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Connection between Fuel Prices and Demand for Electric and Hybrid Cars

Bachelor thesis

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Abstract

Nowadays, the adoption of alternative fuel vehicles, especially electric and hybrid cars, has become one of the most important topics of the current automotive industry. So far, the previously conducted studies suggest various factors to have an impact on the demand for such vehicles. Among other things, some researchers believe that gasoline prices may influence the sales of alternative fuel vehicles in a way that higher gas price leads to an increased demand for those vehicles. This thesis analyzes the relationship between gasoline prices and the sales of hybrid and electric cars in two different environments and time periods. Firstly, we examine the connection between gasoline price and the sales of Toyota Prius in the United States between years 2005 and 2018. Secondly, a current situation among various European countries regarding the market shares of plug-in electric vehicles is analyzed, using data from years 2016-2019. This paper has proven the gasoline price to be a statistically significant factor affecting the demand for electric and hybrid vehicles in a way that higher gasoline price leads to an increased demand for those vehicles. Moreover, this paper also provides some new evidence of the importance of other factors, which are known to affect the demand for alternative fuel vehicles from previously conducted studies. Although we have managed to arrive to such results, the models still partially suffer from some subtle limitations, which are discussed within this thesis as well.

Abstrakt

Nárůst popularity vozidel s alternativním pohonem, především elektromobilů a hybridních automobilů, je bezpochyby jedním z nejvíce diskutovaných témat novodobého automobilového průmyslu. Z již publikovaných studií víme o řadě faktorů, které mají vliv na poptávku po těchto vozech. Mimo jiné, někteří badatelé se domnívají, že jedním z těchto faktorů může být i cena benzinu. Věří, že v obdobích, kdy se zvyšuje cena benzinu, dochází ke zvýšené poptávce po vozidlech s alternativním pohonem, tedy po elektromobilech a hybridech. Tato práce analyzuje vztah mezi cenami benzinu a prodeji elektromobilů a hybridních automobilů ve dvou různých prostředích a časových obdobích. Nejprve se autor zaměřuje na vztah mezi cenou benzinu a prodejem Toyoty Prius v USA v letech 2005-2018. Dále autor zkoumá situaci v evropských zemích, respektive podíl elektromobilů a plug-in hybridních vozů na trhu v těchto zemích, za pomoci dat z let 2016-2019. Tato studie dokazuje signifikantní vliv ceny benzinu jakožto faktoru ovlivňujícím poptávku po elektromobilech a hybridních vozech. Přesněji, tato práce dokazuje, že vyšší cena benzinu vede k zvýšené poptávce po těchto vozidlech. Studie navíc přezkoumává vliv ostatních faktorů, které mohou mít na základě výsledků předchozích studií vliv na prodeje vozidel s alternativním pohonem. Přestože se autorovi podařilo dokázat vliv ceny benzinu na poptávku po těchto vozidlech za pomoci obou hlavních modelů, tyto modely stále vykazují drobné nedostatky, které jsou autorem v této práci rovněž diskutovány.

Keywords

fuel prices, gasoline prices, electric cars, hybrid cars, alternative fuel vehicles

Klíčová slova

ceny paliv, ceny benzinu, elektromobily, hybridní automobily, alternativní paliva

Range of thesis: 83 014 characters without spaces, 47 pages

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Acknowledgment

I would like to express my gratitude especially to my supervisor, doc. PhDr. Ladislav Krištoufek Ph.D. for his expertise, useful comments, and willingness to help. Moreover, I would like to thank my family and my closest friends for their support during the process of writing the thesis and mainly during the whole studies.

Bachelor's Thesis Proposal

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Notes: Please enter the information from the proposal to the Student Information System (SIS) and submit the proposal signed by yourself and by the supervisor to the Academic Director ("garant") of the undergraduate program.

Proposed Topic:

Impact of Electric Cars on Fuel Prices

Preliminary scope of work:

Research question and motivation

Since the start of the new millennium, many automotive companies began to realize that petrol and diesel engines are not the only possibility for powering cars, and as a reaction to the oil depletion and increasing pressure on being environmentally friendly, they started to come up with alternative ways of powering cars. As a result, electric vehicles are becoming more and more popular nowadays and it can be expected, that if this trend will continue in the future, they could have a significant impact on fuel prices.

Firstly, I would like to test the significance of increasing number of sold electric cars as a factor that could possibly affect fuel prices in a few countries, especially Norway and Iceland, where the ratio of electric cars sold has increased most rapidly of all countries in the last five years. It is obvious that the sales of electric vehicles are not the main factor affecting fuel prices, but it is a trend which is getting more and more popular and it could have an influence on the market for fossil fuels, at least in the future, as the number of electric cars sold increases rapidly every year. Therefore, I will discuss most of the factors affecting the prices of fuel within my thesis and I will include these factors in my model, which will test the significance of electric cars sales as a factor affecting the fuel prices. Secondly, I would also like to test the effect of the oil crises and oil price shocks. To be more precise, I would like to test, if the 2008 oil price shock caused increased demand for Toyota Prius, the best-selling hybrid vehicle in that time. Lastly, I would like to make a simple prediction for the future development of fuel prices, based on my models and plans of the governments.

I decided to do research about this topic, because I think that the trend of electric cars is getting more and more important nowadays and most people are trying to study the impact of these vehicles mainly on the environment, but not so many researchers are dealing with the effect on the fuel prices.

Hypotheses:

1. The increased sales of the electric cars could possibly cause a decrease in demand for gasoline and diesel, therefore they could cause a decrease in prices of these fossil fuels. I would like to test this effect in a country in a country with a high ratio of electric cars sold (such as Norway) and eventually compare it with a country where the electric vehicles are not so popular, to see the difference.
2. During the times when the prices of fuel rise, such as oil crises and oil price shocks, people tend to prefer purchasing alternatively powered cars over traditional petrol/diesel powered cars. I would like to test this hypothesis on the Toyota Prius sales during the 2008 oil price shock.
3. As the number of electric cars sold increases over time and it is expected that it will continue to rise even more rapidly in the future, it is likely that the fuel prices will start to fall.

Contribution

The result of this analysis should provide information on whether this trend, which is getting more and more popular over the last decade, can be a significant factor affecting the demand for fossil fuels and therefore affecting the price of fuel. Vice versa, it should provide information, whether customers decide to purchase electric or hybrid vehicles, when the prices of fuel rise due to various reasons. Lastly, this research should help to predict a future development in this field.

Methodology

The method used for testing the first hypothesis will be a linear regression model, which will include most of the factors which are affecting fuel prices and will test the significance of electric cars sales as a factor that could potentially affect these prices. Linear regression will be used for the second hypothesis as well, this time with electric/hybrid cars sales as a dependent variable and will include most of the factors that are affecting sales of these cars as the independent variables. With this model, I would like to test the significance of fuel prices as a factor that could have an influence on customers' decision to purchase an alternatively powered vehicle instead of traditional petrol/diesel one.

Outline

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2.3 Literature review

3. Hypotheses Development
4. Methodology description
5. Data analysis
6. Results and Discussion
7. Conclusion

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Acronyms

ACEA – European Automobile Manufacturers‘ Association

ADF – Augmented Dickey-Fuller

BEV – Battery Electric Vehicle

BP – Breusch-Pagan

BPLM – Breusch-Pagan Lagrange Multiplier

DW – Durbin-Watson

EAFO – European Alternative Fuels Observatory

EPI – Environmental Performance Index

EU – European Union

EV – Electric Vehicle

FE – Fixed Effects Regression Model

GDP – Gross Domestic Product

HEV – Hybrid Electric Vehicle

ICE – Internal Combustion Engine

KPSS – Kwiatkowski–Phillips–Schmidt–Shin

OLS – Ordinary Least Squares

OPEC – Organization of Petroleum Exporting Countries

PHEV – Plug-in Hybrid Electric Vehicle

Prius – Toyota Prius

Prius family – all generations and versions of Toyota Prius

R&D – Research and Development

RE – Random Effects Regression Model

1 Introduction

During the last decades, the arising need for adoption of alternative fuel vehicles has become one of the most important topics in the automotive industry. Among all alternative fuels, electric and hybrid cars have become the biggest subject of attention. In order to analyze the development of the market for electric and hybrid cars, it is necessary to identify and examine the factors which influence the demand for those vehicles.

So far, the researchers have analyzed various factors affecting the consumers attitude towards electric and hybrid vehicles. With this thesis, the author would like to broaden this research and introduce a new variable, which could possibly be responsible for changes in demand for alternative fuel vehicles. Namely, the author would like to examine the relationship between retail gasoline price and the demand for electric and hybrid cars.

Factors affecting the demand for alternative fuel vehicles have been the subject of many studies. For example, Larson et al. (2014) have examined the consumers attitude towards electric cars, finding that the high purchase price of such cars is the most important factor, which makes the potential consumers decide not to buy an electric car. Similar results appear in the study of Thiel et al. (2012), who conducted a survey among European citizens as the potential buyers of an electric car. In order to make the electric and hybrid cars more financially attractive for the customers, many states offer certain incentives for buying such cars either in form of tax benefits or direct financial grants for buying an alternative fuel vehicle.

Moreover, Thiel et al. (2012) have also found out that the low maximum range of the electric car is one of the most important factors causing the customers to prefer a standard gasoline or diesel car over an electric one. However, the technology of the battery has improved substantially during the last few years, providing much larger maximum range of the electric cars, meaning that this factor should be now less important when deciding to buy an electric vehicle.

Furthermore, Achtnicht et al. (2012) claims that the overall availability of charging stations for electric vehicles is also a significant factor influencing the demand for such cars. More precisely, the researchers have found out that better network of charging stations would make the electric cars more attractive for potential consumers.

The low CO_2 emissions of hybrid cars and zero CO_2 emissions of electric cars can also serve as one of the reasons why people would buy one, as confirmed by the survey of Thiel et al. (2012). Moreover, Chua, Lee and Sadeque (2010) suggest that people may buy a hybrid or electric vehicle in order to be perceived as a “green person” by the society, meaning that they want to present themselves as an environmentally friendly person.

Regarding the relationship between the sales of electric and hybrid vehicles and the changes in gasoline price, we already have some evidence of a positive relationship between these two variables, i.e. that higher gasoline price leads to higher demand for EVs and HEVs. Firstly, Høyer (2007) mentions an increased interest in development of electric cars during the 70’s as a consequence of the oil crisis in 1973. Moreover, Diamond (2009) has found that gasoline price serves as a significant factor affecting demand for hybrid vehicles when examining market shares of those vehicles across US states between years 2001 and 2006.

The aim of this thesis is to fill the gap in the research by examining the impact of gasoline price on the demand for hybrid and electric cars during the last years. Although Diamond (2009) has already discovered the occurrence of this relationship during the early and middle 2000’s, the market for alternative fuel vehicles has evolved a lot since then, especially due to the expansion of plug-in electric vehicles, therefore the author thinks that it would be useful to examine this relationship even further. Furthermore, it should also verify the significance of the previously mentioned factors as the factors which are also believed to have an impact on the demand for such cars. The main hypothesis of this thesis is that an increase in gasoline prices causes an increase in the demand for hybrid and electric cars. The author would like to test this hypothesis on two models.

The first model would be designed to examine whether rapid increases in gasoline price in years 2008 and 2012 had an impact on the US sales of Toyota Prius, the best-selling hybrid vehicle in that time. The second model aims to analyze whether different gas price levels across various European countries lead to differences in the demand for plug-in electric vehicles across these states. Furthermore, additional variables, such as those mentioned above (state incentives, availability of charging stations, GDP per capita, environmental index etc.), will be added to the model as well.

