the period studied, the unit root tests are not reliable to determine if the ARDL methodology is or is not appropriated for this analysis. As Wolters & Hassler (2006) confirmed, when the period is short, the unit root tests performed have little power. So, in order to analyse the impact of the battery-electric and plug-in hybrid electric vehicles in the economic growth and the emissions of carbon dioxide, both in the short and the long run, the ARDL model was used.

Lastly, it was performed the Hausman test, presented in **Table 10**, to analyse the presence of individual effects on the estimations. It was tested with fixed effects (FE) against random effects (RE). Because the null hypothesis "the difference in coefficients is not systematic" is rejected for both models, the use of fixed effects is the indicated one to the estimations, which means that the countries individual effects are significant and must be taken into account.

Table 10. Hausman test

	Model I	Model II
Hausman test	FE vs. RE	FE vs. RE
	136.70***	69.51***

Notes: *** denotes statistical significance level at 1%. The Hausman test, for both models, was performed with the *sigmaless* option.

IV. Results

In the panel approach and given the result of the Hausman test, indicating the use of a fixed-effects model, it is necessary to perform specification tests, in order to verify which is the proper estimator to be used. It was tested the presence of heteroscedasticity through the Modified Wald test, which has the null hypothesis "presence of homoscedasticity". Secondly, it was computed the Pesaran's test, that evaluates the existence of contemporaneous correlation, with the null hypothesis "residuals are not correlated and follow a normal distribution". To conclude the analysis, and to test for autocorrelation, the Wooldridge test, with the null hypothesis "no serial correlation" was performed. The results of the three specifications tests are presented in **Table 11**, and as it can be observed, there is presence of heteroscedasticity, contemporaneous correlation and first-order autocorrelation.

Table 11. Specification tests

	Model I	Model II
	Statistics	
Modified Wald test	215.50***	541.99***
Pesaran's test	8.450***	12.004***
Wooldridge test	42.477***	33.693***

Notes: H_0 of Modified Wald test: sigma(i)^2 = sigma^2 for all i; H_0 of Pesaran's test residual are not correlated; H_0 of Wooldridge test: no first-order autocorrelation; *** denotes statistical significance at 1% level.

As shown, from the results of the tests, the most suitable estimator for both models is the Driscoll & Kraay (1998), since it can deal with the presence of cross-sectional dependence, heteroscedasticity, contemporaneous correlation and first-order autocorrelation, by generating standard errors robust to these disturbances.

In **Table 12** are displayed the estimation results of Model I. In the short run, the electricity generation from renewable energies shows strong statistical significance, while the crude oil prices appear to no be statistically significant. The number of BEV and PHEV registrations and the population density are both significant, at 5% and 10% levels, respectively.

Table 12. Estimation Results - Model I

Dependent variable: **DLCO2**	**FE-DK**
Constant	-2.9164***
DLV	-0.0025**
DLR	-0.0706***
DLPD	-1.9238*
DLOIL	0.0140
LCO2 (-1)	-0.5195***
LV (-1)	-0.0053**
LR (-1)	-0.0228*
LPD (-1)	-0.9023***
LOIL (-1)	-0.0631***
Diagnostic statistics	
N	208
R^2	0.4985
F	F(9, 7) = 78.63***

Notes: ***, ** and * denote statistical significance levels at 1%, 5% and 10%, respectively. In order to estimate the models, the Stata command *xtscc* was used.

In the previous table, the long run elasticities were not displayed, so **Table 13** presents these elasticities, which are calculated through the ratio between the variables' coefficients and the LCO2 coefficient, that is, the ECM coefficient, both lagged once, and lastly this ratio is multiplied by -1. It also displays the short run impacts and the speed of adjustment (ECM) of Model I.

As seen, from **Table 13**, the ECM of this model has a negative coefficient and it has strong statistical significance, revealing the presence of long memory between variables. The ECM – error correction mechanism – is the speed of adjustment of models, that is, the speed at which the dependent variable returns to equilibrium after changes in the other variables. The ECM, in this model, could be considered a fast one.