2 Literature review

In this part of the thesis, the author would like to introduce the reader to what we already know about the topics which are relevant to this thesis. Firstly, in the section 2.1, the author would like to acquaint the reader with different types of electric and hybrid vehicles, which will be discussed in the following chapters of the thesis. The section 2.2 is dedicated to Toyota Prius, which will be the subject of discussion in our first model. Last but not least, the section 2.3 focuses on what we already know about factors influencing the demand for alternative fuel vehicles from the previously conducted research.

2.1 Brief insight into types of electric and hybrid vehicles

Since some readers may not be very familiar with the topic of hybrid and electric vehicles, a brief explanation of the different types of these vehicles is needed, since understanding the differences between those types is fundamental for this thesis. Generally, we can divide these vehicles into three main categories. All-electric vehicles (also known as battery electric vehicles or BEVs), plug-in hybrid vehicles (PHEVs) and hybrid electric vehicles (HEVs).

2.1.1 Hybrid Electric Vehicles (HEVs)

Standard hybrid electric vehicles (HEVs) can be defined as such vehicles, where the battery cannot be charged externally by an electric plug or a charging station (Denton 2016). Instead, it combines two sources of power, a standard combustion engine powered by a fossil fuel (generally gasoline or diesel) and an electric motor. Instead of charging the battery which powers the electric motor externally, the combustion engine drives an electric generator, which then powers the electric motor. Usually, this type of car combines both electric and combustion engine while driving, mostly using the electric motor at lower speeds and adding the combustion engine as the car starts to go faster and more power is needed.

Since the battery in these vehicles tends to be rather small, these cars are not able to achieve a great range using purely the electric power (usually only up to few kilometers) and therefore the combustion engine is used to power the car majority of the time. However, they tend to be much more fuel-efficient than standard gasoline or diesel vehicles, since the electric motor is helping mainly during acceleration and therefore is able to save a significant amount of fuel.

As examples of this category, we can mention the standard Toyota Prius (not the plug-in version, which will be mentioned later), other Toyota models, such as Auris Hybrid or Corolla Hybrid as well as few models of the Lexus brand. This type of propulsion gained popularity mostly during the first decade of the 2000's, when there were little technical solutions for a battery which could provide a longer range on fully electric power. As the automotive companies started to come up with technologies providing greater capacity of the batteries and therefore longer range on purely electric power, this category became dominated by plug-in hybrids and battery electric vehicles.

2.1.2 Plug-in Hybrid Vehicles (PHEVs)

A typical plug-in hybrid vehicle is equipped with an internal combustion engine as well as with an electric motor. As the name suggests, the battery used for powering the electric motor can be recharged externally, using either a plug or a charging station. However, the battery is recharging while driving as well, due to the same reasons as in the case of a standard hybrid electric vehicle (HEV). Unlike HEVs, the plug-in hybrids are able to drive for a greater distance on the battery power alone due to a greater capacity of the battery. For example, the newest generation of the Toyota Prius Plug-in Hybrid can cover a range from 18 to 35 miles on fully electric power. As a result, this type of vehicle provides a great opportunity to use the electric power most of the time, taking into account that majority of the people do not cover greater mileage than 35 miles per day and they are able to charge the plug-in hybrid vehicle at home over night.

On the other hand, since these vehicles are able to run using the combustion engine as well, they are able to cover long distances without the need to recharge, as opposed to fully electric vehicles (BEVs). The arrival of plug-in hybrids in the early 2010's aroused interest of many automotive companies, desiring to introduce their own plug-in hybrid models to the market as well. As a result, different models of the plug-in hybrids were offered not only by the Japanese companies such as Toyota (including the previously mentioned Prius Plug-in Hybrid) or Mitsubishi (Outlander PHEV, a compact plug-in SUV) but also by European brands such as Volkswagen (Golf GTE) or BMW (i8, a plug-in hybrid sports car).

2.1.3 Battery Electric Vehicles (BEVs)

Lastly, the category of all-electric vehicles, also known as battery electric vehicles (BEVs) needs to be mentioned. Unlike PHEVs, battery electric vehicles are not equipped with any internal combustion engine and a fuel tank, but only with an electric motor and rechargable battery packs. Thus, although both BEVs and PHEVs are able to drive using solely electric power on shorter distances, the main difference between those types is that PHEVs are able to switch to the combustion engine as the capacity of the battery is depleted, but the BEVs have to rely on the electric power all time. Due to the absence of an internal combustion engine, BEVs have overall zero tail pipe emissions, as opposed to HEVs and PHEVs. Therefore, they can be concerned as the most ecological ones.

BEVs became popular mainly during the last decade, as car manufacturers started to introduce batteries with greater capacity and thus increasing the range of such cars. Typical examples of this category are all Tesla models, particularly Model S, Model X and the relatively new Model 3, as well as Nissan Leaf and Renault Zoe, compact electric cars which gained great popularity in many countries during the last decade. Moreover, a lot of cities are implementing fully electric buses, in order to improve the air quality in those cities.

2.2 Toyota Prius as a pioneer of hybrid cars

A substantial part of this thesis is dedicated to evaluating the effect of the change in gasoline prices on the demand for Toyota Prius – one of the most popular hybrid cars on the market, which managed to maintain its position on the top of the market for hybrid cars for more than two decades. Therefore, this chapter will be devoted to briefly explaining the history and development of this model since the time it was introduced to the market until today. Furthermore, the author would also like to explain why he suggests particularly this model to be the most suitable for testing the first hypothesis.

In order to briefly outline the context of the situation in the automotive industry in the period when first Prius concept was being developed, let the author use the words of Osono et al. (2008), who states that in the early 1990's, the car manufacturers were facing an increasing fear that without a radical improvement in fuel efficiency, the automotive industry would be in danger.

Since Toyota has always been considered as a brand promoting experimentation and implementation of new technologies (Osono et al. 2008), their goal at that time period was to introduce a concept car which would provide a 100 percent improvement in fuel economy. In order to develop such car, Akihiro Wada, the R & D Executive Vice President of Toyota, has created G21, a committee designated to research cars for the 21^{st} century (Fileru 2015). The research team soon came to a conclusion that the only possible way to achieve such improvement would be through a hybrid technology.

Dedicated to introduce such innovative technology to the market, the G21 team came up with a hybrid prototype called Prius for the Tokyo Motor Show in 1995. During the following year, Toyota performed various tests and improvements of this concept, managing to launch the serial production of the first generation of Prius in 1997, available only in Japan so far. This early introduction to the market turned out to be a substantial leap forward for Toyota, taking into account that they managed to launch their first hybrid model two years before other manufacturers (Fileru 2015).

After celebrating its success in Japan, Toyota has developed an improved version of the first generation of Prius for the US market in 2000. In order to satisfy the requirements of the American customers, this version was able to achieve higher speeds and longer distances (Fileru 2015) and turned out to be a great success as well.

However, on of the biggest steps forward in the evolution of the Prius was the introduction of its second generation in 2003. The Toyota engineers managed to make this generation more powerful and efficient than the previous one, while making it more ecological in terms of CO_2 emissions as well. The second generation celebrated a giant success all over the world including the United States, causing the name Prius to become a world-wide known synonym for an eco-friendly hybrid vehicle. The success of the Prius continued with the third generation introduced in 2009, which came not only with a slighly more aerodynamic body, but several improvements have been made regarding both the electric motor and the combustion engine as well (Fileru 2015).

During the beginning of the 2010's, Toyota's team faced a rather serious problem with the increasing number of competitors in the field of hybrid and electric vehicles. As Wilberforce et al. (2017) mentions in his publication about development of electric and hybrid vehicles, a substantial number of plug-in electric cars have been introduced to the market by various car manufacturers during the period between 2009 and 2012. As a response, Toyota has developed a plug-in version of the Prius, which debuted in 2012 under the name Toyota Prius Plug-in Hybrid. Due to the introduction of this version, Toyota has increased its chances to compete with other players on the market, such as Tesla with its Model S or Nissan with its fully electric Leaf, which debuted in 2010. The non-plug-in (HEV) version of the Prius also remained available simultaneously with the plug-in one.

The fourth generation of the Prius was introduced in 2015 and launched in the USA in January 2016, recieving a slight facelift in 2018. Although this generation brought some minor improvements compared to the previous one, its sales were not anywhere as high as of the second and third generation.

2.2.1 Reasons for the choice of Toyota Prius for our first model

Regarding the first model, in which the author would like to evaluate the effect of the changes in fuel prices on the demand for hybrid and electric vehicles, the author decided to choose the sales of Toyota Prius in the US as the dependent variable. As a main reason for this choice, the author would like to emphasize the fact that the Prius is considered a pioneer in the field of alternative fuel vehicles (Fileru 2015), since it is available on the market since 1997. Therefore, there is a long interval of the data available on the sales of Prius, allowing the author to include a rather extensive time series in the model.

Secondly, the Prius gained recognition already during the early years of its production, leading to the fact that more than hundred thousand of Priuses were sold annually during the period between 2005 and 2017. Regarding the fully electric vehicles (BEVs), they usually began appearing on the market during the early 2010's. Therefore choosing the sales of BEVs such as Tesla Model S or Nissan Leaf would not be very appropriate for the model, since one of the purposes of the model is to capture the effect of the 2008 oil crisis and these BEVs were not available on the market yet.

Moreover, since the market for BEVs was still at the development stage during the early 2010's, the BEVs were sold at relatively small amounts during that period, which could lead to difficulties in capturing the impact of the changes in gasoline price if these small sales were used as a dependent variable in the model.

In conclusion, the author suggests using the Prius sales as the best choice for our dependent variable due to the wide interval of data available on its sales, allowing the author to capture the effect of both of the peaks in gasoline price in 2008 and 2012, and due to the fact that Prius has been widely known and popular hybrid model during the whole time interval evaluated in the model.

2.3 Factors affecting the demand for alternative fuel vehicles

Since one of the main purposes of this thesis is to evaluate the impact of gasoline price on the sales of hybrid and electric cars, other factors which could potentially affect the demand for such cars need to be evaluated as well. Subsequently, the author would include some of these factors in the models as well, provided that the data for these variables will be available. Furthermore, in this chapter, the author would also like to evaluate whether we already have some evidence of the relationship between fluctuation in gasoline price and increases in the demand for alternative fuel cars from already published work.

2.3.1 Evidence from European countries

In 2012, Thiel et al. (2012) have conducted a survey among citizens of six European states, with the intention of evaluating the attitude of European drivers towards electric vehicles. More precisely, one of the main purposes of this survey was to detect which parameters of an average electric car should be improved in order to make it more attractive to the customer. The study also included a survey about the reasons why would people not decide to buy an electric car.

In one of the parts of the survey, the participants were presented a table of specifications of a hypothetical electric vehicle, which were Purchase price (30000 EUR), Distance with one recharge (150 km), Re-charge time (2 hours), Possibility to re-charge at home without having private garage (set to NO on default) and Max speed (120 km/h). Subsequently, they were asked to make 3 suggested improvements to this car, which would make this electric car more attractive for them. They could either choose improvement of three different categories, but they could also improve the same category thrice, meaning that they really find improving that particular category important.

The researchers have found out that the participants considered the purchase price, distance with one recharge and possibility to recharge the car at home to be the most important factors for majority of the potential customers, while not many of them considered improving the recharge time or the maximum speed instead. As mentioned before, the researchers have also asked European citizens who were not interested in buying an electric car for the reason why. In accordance to the previously evaluated task, for majority of the people, high price and low capacity of the battery were the main reasons why they were not interested in buying such car (Thiel et al. 2012).

When evaluating the results of this survey, a very important fact that needs to be taken into account is that it was conducted in 2012, i.e. almost 8 years ago. Since that time, the technology has improved substantially, providing now an appreciably higher capacity of the battery and therefore also greater maximum range with one recharge. To back this statement up with facts, the author would like to mention the maximum driving distance of few of the most popular BEVs on the market. The fairly newly introduced Tesla Model 3 has a driving distance over 500 km on one recharge, as well its older sibling Model S. Regarding the category of smaller city cars, let the author mention the Nissan Leaf, which can provide a rather solid driving distance of more than 350 km. Therefore, the range of these typical electric cars is now much greater than of the hypothetical car in the survey, which had only 150 km of maximum range. As a result, we can assume that the driving range with one recharge is now substantially smaller problem than it was almost a decade ago, making the electric cars more attractive to the customers in this way.

However, the high price of the battery electric vehicles still remains until today and a decrease in price of electric vehicles could therefore have a significant impact on the demand for such cars. Since our panel model includes the data on overall market share of all plug-in electric cars in the particular country, we cannot unfortunately directly distinguish between particular models and the changes in their price. However, we can include state incentives for buying electric cars in the model, since they can also be considered as form of a decrease either in the adquisition price of the car (in case when the state directly subsidies purchasing such cars) or in the operating expenses of the car (in form of e.g. free parking for such cars, tax benefits, etc.). On the other hand, Diamond (2009) has proven the state incentives to have a rather unsignificant effect on the HEV sales in the US during the early 2000's. Despite this finding, the author decided to include a dummy variable for the state incentives in the panel data model.

2.3.2 The case of availability of charging stations

The survey conducted by Thiel et al. (2012) has definitely shed some light on what factors are actually affecting the demand for electric cars. However, few other factors were not evaluated, including the price of gasoline, which is the goal of this thesis. Another survey by Achtnicht et al. (2012) among German drivers is, however, dealing with another rather interesting factor. More precisely, they have evaluated the effect of the availability of charging stations on the demand for alternative fuel vehicles.

Overall, the case of charging stations for electric vehicles is rather interesting because of its reciprocal relationship. That is, companies will only provide such stations when the demand for them is sufficient and therefore it is profitable for them to operate these stations. However, the potentional customers will also may not be willing to purchase an electric vehicle, until a sufficient network of charging stations is provided. Achtnicht et al. (2012) suggest some kind of political intervention as one of the possible solutions to this vicious cycle.

Nevertheless, the purpose of Achtnicht's survey was to find out whether the availability of charging stations actually has an effect on customers‘ willingness to buy an alternative fuel vehicle. Regarding the results, the model has shown the fuel availability to be a significant factor, suggesting that people would be more willing to buy an alternative fuel vehicle if the corresponding network of stations was available (Achtnicht et al. 2012).

However, it is necessary to mention again that this study is also from 2012 and the maximum range of the electric cars has overall increased substantially since then, which could have potentially decreased the need for a highly developed network of charging stations. On the other hand, the number of electric cars on the roads is increasing rapidly each year and therefore could lead to an increased need for those stations.

2.3.3 Other factors affecting demand for alternative fuel vehicles

Achtnicht's model, however, included various other variables as well, such as purchase price, CO_2 emissions or fuel costs. As expected, the purchase price turned out to be a highly significant factor, which is in accordance with the results of the previously mentioned study of Thiel et al. (2012). Furthermore, the fuel costs factor turned out to be highly statistically significant as well while having a negative coefficient ($-0,0768$), meaning that higher fuel costs lead to lower demand for vehicles. (Achtnicht et al. 2012). However, the "fuel" variable was not evaluated for each type of fuel separately, providing us only with a general insight into this relationship between fuel price and demand for cars. Moreover, this variable was not evaluated cross-sectionally in terms of different types of fuel, i.e. the model did not evaluate the relationship between demand for electric vehicles and price of gasoline or diesel, but only the connection between demand for gasoline cars and the price of gasoline, etc. Therefore, although this result provides us with the information that fuel costs are an important factor affecting the demand for a particular vehicle, it does not certainly tell us whether higher gasoline prices can cause increased demand for electric and hybrid vehicles.

Moreover, the CO_2 emissions turned out to be highly significant as well, especially for the more environmentally aware participants, suggesting that some kind of environmental index indicating the citizens' concerns about environmental topics and the threats of air pollution will have to be included in our model as well. Regarding the environmental friendliness of hybrid and electric cars, another research was conducted by Chua, Lee and Sadeque (2010) with the intention of analyzing the factors affecting customers' decisions when buying a new car. This study focused mainly on the idea of a so-called "green image", i.e. the fact that being environmentally friendly is nowadays percieved as a honorable trait, therefore customers may buy a hybrid vehicle in order to achieve a good social status by presenting themselves as a "green" person. The results of this study have shown that presenting oneself as a "green" person is an important factor which leads many customers to buy a hybrid. (Chua et al. 2010).

It is important to mention that the research of Chua et al. (2010) was conducted in 2010, i.e. at the time when the popularity of the hybrid cars has reached its peak, while the modern fully electric cars were still at the early phase of development (most of them were not even available on the market yet). Therefore, Chua's study deals solely with the topic of hybrid cars, while the fully electric vehicles were not included in the paper. However, the author of this thesis believes that the results of this study can be generalized to the field of battery electric vehicles as well, since the ownership of a BEV provides the owner with a "green image" as well as the ownership of a hybrid vehicle would do.

Since the work of Achtnicht et al. (2012) and Chua, Lee and Sadeque (2010) suggests that the factors related to the ecological footprint, such as CO_2 emissions or being perceived as a environmentally friendly person, are crucial when deciding to buy an alternative fuel vehicle, some kind of ecological index needs to be included in our model. Therefore, the author decided for the inclusion of the EPI (Environmental Performance Index) in the panel data model. This index is designed to measure overall environmental performance of individual countries, therefore it could serve as a good instrument for the social perception of environmental topics in those states. Furthermore, few subcategories are also evaluated within this index. The author suggests including the "CO_2 - total" category, since it is directly connected to the amount of CO_2 emissions in the air and therefore indirectly connected to the general attitude towards alternative fuel vehicles.

2.3.4 1973 oil crisis and the increased interest in electric vehicles

So far, the literature dealing with demand for alternative fuel vehicles has provided us with many factors, which seem to be influencing the demand for such cars. However, only few of these academic works have directly tested the effect of changes in price of gasoline or diesel. Therefore, it raises a question whether we actually already have any evidence of the relationship between these two variables.

In order to find more information on this relationship, we have to fasten on the time periods when the prices of gasoline has increased rapidly and examine whether a higher interest in the development of electric and hybrid cars occured at these periods. To be more specific, we have to concentrate on the oil crisis of the 1970's.

In his publication, Høyer (2007) describes the history of development of hybrid and electric cars and he dedicates a rather large part of this work to the situation during the 1970's. In 1973, an embargo has been imposed against the US by the Arab members of OPEC, as a result of the Arab – Israeli war, in which the US was on the Israeli side. This has had a fatal impact on the oil prices in the US as well as in other countries, leading to delays at the gasoline stations, decreasing interest in so-called muscle cars in the US and rising demand for smaller cars with lower gas consumption instead, maximum limit of 55 miles per hour at the highways, but also in the rising interest in the alternative fuel vehicles during the 70's (Denton 2016).

At that time, many automotive companies were aware of the current situation on the market for oil and therefore started with the development of their own model of electric car, which, in vast majority of cases unfortunately ended only as a prototype and did not manage to get to the serial production (Høyer 2007), mainly due to the fact that the battery technology was not very developed at that time and therefore these cars were not able to cover very long distances, and due to the expensiveness of the production of such cars.

2.3.5 Findings from the early 2000's

Another evidence of the direct relationship between gasoline price and demand for alternative fuel vehicles has been discovered by Diamond (2009). Although the primary aim of Diamond's study was to examine the efficiency of state incentives for hybrid vehicles, he has also included gasoline price in his models as one of the independent variables. In his models, Diamond has used the annual data from years 2001-2006 on market shares of various hybrid vehicles in the US states, state incentives, gasoline price and few other variables related to the topic. As previously mentioned, he has proven the state incentives to be rather inefficient, i.e. they did not seem to have a significant impact on the demand for the hybrid cars in the tested time period.

On the other hand, he noticed a highly significant relationship between gasoline prices and market shares of hybrid vehicles, in a way that higher gasoline price leads to higher sales of those hybrid vehicles. This could be a very important finding for our thesis, since it serves as a direct evidence of this relationship. However, the market for alternative fuel vehicles has developed a lot since the time period tested by Diamond (2009), therefore we may expect to achieve slightly different results when examining newer data.

2.3.6 Filling the gap in the research

Although the previously conducted research has provided us with many factors influencing the demand for alternative fuel vehicles, such as purchase price (Thiel et al. 2012), fuel availability (Achtnicht et al. 2012) and the factors related to ecological footprint (Achtnicht et al. 2012 and Chua, Lee and Sadeque 2010), there seems to be little evidence of the relationship between prices of fossil fuels (gasoline, diesel) and the demand for alternative fuel vehicles in the current research.

Despite the fact that we already have some evidence of this relationship from the 70's (Høyer 2007) in form of increased interest in the development of electric vehicles during the 1970's oil crisis, as well as from the early 2000's (Diamond 2009), we do have little evidence of the occurrence of a similar trend in the modern age, when the popularity of alternative fuel vehicles is increasing rapidly. Therefore, the aim of this thesis is to shed some light on this gap in the research, with the first model concentrating on the rapid increases of gasoline price in 2008 and in 2012, and the second model focusing on the current situation among European countries.

3 Data overview

The purpose of this chapter of the thesis is to describe the data used within our models. The data were collected from various sources and processed by the author in order to create the dataset for the models included in the thesis. These models aim to test the author's hypotheses.

The first model is dealing with sales of Toyota Prius in the United States and includes various variables which may be responsible for influencing the demand for Prius. The second model is a panel including market shares of BEVs (battery electric vehicles) and PHEVs (plug-in hybrid vehicles) across various European countries, as well as a range of variables potentially affecting the demand for electric and hybrid vehicles.

3.1 Data collection

The data on sales of Toyota Prius used in the first model were collected monthly from the time period between January 2005 and December 2018. These data represent the sales of the whole Toyota Prius family (all generations including plug-in version) in the United States. The choice of this particular time period allows us for capturing the effects of the rapid increases in the gasoline price in years 2008 and 2012. The sales data were retrieved from the page GoodCarBadCar (*goodcarbadcar.net*), a car webpage which specializes on automotive sales data and statistics. The monthly data on U.S. retail gasoline prices were collected from U.S. Energy Information Administration (*eia.gov*). The gasoline price is in USD per gallon.

Furthermore, Industrial Production Index (INDPRO) retrieved from *fred.stlouisfed.org* was intended to be included in the model as a macroeconomic variable, but was excluded from the model later on. Moreover, dummy variables for each generation of the Prius will be included, as well as for the plug-in version, due to the fact that the generations differ in their technical specifications, therefore introduction of a new generation of the Prius to the market could boost the demand for the Prius, since the new generation has overall better technical parameters than the previous one.

Same logic applies to the inclusion of the dummy variable for the plug-in version of the Prius which was introduced in 2012, since its introduction to the market could boost the total sales of the Prius family. Last but not least, the author has also decided to include dummy variables indicating the months in which the main competitors of the Prius were available on the market, since their presence on the market may lead to a decrease in the sales of the Prius itself.

The data on the market shares of plug-in electric vehicles (BEVs and PHEVs) in our second model were collected yearly from years 2016-2019 in 23 European countries. The data were provided by European Alternative Fuels Observatory (EAFO) and are publicly available on the webpage *eafo.eu*. Moreover, the data on yearly average gasoline price (unleaded 95 gasoline) collected from Bundesministerium für Wirtschaft und Energie (*bmwi.de, German Federal Ministry of Economic Affairs and Energy*) were used in this model as the independent variable. These data include yearly average gasoline price across various European countries in recent years, therefore they are considerably suitable for our model. The price is in EUR per liter.