Table 13. Impacts, elasticities and speed of adjustment - Model I

Dependent Variable: **DLCO2**	**FE-DK**
Short-run impacts	
DLV	-0.0025**
DLR	-0.0706***
DLPD	-1.9238*
DLOIL	0.0140
Long-run (computed) elasticities	
LV	-0.0103***
LR	-0.0438**
LPD	-1.7367***
LOIL	-0.1215***
Speed of adjustment	
ECM	-0.5195***

Notes: ***, ** and * denote statistical significance levels at 1%, 5% and 10%, respectively. The ECM denotes the coefficient of the variable LCO2 lagged once.

By observing **Table 13**, it is possible to state that the number of BEVs and of PHEVs in the European Union affects the CO_2 emissions negatively, both in the short and long run. However, it is more significant in the long than in the short run. This means that an increase in the number of BEVs and PHEVs reduces CO_2 emissions.

The electricity generation is more significant in the short run, comparing to the long run. It negatively affects CO_2 emissions, which means that by increasing the production of electricity from renewable energies, there is a decrease in emissions.

Regarding the population density and the price of crude oil, the population density, in the short run was statistically significant at a 10% level, while the price of oil was not at all, but in the long run, they both became significant at a 1% level, and both affect the CO_2 negatively. This means then that the increase in population density decreases CO_2 emissions, as cited before by Gudipudi et al. (2016). Even though the oil prices affected positively in the short run, in the long run, they affect the CO_2 emissions negatively, meaning that an increase in these ones, decreases the emissions too.

In **Table 14** are exhibited the estimation results for Model II. As observed, in the short run, only the investment in electric mobility shows strong statistical significance, that is, is significant at a 1% level. Both the number of BEVs and PHEVs and the employment rate are statistically significant at a 10% level, while the final consumption of the transport sector is not significant at all.

Table 14. Estimation Results - Model II

Dependent variable: DLY	FE-DK
Constant	7.8984***
DLV	-0.0027*
DLFC	-0.0061
DLI	0.2859***
DLEMP	-0.1856*
LY (-1)	-0.4176***
LV (-1)	0.0036***
LFC (-1)	-0.0549***
LI (-1)	0.1134***
LEMP (-1)	0.4239***
Diagnostic statistics	
N	192
R^2	0.7545
F	F (9, 7) = 10161.04***

Notes: ***, ** and * denote statistical significance levels at 1%, 5% and 10%, respectively. In order to estimate the models, the Stata command *xtscc* was used.

Once more, this estimation results table does not present the elasticities for Model II. So, from **Table 15** it is possible to examine the short run impacts, the speed of adjustment of this model and the long run elasticities, calculated again with the lagged coefficients of the variables divided by the LY coefficient, lagged once and multiplied by -1. Being the LY, lagged once, the ECM of this Model II, it is feasible to state that it has a negative coefficient and it is statistically significant at 1%, showing long-memory between variables, and, thus, being the speed of adjustment fast.

Table 15. Impacts, elasticities and speed of adjustment - Model II

Dependent Variable: **DLY**	**FE-DK**
Short-run impacts	
DLV	-0.0027*
DLFC	-0.0061
DLI	0.2859***
DLEMP	-0.1856*
Long-run (computed) elasticities	
LV	0.0085**
LFC	-0.1314***
LI	0.2715***
LEMP	1.0150***
Speed of adjustment	
ECM	-0.4176***

Notes: ***, ** and * denote statistical significance levels at 1%, 5% and 10%, respectively. The ECM denotes the coefficient of the variable LY lagged once.

Regarding the information in **Table 15**, the number of BEVs and PHEVs affects the economic growth negatively in the short run. However, in the long run, it influences the dependent variable positively, meaning that when there is an increase in the number of these vehicles, there is an increase in economic growth. Both the investment and the employment rate are strongly significant and affect economic growth positively in the long run. However, the employment rate, in the short run, had a negative influence. So, in the long run, when these two variables exhibit increase, there is also an increase in economic growth. Viewing the final consumption of electricity, in the short run has no impact, but in the long run it is statistically significant at a 1% level. It presents a negative coefficient, implying that when there is an increase in consumption, there is a decrease in economic growth.