Furthermore, a rather wide range of variables which may have an impact on the demand for electric and hybrid cars is included in the model. More precisely, GDP, state incentives for buying alternative fuel vehicles, number of charging stations, Environmental Performance Index (EPI) and the CO_2 index (subcategory of the EPI) are analyzed within the second model. The data on the GDP were retrieved from Eurostat, the numbers of charging stations were collected from EAFO and the data on the EPI index and its subcategories are available at the official EPI webpage, *epi.envirocenter.yale.edu*. The information on the state incentives has been retrieved from ACEA (*European Automobile Manufacturers Association*).

3.2 Reasons for choice of the variables in the first model

For the first model dealing with sales of Toyota Prius in the US and their relationship with retail gasoline price, the author decided to include other regressors as well. Originally, the author has intended to include the Industrial Production Index in the time series model, which would serve as a macroeconomic indicator on a monthly basis. However, this variable has been removed from the model subsequently, due to its non-stationarity and its potential correlation with the gas price variable.

Furthermore, the author decided to include various dummy variables related to the Toyota Prius itself. As mentioned before, Toyota Prius has been sold in many generations during its production, from the first generation in 1997 up to the fourth generation, which is available on the market up to the present. Since a newer generation often came with improved technical parameters and design, an introduction of the new generation to the market could boost the demand for the Prius. Therefore, dummy variables for the different generations will be included in the model.

Moreover, Toyota has also launched a plug-in version of the Prius in 2012, sold under the name Prius Plug-in Hybrid. Since the plug-in version attracts the customer with higher maximum range purely on electric power than the standard HEV Prius as well as with some other features, the introduction of this version to the market could also boost the sales of the whole Prius family.

Lastly, it is important to mention that for many years, Prius did not have many direct competitors. During the first decade of its production, there were only few other hybrid cars on the market, but they were not nearly as successful as the Prius. However, the increasing interest in the PHEVs and BEVs during the early 2010's brought many new successful models to the market.

Firstly, the fully electric Nissan Leaf launched in 2010 soon gained popularity among the customers desiring for a compact alternative fuel car, and therefore could serve as a serious competitor for the Prius. Furthermore, the launch of the well-known Tesla Model S in 2012 could also result in a decreased demand for the Prius, since the Model S has immediately become a synonym of a modern-age electric vehicle. Therefore, dummy variables for the production years of the Leaf and Model S will also be included in the model, since they can have a negative impact on the sales of Toyota Prius family.

3.3 Graphical visualization of the Prius sales and the gas price

In order to make the data used in the time series more clear for the reader, the author decided to visualize some of the analyzed series graphically. Firstly, the author would like to present the graph of the Toyota Prius sales in the United States between years 2005 and 2018, since some of the readers may not be familiar with this series.

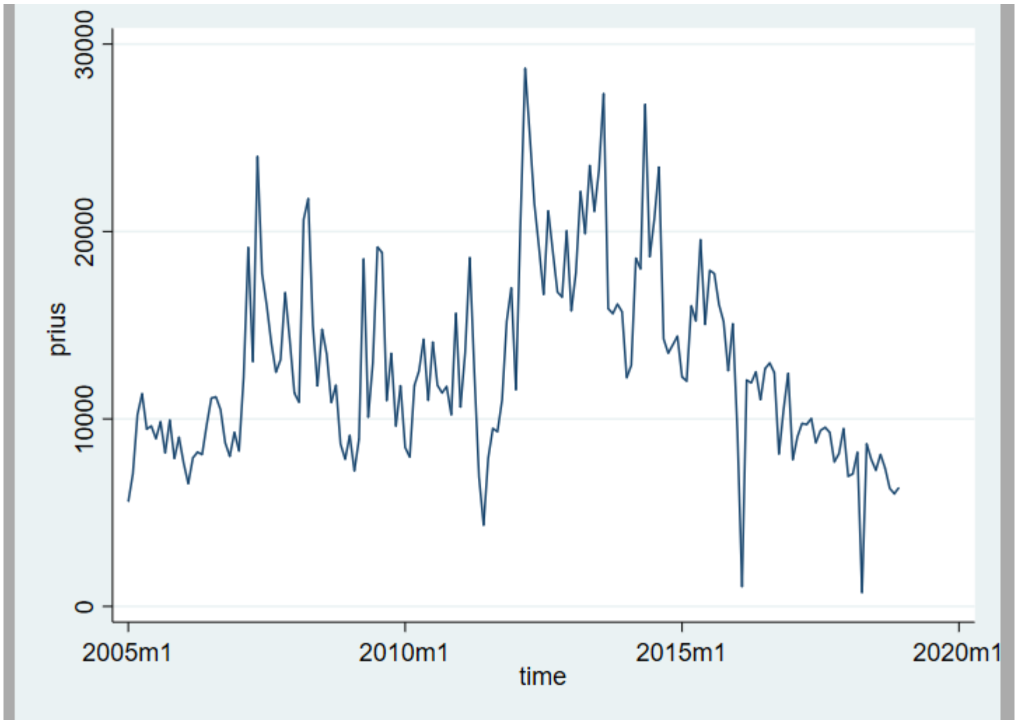

Figure 1: Sales of Toyota Prius in the United States, 2005-2018, in units

A quick look at the graph can already offer us some insight into the potential relationship between Prius sales and the gasoline price. Note that the two biggest peaks in the Prius sales occured around years 2008 and 2012, i.e. at the time period when the gasoline price has increased rapidly. One can also observe a gradual decrease in the demand for Prius during the last years of the tested time period; the author's belief is that this decreasing trend could be caused by the increasing number of competitors on the market, such as Tesla Model S and other alternative fuel vehicles.

Furthermore, the author would like to present a graph depicting the development of the retail gasoline price in the United States on a monthly basis from 2005 to 2018.

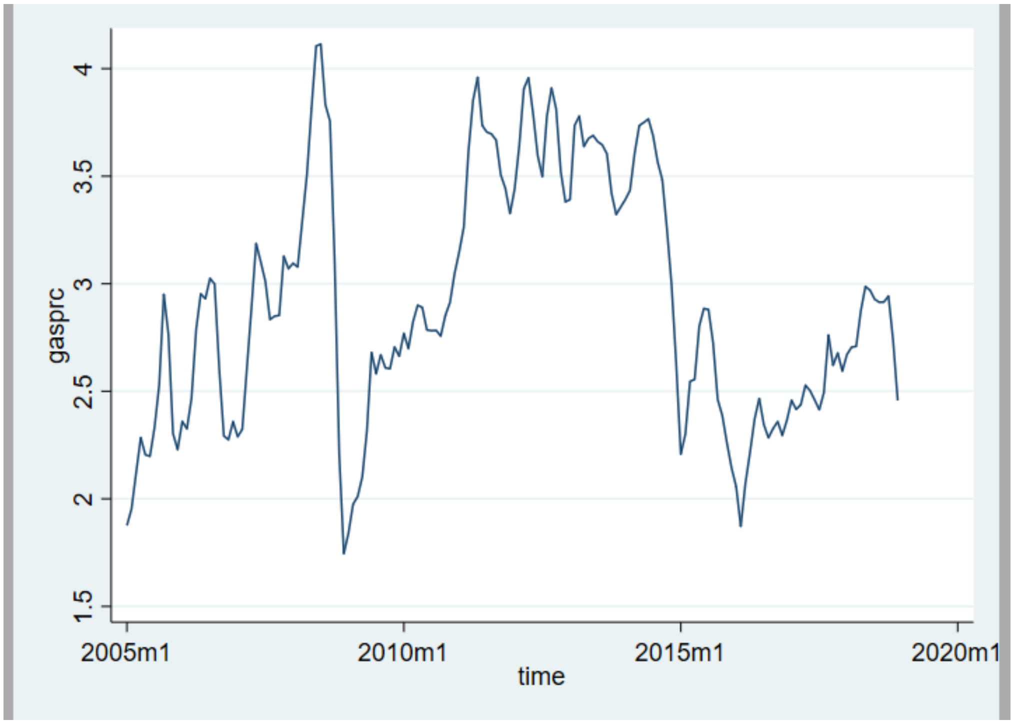

Figure 2: Retail gasoline prices in the United States, 2005-2018, in USD per gallon

Regarding the gasoline prices, one can observe from the graph that the retail gasoline price in the United States has reached its peak in the middle of 2008 (over 4 USD per gallon), followed by a rapid decrease during the last months of 2008 and the early months of 2009. Another rapid increase in the prices of gasoline can be observed around year 2012.

3.4 Reasons for choice of the variables in the second model

The variables included in our panel data model were chosen since they may have an impact on the demand for electric and hybrid vehicles, according to previously conducted research. According to the presented hypothesis, the author expects the countries with higher average gasoline price to have a higher market share of electric and hybrid vehicles. Since purchase price turned out to be a crucial factor affecting demand for alternative fuel vehicles (Thiel et al. 2012), an indicator for the price needs to be included in the model.

However, since the panel data model works with the market shares of all BEVs and PHEVs sold and not with the sales of a particular car model, we cannot use the purchase price as our variable, since the purchase price differs for each model of electric or hybrid car. Instead, the author decided to use the state incentives for purchasing alternative fuel vehicles as one of our variables, since the presence of a state incentive lowers the adquisition price of the car. Although Diamond (2009) disputes the efficiency of the state incentives for alternative fuel vehicles in his research, this model is set in completely different environment and time, therefore we may achieve slightly different results regarding this variable.

Regarding the charging stations, Achtnicht et al. (2012) claims that the availability of fuel stations is also a significant factor affecting demand for alternative fuel vehicles, therefore it will be included in the model as well. However, EAFO provides us only with the overall amount of the charging stations in the countries, which should naturally be bigger in the countries with larger area or larger population. Therefore, the data on this variable needs to be adjusted, for example to the amount of citizens per one charging station, or to charging stations per square kilometer.

Moreover, as Achtnicht et al. (2012) and Chua, Lee and Sadeque (2010) claim in their work, consumers with higher environmental awareness or those who want to be perceived as "green" are also more likely to choose an electric or hybrid vehicle, therefore some kind of variable measuring environmental performance of a particular country needs to be included in the model as well. Hence, the author decided to include the Environmental Performance Index and its CO_2 subcategory. Last but not least, macroeconomic indicators can also affect the overall demand for cars, therefore the Gross Domestic Product per capita will serve as one of the regressors as well.

4 Hypotheses and Methology

In this part of the thesis, the author would firstly like to clearly state his hypotheses which will be tested with the help of our models. Secondly, the methodology used in the models will be reviewed briefly and the models will be specified. The author will explain what models he aims to use and what additional assumptions will need to be tested in order to achieve accurate and consistent results.

4.1 Hypotheses

The main hypothesis is that higher retail gasoline price leads to increased demand for alternative fuel vehicles, namely for electric and hybrid cars. More precisely, in the first model, the following hypothesis will be evaluated: Increases in the retail price of gasoline lead to higher sales of Toyota Prius in the United States in the time periods when the gas price increase occured. In the second model, the author would like to test the hypothesis: Higher average retail price of gasoline leads to a higher market share of plug-in electric vehicles (BEVs + PHEVs).

Moreover, various other factors which are believed to influence the demand for alternative fuel vehicles will be included in the models as well. Although we already have some historical evidence that an increase in gasoline price can lead to an increased interest in alternative fuel vehicles (Høyer 2007 and Diamond 2009), this thesis aims to analyze this phenomenon in a modern environment, when electric and hybrid vehicles are getting much higher attention.

4.2 Methodology

In this section, the author would like to discuss the methodology that will be used in order to evaluate our models. Firstly, the author would like to describe the procedure of testing for stationarity using ADF, KPSS and Phillips-Perron test. Secondly, the time series model examining the relationship between the sales of Toyota Prius and the gasoline prices in the US will be specified and the analysis of the residuals will be described. Furthermore, the author will describe the three tests used for choosing the panel data model and lastly, the panel data model will be specified.

4.2.1 Stationarity of the time series

As Mushtaq (2011) emphasises in his work, testing for stationarity is extremely important when working with variables, which are time dependent. Since our first model is a time series model, testing for stationarity needs to be included. Including non-stationary series in the model can potentially lead to a spurious regression and therefore to misleading results. By spurious regression, one can mean a relationship between two variables y and x related through a correlation with a third variable z, leading to the situation when a regression of y on x identifies a significant relationship between those variables, but after controlling for the variable z as well, the effect of x on y turns out to be zero (Wooldridge 2013).

According to Verbeek (2004), a stochastic process is believed to be stationary if the joint probability distribution does not change by a shift in time. Usually, it is sufficient to provide that the means, variances and covariances are stable over time, rather than the whole distribution. A non-stationary process is such stochastic process, which is not stationary. As Wooldridge (2013) states, in some cases it can be rather challenging to identify whether a time series was generated by a stationary process. However, it seems less difficult to identify certain sequences which are non-stationary.

In order to identify whether an economic time series is stationary or non-stationary, we can use various tests. One of the most commonly used unit root tests is an Augmented Dickey-Fuller (ADF) test, which can be considered as an improved version of a standard Dickey-Fuller test. This test introduced by Dickey and Fuller in 1979 tests the null hypothesis of the presence of a unit root in the series against the alternative of stationarity, or in some cases, trend-stationarity of the series. In other words, rejecting the null would lead to the conclusion that the tested series is stationary (Dickey and Fuller 1979).

Secondly, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test sets the null hypothesis of stationarity against the alternative of unit root. This test was developed by the four researchers mentioned above in 1992 as a potential solution to their belief that standard unit root tests, such as ADF or Phillips-Perron test, often suffer from lack of power against the alternatives and therefore lead to the conclusion that most of the aggregate economic time series contain a unit root. In order to prevent this, the KPSS test is designed in a different way. Namely, its null hypothesis is that the time series is stationary, as opposed to the ADF and Phillips-Perron test (Kwiatkowski et al. 1992).

Executing the KPSS test in Stata provides us with a test statistic, which can be compared to the critical values for the null hypothesis. Whenever the test statistic is lower than the critical values, we cannot reject the null of stationarity of the tested time series and therefore we can assume that the series is I (0). On the other hand, when the null is rejected, the KPSS test tells us that we are dealing with a series integrated of order one, i.e. a I (1) series.

Lastly, we can make use of the previously mentioned Phillips–Perron test, which is designed similarly to the classic ADF test. The Phillips–Perron test has been introduced in 1988 by Phillips and Perron as an alternative to the commonly used Augmented Dickey-Fuller test. The null hypothesis of this test is that the tested series is integrated of order one, meaning it is non-stationary. Therefore, upon rejecting the null, we can assume that the time series is I (0), i.e. it is stationary. (Phillips and Perron 1988). Verbeek (2004) claims that Monte Carlo studies did not provide a clear ranking of the ADF and Phillips-Perron tests in terms of their power in finite samples.

4.2.2 Specification of the time series model

The basic model dealing with the impact of US retail gasoline prices on sales of Toyota Prius could be expressed by the following equation:

$$prius_t = \alpha + \beta_1 gasprc_t + e_t$$

In such model, sales of the Toyota Prius in the United States ($prius_t$) in the month (t) are regressed on average retail gasoline price ($gasprc_t$). The constant would be represented by α and the error term will be represented by the symbol e_t.

However, such model has several limitations. Firstly, it is nor controlled for different generations of the Prius neither for the introduction of the plug-in version to the market. As already mentioned, the introduction of a new generation could potentially boost the demand for the Prius, due to the improved design and technical parameters. Moreover, the introduction of the plug-in version could also cause higher sales of the Prius family, since it could attract a new spectrum of customers.

Therefore, an improved model will be introduced and used within this thesis instead. A dummy variable will be added for each generation as well as for the plug-in version.

These dummy variables will be equal to 1 in the months in which that particular generation or version was available on US market, and to 0 in the rest of the months.

Moreover, market launch of the main competitors of the Prius could also have a negative impact on the demand for the Prius itself. More precisely, dummy variables for the presence of Tesla Model S ($tesla_t$) and Nissan Leaf ($leaf_t$) at the market will be examined in the model, due to the fact that these two models belong to the long-time top-selling EVs in the United States and are well recognised by the society.

These dummy variables will be equal to 1 if the competitor was available at the market during that particular month and equal to 0 if not. For example, sales of the Tesla S in the United States were launched in June 2012 and the model is still available until now, therefore the dummy variable for this model will be equal to 1 since June 2012 until the end of the measured time series.

Lastly, a logarithmic specification of the *prius* variable will be used instead of the level specification, since it simplifies the interpretation of the model. The log-specification of *prius* will be denoted as *lprius*. The improved model, including all of the dummy variables mentioned above, can be described by the equation:

$$lprius_t =$$
$$\alpha + \beta_1 gasprc_t + \beta_3 pri2_t + \beta_4 pri3_t + \beta_5 plg1_t + \beta_6 plg2_t + \beta_7 tesla_t + \beta_8 leaf_t + e_t$$

In this model, we examine the relationship between log-sales of Toyota Prius in the US ($lprius_t$) and the average retail gasoline price ($gasprc_t$) in a month t. In addition to the previously mentioned simple version of the model, the dummy variables for the generations, plug-in version and the competitors were added.

Namely, $pri2_t$ and $pri3_t$ stand for the second and third generation of the standard Prius, respectively, $plg1_t$ and $plg2_t$ represent first and second generation of the Prius Plug-in Hybrid, and $tesla_t$ and $leaf_t$ indicate in which months Tesla Model S and Nissan Leaf were available on the market. The dummy variable for the first generation of the standard HEV Prius is not included in the model, since this generation was sold only until 2003 and the time series in this model begins in January 2005. The dummy variable for the fourth generation will serve as the base one, therefore will be excluded from the regression. Originally, the author intended to include the *indpro* variable as well, which would stand for the Industrial Production Index, but this variable has been removed from the model due to the potential correlation with the *gasprc* variable and its non-stationary nature.

In order to make the specification of our time series model more clear for the reader, a table with all variables and their respective descriptions is depicted below:

variable	**description**
prius	*sales of Toyota Prius in the United States*
lprius	*log of the prius variable*
gasprc	*average retail gasoline price in the US, in USD per gallon*
indpro	*Industrial Production Index, base year 2012*
pri2	*dummy variable equal to 1 in the months when the* 2^{nd} *generation of Toyota Prius was available on the US market, 0 otherwise*
pri3	*dummy variable equal to 1 in the months when the* 3^{rd} *generation of Toyota Prius was available on the US market, 0 otherwise*
plg1	*dummy variable equal to 1 in the months when the* 1^{st} *generation of Toyota Prius Plug-in Hybrid was available on the US market, 0 otherwise*
plg2	*dummy variable equal to 1 in the months when the* 2^{nd} *generation of Toyota Prius Plug-in Hybrid was available on the US market, 0 otherwise*
tesla	*dummy variable equal to 1 in the months when the Tesla Model S was available on the US market, 0 otherwise*
leaf	*dummy variable equal to 1 in the months when the Nissan Leaf was available on the market, 0 otherwise*

Table 1: Variables used in the time series model

4.2.3 Stationarity of residuals, autocorrelation and heteroskedasticity

According to Wooldridge (2013), it is important for the residuals to be stationary when evaluating a time series model, in order to avoid a spurious regression. After performing the regression, the residuals will be stored and the stationarity will be tested with the help of the ADF test. Moreover, one can use a Durbin-Watson test for autocorrelation in residuals. Executing the command *estat dwatson* in Stata provides us with Durbin-Watson statistic, which is used to detect autocorrelation in the residuals.

The Durbin-Watson statistic ranges from 0 to 4, where the values close to 2 indicate no significant autocorrelation in residuals. On the other hand, values close to 0 and 4 are a sign of a positive or negative serial correlation, respectively. Generally, the rule is that whether the D-W statistic is lower than 1.5 or larger than 2.5, it is a sign that a significant serial correlation is present in the residuals.

Moreover, it is also neccessary to test for the presence of heteroskedasticity in our model. In order to do that, one can use the Breusch-Pagan test for heteroskedasticity, which can be executed in Stata under the command *hettest*. The null hypothesis of this test is homoskedasticity, i.e. variance in the residuals does not depend on the independent variables in the regression. Upon rejection of the null hypothesis of this test, the tested model suffers from heteroskedasticity. In such case, robust standard errors, which are consistent under heteroskedasticity, need to be implemented (Breusch and Pagan 1979).

4.2.4 Choosing the best panel data model

Regarding our panel data model, our aim is to analyze the relationship between market shares of plug-in electric vehicles and average retail gasoline prices in various European countries. Since we have access to the data for more years, the author decided to analyze the data using a panel data model. According to Verbeek (2004), choosing the panel data model allows us to analyze the data in a more advanced and realistic way. However, one can approach the panel data in three different ways. Namely, our aim is to choose between Pooled OLS, Fixed Effects (FE) and Random Effects (RE) in terms of how good they fit our model.

The simplest approach to evaluate the panel data is by using Pooled OLS. By deciding to use Pooled OLS, one simply ignores the panel structure of the data. Nevertheless, it is believed that using Random Effects generally leads to more efficient results. In order to decide whether Pooled OLS or Random Effects method is more suitable for our model, we can use the Breusch-Pagan Lagrange Multiplier test. The null hypothesis of this test is that variances across entities are zero. In other words, the null hypothesis states that there are no significant differences across the units, therefore there is no need to aprroach the data as a panel. If such situation occurs, usage of the Pooled OLS would be more effective than using RE. Upon rejecting the null hypothesis, the Random Effects model is more suitable.

In order to decide between Pooled OLS and Fixed Effects, one can perform an F-test. The null hypothesis of the F-test is that the fixed effects in the model are zero. Thus, rejecting the null will lead to the conclusion that there are non-zero fixed effects in the model, therefore Pooled OLS will most likely lead to biased results. In that case, one should prefer Fixed Effects over Pooled OLS.

Regarding the choice between Fixed Effects and Random Effects, Wooldridge (2013) claims that although FE is often thought to be more convincing when evaluating ceteris paribus effects, it is usual for many researchers to use both FE and RE and then test whether there are significant differences between the coefficients gathered from those two methods. This comparison can be done by performing a Hausman test. Verbeek (2004) states that the idea of the Hausman test is to compare the FE estimator, which is consistent under both null and alternative hypothesis, and the RE estimator, which is consistent under the null only. The null hypothesis is rejected when there are significant differences between those estimators, and in that case, Fixed Effects estimator should be chosen as the preferred one. On the other hand, when the null is not rejected, meaning both estimators are consistent, the Random Effects estimator is preffered due to its better efficiency.

After performing the three tests mentioned above, one should be able to choose the best approach to evaluating the panel data model.

4.2.5 Specification of the second model

Our panel data model aims to study the relationship between market shares of BEVs and PHEVs and the average gasoline price in 23 European countries. Moreover, the author has decided to include various other variables, which are known to influence the demand for electric vehicles from the previously conducted research. This panel data model can be expressed by the following equation:

$$mktshare_{it} =$$
$$\alpha + \beta_1 gasprc_{it} + \beta_2 gdp_{it} + \beta_3 cpchs_{it} + \beta_4 sttinc_i + \beta_5 epi_i + \beta_6 co2_i + e_{it}$$

In this model, we regress the market share of plug-in electric cars ($mktshare_{it}$) in country i and year t on the average retail gasoline price in that particular country and year ($gasprc_{it}$). Gross domestic product per capita (gdp_{it}) serves as a macroeconomic indicator in the model. Furthermore, the variable $cpchs_{it}$ represents the number of citizens per one EV charging station in a country i and time t. $Sttinc_i$ is a dummy variable equal to 1 for a country i, if the country provides direct state incentives for purchasing plug-in electric vehicles. Moreover, epi_i and $co2_i$ are indicating the score of a country i in the Environmental Performance Index 2018 and in the subcategory of the EPI index dealing with CO_2 pollution, respectively. This score ranges from 0 to 100, where 100 stands for the best overall environmental performance possible. Last but not least, e_{it} represents the error term.