V. Discussion

Considering the results of Model I, an increase of BEVs and PHEVs had the intended outcome on CO_2 emissions. As the literature has shown, these vehicles improve energy efficiency, attenuate air pollution and, as stated above, reduce CO_2 emissions (Yan, 2018). Another effective way to reduce these emissions, as proven by the model's results, is by increasing electricity produced from renewables energies. Indeed, to produce clean electric vehicles, and also to charge them, it is necessary to support the increasing investment in renewable energies sources. Otherwise, the increase in the consumption of electricity will continue to emit pollutants. There has been a growth in the investment of wind and solar electricity, in the European Union, and, given the abundance of wind resources, the European Wind Energy Association predicts that by the year of 2030, wind electricity will supply 19 to 31% of the EU's electricity demand (Nguyen & Gustavsson, 2020). Even though these types of energies are cleaner, it is difficult to change from natural gas or coal to only renewable energies. However, despite it, studies show that even in regions where coal power prevails, by having cleaner energies integrated into the power system, the CO_2 emissions decrease (Richardson, 2013).

As previously mentioned, Gudipudi et al. (2016) developed a study in the US, proving that the increase of population density has a positive impact on CO_2 emissions, in both on-road transportation and in-building sectors, especially in the first one. It is expected that cities with higher population density lead to higher greenhouse gas emissions. However, higher population density presents more environmental benefits, in both mobility and housing. By comparing low-density dispersed cities with populous cities, it is presumable that public transport infrastructures are better and more abundant in the last ones, contributing positively to lower carbon dioxide releases (Muñiz & Dominguez, 2020). A research made by the European Parliament acknowledges the rise in the demand for electric buses, and that some cities aspire to electrify their bus fleet in a few years. E-bikes, scooters and motorcycles are now integrated into the road transportation in some countries in the European Union (Niestadt & Bjørnåvold, 2019).

In his study about oil prices and CO_2 emissions in OECD countries, Zaghdoudi (2017) concluded that in both the short and long run, an increase in oil prices reduces fossil fuel energy consumption, and as consequence pollution registers a decline. This corroborates the long run results of Model I, concluding that when oil prices rise, CO_2 emissions decline (Zaghdoudi, 2017). As the author stated, some countries still are somewhat dependent on oil, in the production of goods and services, so higher oil prices lead to lower emissions due to lower energy consumption. In the short run, an increase in oil prices revealed to be statistically non-significant. Indeed, "firms and consumers cannot change their production or consumption patterns immediately, so the effects of higher oil prices on GDP might be small (at least initially)" (Depratto et al. 2009, pp. 4). This explanation is also feasible in the sense that, if consumption of oil does not drop in the short run, carbon dioxide emissions will continue to rise. Indeed, the consumers do not switch from an ICE to an EV if oil prices suffer an increase in the short run, but in the long run, with rising prices, families and industries are encouraged to shift to renewable energy sources and to assume more sustainable behaviors.

Regarding Model II, in the short run, and given that the market share of EVs is low in comparison to ICEs (Almeida et al. 2018), an increase of battery-electric and plug-in hybrid electric vehicles, may have a negative effect on GDP. So, by decreasing the sales of ICEs, and since European countries have been taking measures like lower taxes and free parking for EV drivers, there might be a slight decrease in the economic growth. Despite this, in the long run, an increase in the electric vehicles raises the GDP. To meet the goals defined by the EU's Energy and Climate Change Packages, meaning that there is a diminishing in the dependency on oil, and an increase in the investment of electric vehicles, the production and the expansion of the fleet, the GDP of the European Union increases (European Commission, 2020).