4.2.6 Alternative specification of the second model

One can also approach the panel data model slightly differently by modifying the charging stations variable. Namely, one can use a variable representing the number of charging stations relative to the area of the country rather than to its population. Therefore, in the alternative specification of the panel data model, we can try to substitute the variable *cpchs* (citizens per one charging station) from our original model for a new variable *chspkm*, which stands for charging stations per km^2. Thus, the alternative model would be expressed by the equation:

$$mktshare_{it} =$$
$$\alpha + \beta_1 gasprc_{it} + \beta_2 gdp_{it} + \beta_3 chspkm_{it} + \beta_4 sttinc_i + \beta_5 epi_i + \beta_6 co2_i + e_{it}$$

However, it is notable to mention that the nature of this variable will most likely lead to discrimination of large countries with lower population density, such as Norway, Finland or Sweden. On the other hand, smaller countries probably feel less need for implementation of a large number of the charging stations despite their potentially high population density, since the average travel distances in those countries may be shorter. Therefore, measuring the amount of charging stations relatively to the area of the country rather than to its population could be more logical. In order to make the specification of the models more clear for the reader, a table with all variables and their descriptions is presented below:

variable	description	source
mktshare	*market share of BEVs + PHEVs relative to all registered vehicles in the particular country*	*EAFO*
gasprc	*average retail price of unleaded 95 gasoline, in EUR per liter*	*German Federal Ministry of Economic Affairs and Energy*
gdp	*GDP per capita, in EUR*	*Eurostat*
cpchs	*citizens per one EV charging station*	*author's calculations based on data from EAFO*
chspkm	*EV charging stations per square kilometer*	*author's calculations based on data from EAFO*
sttinc	*dummy variable equal to 1 if a state provides direct state incentives for purchasing electric vehicles, 0 otherwise*	*ACEA*
epi	*result of the latest Environmental Performance Index release, i.e. in 2018*	*EPI*
co2	*results of the CO_2 category of the latest Environmental Performance Index release, i.e. in 2018*	*EPI*

Table 2: Variables used in the panel data models

5 Results

In this chapter, the author will analyze the results obtained from our models. Firstly, the time series model examining the Toyota Prius sales will be discussed, and both the original and the alternative specification of the panel data model will be examined subsequently.

5.1 Time series model

As mentioned in the Methodology chapter, three tests for unit root were applied in order to examine whether the series used in our first model are stationary or not. Namely, the ADF test, the KPSS test and the Phillips-Perron test have been used. Firstly, let the author discuss the results of the Augmented Dickey-Fuller test. The results are presented in the table below:

Augmented Dickey-Fuller test						
	Test statistic Z(t)	**1% CV**	**5% CV**	**10% CV**	**p - value**	**# of lags**
prius	−2.979	−3.489	−2.886	−2.576	0.0369 **	3
lprius	−3.212	−3.488	−2.886	−2.576	0.0193 **	3
gasprc	−2.980	−3.488	−2.886	−2.576	0.0368 **	3
indpro	−3.112	−4.020	−3.442	−3.142	0.1035	6

Table 3: Augmented Dickey-Fuller test for unit root

Description: Table 3 depicts the results of the ***Augmented Dickey-Fuller test*** *for unit root. In the columns, the test statistic, critical values for 1%, 5% and 10% and the MacKinnon p-value are presented. Furthermore, an optimal number of lags was chosen in order to allow for higher-order autoregressive process. The null hypothesis of the ADF test is that the series is integrated of order 1, i.e. is non-stationary. Significance levels are represented by stars, where: 0.01 (***), 0.05 (**), 0.1 (*).*

As depicted in the table, the null hypothesis of the unit root has been rejected on the 5% significance level for *prius*, *lprius* and *gasprc* variables. On the other hand, we have failed to reject the null on all significance levels for the *indpro* variable. As a conclusion, the *prius*, *lprius* and *gasprc* variables should be treated as stationary, while the *indpro* variable seems to contain a unit root, according to the Augmented Dickey-Fuller test.

Secondly, the KPSS test has been performed. The results of the KPSS test are presented in the table below:

KPSS test for unit root						
	Test statistic	**10% CV**	**5% CV**	**2.5% CV**	**1% CV**	**trend**
prius	.285	0.347	0.463	0.574	0.739	no
lprius	.290	0.347	0.463	0.574	0.739	no
gasprc	.252	0.347	0.463	0.574	0.739	no
indpro	.212	0.119	0.146	0.176	0.216	yes

Table 4: KPSS test for unit root

Description: Table 4 depicts the results of the ***Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test****. In the columns, the test statistic and critical values for 10%, 5%, 2.5% and 1% are presented. Furthermore, an information on whether the particular series includes a trend is included in the last column. If the test statistic is sufficiently high, one can reject the null hypothesis of stationarity on the corresponding significance level. In Stata, the option "auto" has been included in the kpss command, selecting the optimal number of lags automatically.*

As seen from the results, we have failed to reject the null hypothesis of stationarity for *prius*, *lprius* and *gasprc* variables even at the 10% significance level. Therefore, we can assume that those variables are stationary. On the other hand, we have rejected the null hypothesis on all significance levels except 1%. Therefore, it leads us to the conclusion that *indpro* is non-stationary. Note that the author decided to include the *trend* option for *indpro*, since this series seemed to include a linear trend. Regarding the other variables, there was no perceptible evidence of a trend being present in those series, therefore the author did not use the *trend* option in these cases.

Lastly, the author has performed the Phillips-Perron test with the null hypothesis of a unit root. The results of this test are presented in the following table:

Phillips-Perron test for unit root					
	Test statistic Z(t)	**1% CV**	**5% CV**	**10% CV**	**MacKinnon p - value**
prius	−5.050	−3.488	−2.886	−2.576	0.0000 ***
lprius	−7.155	−3.488	−2.886	−2.576	0.0000 ***
gasprc	−3.021	−3.488	−2.886	−2.576	0.0329 **
indpro	−0.677	−3.488	−2.886	−2.576	0.8525

Table 5: Phillips-Perron test for unit root

Description: Table 5 depicts the results of the ***Phillips-Perron test*** *for unit root. In the columns, the test statistic, critical values for 10%, 5%, 2.5% and 1% and the MacKinnon p-value are presented. The null hypothesis of the Phillips-Perron test is that the series is integrated of order 1, i.e. is non-stationary. Significance levels are represented by stars, where: 0.01 (***), 0.05 (**), 0.1 (*).*

As depicted in the table above, one can reject the null hypothesis of a unit root for both *prius* and *lprius* on all significance levels, therefore we can assume that these variables are stationary. Regarding the *gasprc* variable, we have failed to reject the null only on the 1% significance level, therefore we can conclude that this variable is stationary as well. However, the *indpro* variable seems to be non-stationary, since we have failed to reject the null of the unit root on all significance levels.

As a conclusion, all of the three performed tests indicate stationarity of *prius*, *lprius* and *gasprc*, while the *indpro* variable seems to be non-stationary according to all three tests. The other regressors are dummy variables, therefore there was no need to execute the unit root tests for these variables. Although the author intended to include the *indpro* variable in the model originally, we have decided to exclude the variable from the model due to the potential correlation with the *gasprc* variable. Thus, all of the variables in the model are stationary and there is no need for differencing the model. Furthermore, the robust standard errors were used within the model in order to deal with heteroskedasticity. The results obtained from the regression are depicted in the table below:

lprius	coef.	robust SE	t	p - value
gasprc	.2378275 ***	.0498115	4.77	0.000
pri2	.3217926	.2199987	1.46	0.146
pri3	.4126565 *	.2101557	1.96	0.051
plg1	.6971874 ***	.1326159	5.26	0.000
plg2	.4377426	.2677147	1.64	0.104
tesla	−.2212802 ***	.0764814	−2.89	0.004
leaf	−.238996 *	.1272339	−1.88	0.062
cons	8.32948 ***	.2833083	29.40	0.000
number of observations = 168				
$R^2 = 0.4363$				

Table 6: Results of the time series model

Description: Table 6 depicts the summary of results of the Time Series model, in which we regress the variable ***lprius*** *on the independent variables displayed in the table. Significance levels are represented by stars, where: 0.01 (***), 0.05 (**), 0.1 (*).*

After performing the regression, the residuals were stored and tested for stationarity using the ADF test in order to avoid spurious regression. The *varsoc* command in Stata has recommended including 1 lag in the ADF test. As depicted in the table below, the residuals turned out to be stationary, since we have rejected the null of an unit root on all significance levels.

Augmented Dickey-Fuller test						
	Test statistic Z(t)	**1% CV**	**5% CV**	**10% CV**	**p - value**	**# of lags**
resid	−7.415	−3.488	−2.886	−2.576	0.0000 ***	1

Table 7: Augmented Dickey-Fuller test

Description: Table 7 depicts the results of the ***Augmented Dickey-Fuller test*** *for unit root. In the columns, the test statistic, critical values for 1%, 5% and 10% and the MacKinnon p-value are presented. The null hypothesis of the ADF test is that the series is integrated of order 1, i.e. is non-stationary. Significance levels are represented by stars, where: 0.01 (***), 0.05 (**), 0.1 (*).*

Furthermore, the Durbin-Watson statistic for this model has been obtained using the Stata command *estat dwatson*. This command yielded a Durbin-Watson statistic equal to 1.577531, leading to a conclusion that although our model includes a slight positive autocorrelation, the Durbin-Watson statistic of this model lies in the interval for which the autocorrelation should not be a serious point of concern.

Regarding the results of the regression itself, the *gasprc* variable turned out to be statistically significant at all crucial significance levels and has a positive coefficient of 0.2378275. This finding is consistent with our hypothesis that higher gas price leads to the increased demand for Toyota Prius. More precisely, an increase in the price of unleaded gasoline by 1 USD per gallon would lead to an increase in the sales of Toyota Prius by 23.78%.

Regarding the dummy variables for different generations, 2^{nd}, 3^{rd} and 4^{th} generations were sold during the evaluated time series and the 4^{th} generation has been selected as the base one. Therefore, the regression results include only coefficients for 2^{nd} and 3^{rd} generation. While the 2^{nd} generation sold in years 2003-2009 has a coefficient which is statistically insignificant at all important significance levels, the introduction of the 3^{rd} generation seems to have a positive impact on the sales of Prius, with the coefficient equal to 0.4126565. Judging from this coefficient, the 3^{rd} generation seems to boost the sales of Prius by circa 41% compared to the following 4^{th} generation. Such result does seem to be realistic, since the Prius gained popularity mainly due to the 2^{nd} and 3^{rd} generation, while the 4^{th} generation was mostly outperformed by its competitors.

Moreover, the introduction of the Plug-in Hybrid version seems to have a big influence on the sales of the Prius family in a positive way. More precisely, the $plg1$ variable, which stands for the 1^{st} generation of the Prius Plug-in Hybrid, is significant at all conventional significance levels. The coefficient of $plg1$ is 0.6971874, meaning that the introduction of the plug-in version increased the sales of Prius family by circa 69.7%, compared to the time period when only the standard HEV version of Prius was available on the market.

Such result is quite logical, since the Prius Plug-in Hybrid was introduced during the early 2010's, i.e. the time period when the PHEVs were rapidly gaining popularity, while the sales of classic HEVs began to decrease slowly. However, the coefficient for $plg2$ with the p-value of 0.104 does not seem to be very significant compared to $plg1$. In author's opinion, the reason for this could be the increasing number of other PHEVs coming to the market at the time when the 2^{nd} generation of Prius Plug-in Hybrid was introduced.

As expected, the arrival of the main competitors to the market had a negative impact on the sales of the Prius family, since both of the dummy variables for the competitors are statistically significant with a negative coefficient. Firstly, the launch of Tesla Model S led to a decrease in the sales of Prius by circa 22.1%. The arrival of Nissan Leaf has decreased the demand for Prius family by circa 23.9%. However, the coefficient for Leaf is statistically significant only at the 10% significance level.

5.2 Panel data model

5.2.1 Original specification

Firstly, let the author discuss the choice of the best fitting model. As mentioned in the Methodology chapter, a choice will be made between Pooled OLS, Fixed Effects and Random Effects model, whereas one can select the preferred model based on the results of three statistical tests. Performing the F-test has resulted in rejecting the null hypothesis ($Prob > F = 0.0000$), from which we can conclude that Fixed Effects model is preferred over Pooled OLS.

Consequently, the Breusch-Pagan Lagrange Multiplier test for random effects was performed in order to make a choice between Pooled OLS and Random Effects. In this test, the null hypothesis was rejected as well ($Prob > chibar2 = 0.000$), meaning that the variances across entities are non-zero. Therefore, Random Effects model is preferred over Pooled OLS as well.

Breusch-Pagan Lagrange Multiplier test	
	Var
mktshare	.0089547
e	.0009238
u	.0032757
Test: $Var(u) = 0$	
chibar2(01) = 68.55	
Prob > chibar2 = 0.0000	

Table 8: Breusch-Pagan Lagrange Multiplier test - original specification

Description: Table 8 depicts the results of the ***Breusch-Pagan Lagrange Multiplier test.*** *The null hypothesis of this test is that the variances across entities are zero. Upon* *rejecting the null hypothesis, one should prefer RE over Pooled OLS.*

Lastly, the choice between Fixed Effects and Random Effects needs to be made based on the results of the Hausman test. Executing the test yielded a rather high p-value ($Prob > chi2 = 0.6259$), meaning that we do not have enough evidence to reject the null of significant differences between coefficients gathered from FE and RE. In such case, we can conclude that the Random Effects are more suitable than FE.

Hausman test	**Coefficients**		
	FE	**RE**	**diff.**
gasprc	.1795649	.2028147	$-.0232499$
gdp	4.91 x 10^{-6}	4.96 x 10^{-6}	-4.89 x 10^{-8}
cpchs	3.15 x 10^{-7}	3.93 x 10^{-7}	-7.74 x 10^{-8}
H0: difference in coefficients not systematic			
Prob > chi2 = 0.6259			

Table 9: Hausman test - original specification

Description: Table 9 depicts the summary of results of the ***Hausman test****, which is comparing the coefficients yielded from Fixed Effects and Random Effects model. If the null hypothesis is rejected, there are significant differences between the estimators, thus FE should be chosen. Upon not rejecting the null, one should prefer the Random Effects model. Note that variables which are stable over time were omitted due to collinearity.*

As a conclusion, Random Effects model will be used for evaluating the model, since both RE and FE are preferred over Pooled OLS and Random Effects are as well preferred over Fixed Effects. Further, the author has decided to use robust standard errors within the model, in order to achieve consistent results even under presence of autocorrelation or heteroskedasticity. The results of the Random Effects model are summarized in the following table:

mktshare	**coef.**	**Robust SE**	**z**	**p - value**
gasprc	.2028147 ***	.073194	2.77	0.006
gdp	4.96 x 10^{-6} **	2.48 x 10^{-6}	2.00	0.046
cpchs	3.93 x 10^{-7} **	1.59 x 10^{-7}	2.47	0.013
sttinc	.012705	.0272768	0.47	0.641
co2	−.0005263	.0006989	−1.68	0.451
epi	−.008985 *	.0053374	−0.75	0.092
cons	.3063308	.295463	1.04	0.300
# of observations = 92		$Wald\ chi2(6) = 15.76$		
# of groups = 23		$Prob > chi2 = 0.0151$		
obs. per group = 4		**overall** $R^2 = 0.6361$		

Table 10: Results of the panel data model - original specification

*Description: Figure 10 depicts the summary of results of the Random Effects model, in which we regress the variable **mktshare** on the independent variables displayed in the table. Significance levels are represented by stars, where: 0.01 (***), 0.05 (**), 0.1 (*).*

From the results, we can observe that gas price variable is highly statistically significant with a positive coefficient of 0.2028147, leading to a conclusion that an increase in the price of gasoline by 1 EUR per liter should lead to an increase in the market share of plug-in electric vehicles by circa 20.28 percent. Since such rapid increase of the gasoline price in the short term is not very realistic, a more suitable example would be that an increase in gas price by 10 cents would cause an increase in the market share of EVs by 2 percent.

Moving on to the GDP variable, one can notice that it is statistically significant at the 5% significance level, with the coefficient equal to 4.96 x 10^{-6}, which is circa 0.000005. The interpretation of this coefficient would be that when the annual GDP per capita increases by 10000 EUR, the market share of plug-in electric vehicles should increase by 5 percent.

Other two variables, which turned out to be statistically significant, are *cpchs* and *epi*. These variables are significant at 5% and 10% significance level, respectively. However, the coefficients of those variables seem to be quite unexpected, since the coefficient is positive for *cpchs* and negative for *epi*. Such coefficients would mean that a higher number of citizens per one charging station leads to greater market share of EVs, while the higher score in the EPI index of a particular country would lead to lower sales of those vehicles. In author's opinion, both of these findings seem to be quite counter-intuitive. Other variables, namely *sttinc* (direct state incentives) and $co2$ (subcategory of EPI indicating CO_2 pollution) turned out to be statistically insignificant. The reasons behind such results will be further discussed within the Discussion chapter of this thesis.

The goodness-of-fit of this model is described by R^2, which is also known as a so-called coefficient of determination. Generally, the coefficient of determimation ranges from 0 to 1 and describes the proportion of the variance in the dependent variable explained by the independent variables in the model (Wooldridge 2013). Thus, a too low R^2 generally means that the model is wrongly specified and is probably missing some of the important variables, since it does not explain the variance in the dependent variable very well. In the case of this model, R^2 is equal to 0.6361, meaning that we have managed to explain 63.61 percent of the variance in $mktshare$ with our model.

5.2.2 Alternative specification

In this section, results of the alternative specification including the *charging stations per km squared (chspkm)* will be evaluated. Firstly, let the author choose the best method for evaluating this model. Similarly to the original specification, a choice will be made based on the results of the three tests (F-test, BPLM test and Hausman test).

As in the original specification, the null hypothesis of the F-test was rejected ($Prob > F = 0.0000$), leading to the conclusion that Fixed Effects model is preferred over Pooled OLS. Further, performing the Breusch-Pagan Lagrange Multiplier test has resulted in rejecting the null hypothesis as well ($Prob > chibar2 = 0.000$), meaning that Random Effects model is more efficient than Pooled OLS. The results of the Breusch-Pagan Lagrange Multiplier test are presented in the following table:

Breusch-Pagan Lagrange Multiplier test	
	Var
mktshare	.0089547
e	.0009043
u	.0031142
Test: $Var(u) = 0$	
chibar2(01) = 62.62	
Prob > chibar2 = 0.0000	

Table 11: Breusch-Pagan Lagrange Multiplier test - alternative specification

Description: Table 11 depicts the results of the ***Breusch-Pagan Lagrange Multiplier test****. The null hypothesis of this test is that the variances across entities are zero. Upon rejecting the null hypothesis, one should prefer RE over Pooled OLS.*

Lastly, the decision between FE and RE has to be made based on the result of the Hausman test. The Hausman test yielded a p-value of 0.0863, meaning that we do not have enough evidence to reject the null hypothesis of the test on the 0.05 significance level. As a result, we can conclude that RE is preferred over FE in terms of efficiency.

Hausman test	**Coefficients**		
	FE	**RE**	**diff.**
gasprc	.1321811	.1748649	$-.0426838$
gdp	4.56 x 10^{-6}	4.99 x 10^{-6}	-4.89 x 10^{-7}
chspkm	.1112361	.0152553	.0959808
H0: difference in coefficients not systematic			
Prob > chi2 = 0.0863			

Table 12: Hausman test - alternative specification

Description: Table 12 depicts the summary of results of the ***Hausman test****, which is comparing the coefficients yielded from Fixed Effects and Random Effects model. If the null hypothesis is rejected, there are significant differences between the estimators, thus FE should be chosen. Upon not rejecting the null, one should prefer the Random Effects model. Note that variables which are stable over time were omitted due to collinearity.*

In conclusion, the author decided to evaluate this model using Random Effects as in the case of the original specification, since this method is preferred over both Pooled OLS and Fixed Effects. Similarly to the original specification, the robust standard errors were used within this model as well, in order to deal with heteroskedasticity and/or autocorrelation in residuals. The results of the Random Effects model are depicted in the following table:

mktshare	**coef.**	**Robust SE**	**z**	**p - value**
gasprc	.1748649 **	.0747179	2.34	0.019
gdp	4.99 x 10^{-6} *	2.59 x 10^{-6}	1.93	0.054
chspkm	.0152553	.0437134	0.35	0.727
sttinc	.0133937	.0302621	0.44	0.658
co2	−.0003554	.0008235	−0.43	0.666
epi	−.0094375 *	.0055106	−1.71	0.087
cons	.3707802	.3149788	1.18	0.239
# of observations = 92		$Wald\ chi2(6) = 150.43$		
# of groups = 23		$Prob > chi2 = 0.0000$		
obs. per group = 4		**overall** $R^2 = 0.6117$		

Table 13: Results of the panel data model, alternative specification

Description: Table 13 depicts the summary of results of the Random Effects model, in which we regress the variable ***mktshare*** *on the independent variables displayed in the table. Significance levels are represented by stars, where: 0.01 (***), 0.05 (**), 0.1 (*).*

Similarly to the original specification, the gas price variable turned out to be highly statistically significant. In this case, however, the coefficient is slighly lower (0.1748649), meaning that an increase in the gas price by 1 EUR would boost the market share of plug-in EVs by circa 17.5 percent.

Regarding the GDP variable, the alternative specification yields a statistically significant coefficient of 4.99 x 10^{-6}, which is a very similar result to the one obtained in the original specification. One could interpret this coefficient in a way that an increase in annual GDP per capita by 10000 EUR will lead to an increase in the market share of plug-in EVs by circa 5 percent.

The variable *charging stations per* km^2 *(chspkm)*, which was used in this model instead of the *citizens per charging station (cpchs)* variable, turned out to be insignificant, as well as the dummy variable for direct state incentives. Regarding the Environmental

Performance Index, the results are quite similar to the original specification. While the subcategory *co2* is not statistically significant, the *epi* variable is significant at the 10% significance level and has a negative coefficient of $-.0094375$, which could be interpreted in a way that an increase of the EPI index by 1 will decrease the market share of plug-in EVs by 0,9 percent.

As depicted in the table above, this model has slighly lower R^2 compared to the original specification. The R^2 of the alternative specification is equal to 0.6117, meaning that we managed to explain 61.17 percent of the variance in mktshare with this model.

Since we have obtained rather high p-values for the variables $chspkm$, $sttinc$ and $co2$ from the regression, we have assumed that their individual impact on $mktshare$ is insignificant. However, all of these variables are somehow connected to the environmental performance of the country, as well as the variable *epi*. Therefore, those variables may be correlated, which would lead to multicollinearity. Thus, although those variables turned out to be insignificant individually, it may be possible for them to be jointly significant.