With regard to the increase of consumption of electricity on the transport sector, in the short run, as seen, it does not affect GDP, and this might be given to the fact that in the transition to electric mobility, people will not immediately change to EVs, a measure that would imply a higher consumption of electricity. Therefore, an increase of this variable, in the short run, will not have a significant impact on the economy. In the long run, it has a negative effect on GDP, since the increase of electricity consumption on the transport sector will be linked to more expensive electrification of this sector, mainly due to introducing renewable energies in the electricity mix (Neves et al. 2017).

As seen from the results of Model II, by increasing the investment in electric mobility, there is an increase in the European Union GDP. Throughout the years, more importance has been given to the electrification and reduction of CO2 emissions, and one good consequence of this, is the lower dependency on oil (Petit, 2017), that hopefully will be lower each year. Lower imports of petroleum will intensify the circulation of money in the EU, which can be invested in electric mobility that, by its turn, will affect the employment positively in the EU (Connolly et al. 2016). In the long run, due to the decrease in spending on oil imports (Petit, 2017), and to the expansion of some sectors (such as, hydrogen, construction and manufacturing), there will be an increase in employment, which will increase GDP (Harrison, 2018), as observed in the model. Despite this, as predicted by the model, in the short run, economic growth is negatively affected by an increase in employment. The EU has been one of the leading manufacturers of motor vehicles in the world. This sector only employs about 13.8 million people (European Commission, 2020), so regardless of the increase of jobs in other sectors, in the automotive sector, there will be a loss of jobs, at least in the short run, given that the production of EVs requires less workforce (Petit, 2017). The automotive sector is essential to the EU's economy, given it has a multiplier effect in the economy and its volume of business represents more than 7% of the EU GDP (European Commission, 2020). Adding this, to the fact that industry cannot switch entirely and promptly from the production of ICEs to EVs, GDP will be affected negatively.

VI. Conclusion

This thesis is focused on the analysis of the electric vehicles in the European Union, specifically, about the impacts of these in the carbon dioxide emissions and economic growth. In order to perform this study, it was used annual data from 2008 to 2016 for a micro panel of 26 countries in the model I, where the dependent variable is the CO_2, and a micro panel, with the same period, for 24 countries in the second model, in which the dependent variable is the economic growth. The ARDL structure, used to estimate both models, provides better results given its analysis of the variables impacts over time.

This study contributes to the literature of electric mobility and its potential benefits to both the environment and economic growth. The results achieved in this thesis show that by expanding the electric vehicle fleet, specifically, battery-electric and plug-in hybrid electric vehicles, carbon dioxide emissions decrease. Something that is linked to the diminishing of oil usage, which by its turn, also reduces these. Also, an expansion of the fleet, in the long run, increases GDP, which is linked, as well, to a reduction of the dependency on oil and by a rise of the investment in electric mobility. Some European countries are the greatest manufacturers of ICEs, however, due to the problematic of climate change and the depletion of oil, there is a need to innovate and invest in electric mobility. So, by decreasing imports of petroleum, and increasing circulation of money, the capability of investing in new alternatives, gives the producers of cars in the EU, a chance to change its direction in transportation, to a cleaner one, which means that by expanding the EV fleet, economic growth will be higher.

As any study it has its limitations and given that electric mobility is still a recent thematic, there is still limited data available about it, thus the period of this thesis being only of 2008 to 2016. Another limitation is the fact that this thesis is only focused on the European Union countries, and given that global warming is a world problem, there is not a perspective of how changing to electric mobility would affect the entire planet, only part of it. Also, the incentives made by the government, to encourage the change to EVs, were not studied, and they are also crucial to the understand how consumers may benefit with it, and consequently how they may affect the speed of this change.

Future investigation should include the Smart Grid impacts on the economy since electrification might be expensive and negatively affect the European Union GDP. The Smart Grid implementation is the smartest alternative to cheaper and sustainable electrification. Another important factor to this is the usage of renewable energies when producing electricity, so it would be interesting to add to the study how countries would be affected economically by changing powerplants energy sources to only renewable ones.

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