In order to test for joint significance, one can make use of the F-test. The null hypothesis of such test is that the coefficients of the variables included in the test are equal to zero. Hence, upon rejecting the null hypothesis, we arrive to a conclusion that at least one of the coefficients is non-zero. When conducting the test, the F-statistic needs to be calculated first. The computation of the F-statistic can be expressed by the following equation:

$$F_{q,n-k-1} = \frac{(SSR_R - SSR_u)/q}{SSR_u/(n-k-1)}$$

In this equation, SSR_R and SSR_u stand for the sum of the squared residuals of the restricted and the unrestricted model, respectively. By the restricted model, the author means the model which excludes those tested variables, i.e. $chspkm$, $sttinc$, epi and $co2$ in our case. Further, q stands for the number of the restrictions, n for the number for observations and k for the number of independent variables in the unrestricted model. The computed F-statistic is then compared to the critical values for this test and is either rejected or not rejected. However, Stata offers a single command *test* which can be used in order to test for joint significance without the need for manually calculating the test statistic. Since we are dealing with panel data, Stata has automatically selected a Chi-squared test instead of an F-test. Thus, the test statistic is compared to a Chi-squared distribution instead. The results of the test are presented in the table below:

Chi-squared test for joint significance
(1) $chspkm = 0$
(2) $sttinc = 0$
(3) $epi = 0$
(4) $co2 = 0$
chi2(4) = 20.95
Prob > chi2 = 0.0003

Table 14: Chi-squared test for joint significance, alternative specification

Description: Table 14 depicts the results of the Chi-square test for joint significance. The null hypothesis of the test is that coefficient of all tested variables are equal to zero. Upon rejecting the null, the test tells us that at least one of the coefficients is non-zero.

As depicted in the table, we have rejected the null hypothesis of the joint significance test, thus we can conclude that these variables are jointly significant. As mentioned before, the reason for such result may be the correlation between the tested variables, since all of these variables are somehow connected to the environmental performance of a particular country.

The test for joint significance has been performed in the original specification of the panel data model as well, namely with the variables $cpchs$, $sttinc$, epi and $co2$. However, we did not have enough evidence to reject the null hypothesis of the joint significance test in that case, meaning that we have failed to conclude that $cpchs$, $sttinc$, epi and $co2$ are jointly significant. The results of the joint significance test for these variables are presented in *Appendix 1*.

6 Discussion

In this chapter of the thesis, the obtained results will be discussed. The author would like to discuss whether the results of the models are in accordance with the previously conducted research and with the author's original expectation. Furthermore, potential explanations of why we have obtained same or different results will be presented. Last but not least, the author would like to describe the limitations of the models and their potential solutions.

Regarding the results of the time series model, our findings regarding the *gasprc* variable seem to be consistent with the work of Diamond (2009), who has also discovered a significant effect of the gasoline price on the sales of hybrid cars. The statistical significance of the third generation also seems to be quite logical, as well as of the launch of the plug-in version. However, the coefficient for the first generation of the plug-in version seems to be slightly larger than expected. Regarding the coefficients of the variables $tesla$ and $leaf$, they turned out to be negative, which matches the author's original expectations as well.

However, the model has some limitations. For example, the model could not capture the effect of state incentives, since this model has dealt with the sales for the whole United States and the states incentives differ for each state in the US. Therefore, the author was not able to include the variable for state incentives in the model.

Regarding the panel data model, both the original and the alternative specification of the model have yielded a highly statistically significant coefficient for *gasoline price*. This finding is in accordance with our hypothesis that higher gasoline price leads to an increase in market share of plug-in electric vehicles. Such result would also confirm the findings of Diamond (2009), who has discovered a strong relationship between gasoline price and market shares of various hybrid vehicles in the 2000's.

The statistical significance of GDP per capita as a factor which is positively affecting the demand for alternative fuel vehicles is not surprising as well. One of the main barriers of the adoption of EVs is their purchase price, which is usually substantially higher than a purchase price of an average gasoline powered car of the same class. Therefore, the author believes that plug-in electric vehicles are adopted more successfully in well-developed countries than in those with lower GDP per capita.

The *sttinc* variable turned out to be insignificant in both of the models, leading to a conclusion that direct state incentives do not seem to influence the demand for plug-in electric vehicles very much. This finding would also partially confirm the findings of Diamond (2009), who argues that state incentives have little impact on sales of hybrid cars.

However, the insignificance of this variable could as well be caused by wrong specification. Namely, the state incentives were only included as a dummy variable for direct state incentives, meaning that it did not include particular tax benefits, exemptions for company cars and benefits of another kind.

Judging from the results, the availability of charging stations does not seem to serve as an important factor boosting the demand for plug-in EVs. This finding does not seem to be consistent with the research of Achtnicht et al. (2012), who claims that an increase in the number of charging stations would lead to higher sales of alternative fuel vehicles.

However, the author would like to present a possible explanation of why we have obtained such result for this variable. As mentioned before, Achtnicht's study has been published almost a decade ago, i.e. in the time period when the technology of the batteries in EVs was still at the early stage of development, therefore the maximum range of such vehicles was much lower than in the time period included in our panel data model.

As an example, let the author mention that the 2010 Nissan Leaf has a range of 73 miles on average, whereas the 2018 Nissan Leaf is able to cover a distance of 151 miles on one recharge. Thus, majority of the journeys can be managed within one recharge and the electric car can be recharged at home overnight. Therefore, a developed network of charging stations may not serve as a very important factor when making a decision whether or not to buy a plug-in electric car nowadays.

Moreover, the variable *mktshare* in the panel data model includes not only sales of BEVs, but also sales of PHEVs, which are able to switch to an ICE when the battery is depleted. Therefore, the developed network of charging stations should not be a necessary condition for owners of these cars as well. In conclusion, the author believes that the availability of charging stations may not be as important as a decade ago, due to the reasons discussed above.

A rather surprising result has been obtained for the *epi* variable. A negative coefficient for this variable suggests that a higher Environmental Performance Index actually leads to lower market share of plug-in electric vehicles. Since Achticht et al. (2012) mention that environmental friendliness of BEVs and PHEVs is one of the factors positively influencing the popularity of electric vehicles, one should probably rather expect a positive sign of the coefficient for the *epi* variable.

One of the possible explanations of such result would be that the countries with lower environmental performance may try to improve their environmental status by promoting the electric cars more. Alternatively, the reason could also be that this index is measuring not only air pollution caused by cars, but also various other factors related to environment. Therefore, there may not be a direct relationship between this index and sales of plug-in electric vehicles.

However, the panel data model has several limitations. First potential disadvantage of the model is the fact that it deals with data from only 23 countries and 4 years, providing us with total 92 observations, which stands for a rather small-sized dataset. The low amount of data available could therefore lead to biased results. Although the author had access to data even from years before 2016, the market shares of the EVs in those years were so low, that it did not make much sense to analyze the data from those years. The author suggests conducting a more extensive research on this topic in the following years, when more data will be available.

Secondly, this model does not capture the time trend, since the time variable is not directly included in the model. By that, the author means that the market share of EVs tends to increase every year, since electromobility is getting more and more attention in the current world. Thus, the author has also worked with the version of the model which included the *year* variable. However, the *year* variable turned out to be insignificant in both the original and the alternative specification.

Last but not least, one could suggest using a log-specification of the *gdp* variable rather than its level-specification. The main disadvantage of the level-specification of the *gdp* is its difficulty to interpret. As an example, the author means that according to the model using the level-specification of GDP per capita, an increase in GDP per capita by 10000 EUR would lead to an increase in the market share of plug-in EVs by 5 percent in general. However, that is not a very accurate statement, since such change in GDP per capita could have a different impact across the countries. For example, an increase in GDP per capita by 10000 EUR will definitely have a larger impact in a country with an average GDP per capita equal to 20000 EUR compared to a country with a GDP per capita of 60000 EUR. Therefore, the log-specification of this variable could potentially be more meaningful since we would be able to evaluate the effect of this variable on a percentual basis rather than on a nominal one.

On the other hand, logging the variable could lead to its flattening, meaning that the differences between the countries in terms of this variable will be less prominent. In *Appendices A2 and A3*, the results of the original and alternative specification using the log-specification of *gdp* variable are presented. The logarithm of *gdp* is denoted as *lgdp*. As can be observed from the results, *lgdp* turned out to be insignificant in both original and alternative specification. The author's belief is that such result could have been caused by the flattening of the variable and by the low amount of observations.

7 Conclusion

This thesis has succeeded to provide a new evidence of the relationship between gasoline prices and the demand for alternative fuel vehicles. This finding is consistent with the previously conducted study of Diamond (2009) as well as with the literature dealing with the history of electric and hybrid vehicles. More precisely, the time series model has proven a positive relationship between retail gasoline price and the sales of Toyota Prius in the United States. Both specifications of the panel data model dealing with data from various European countries have also shown the gasoline price to be a significant factor affecting the sales of PHEVs and BEVs. More precisely, a higher retail gasoline price leads to higher market shares of those vehicles.

Apart from the gasoline prices, the first model has also proven the statistical significance of some of the other variables in the regression. Namely, the results show that the launch of the 3rd generation of the Prius as well as introduction of the plug-in version to the market have increased the sales of the Prius family. As expected, the arrival of the main competitors (Tesla Model S, Nissan Leaf) to the market has influenced the demand for Toyota Prius in a negative way.

In the panel data model, the author has included the data on variables which were believed to have an impact on the demand for electric and hybrid vehicles from the previously conducted studies. Firstly, both of the specifications of the panel data model have succeeded to prove that GDP per capita influences the market share of PHEVs and BEVs in a way that higher GDP per capita increases the market shares of those vehicles. Such finding may lead to a conclusion that richer and more developed countries tend to perform better in terms of adoption of alternative fuel vehicles.

Regarding the availability of charging stations, our models have yielded different results from the study of Achtnicht et al. (2012). The reason behind this could be that the maximum range within one recharge of the electric vehicles has increased a lot since the time when Achtnicht's study was conducted, therefore a widely developed network of charging stations may not be a necessary condition for purchasing an electric car anymore. Our model also suggests that state incentives do not seem to influence the sales of electric vehicles very significantly, which seems to be in accordance with the study of Diamond (2009). On the other hand, this variable has been represented in the model only as a dummy variable standing for direct state incentives, while the indirect incentives such as tax exemptions or company benefits were not included due to the difficulty of expressing this variable in such way. Therefore, an insufficient specification of this variable could potentially lead to a biased result.

However, the panel data model as it was presented in the thesis definitely still has some limitations. Mainly, since the adoption of electric cars on a global scale is still quite a new topic in the automotive industry, not much data is available on this topic, therefore our panel data model includes only a rather limited amount of observations. Therefore, the author suggests that further research should be conducted on this topic in the following years, since we can definitely expect the popularity of the alternative fuel vehicles to rise.

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Appendices

Appendix 1

Chi-squared test for joint significance
(1) $cpchs = 0$
(2) $sttinc = 0$
(3) $epi = 0$
(4) $co2 = 0$
chi2(4) = 6.90
Prob > chi2 = 0.1411

Description: Figure 14 depicts the results of the Chi-square test for joint significance. The null hypothesis of the test is that coefficient of all tested variables are equal to zero. Upon rejecting the null, the test tells us that at least one of the coefficients is non-zero.

Appendix 2

mktshare	**coef.**	**Robust SE**	**z**	**p - value**
gasprc	.2102716 **	.0791829	2.66	0.008
lgdp	.1273437	.0845062	1.51	0.132
cpchs	4.93×10^{-7}	2.39×10^{-7}	2.06	0.039
sttinc	.0020976	.02549	0.08	0.934
co2	−.0006448	.0007028	−0.92	0.359
epi	−.0079839	.005988	−1.33	0.182
cons	−.913907	.457192	−2.00	0.046
# of observations = 92		$Wald\ chi2(6) = 12.91$		
# of groups = 23		$Prob > chi2 = 0.0445$		
obs. per group = 4		**overall** $R^2 = 0.5458$		

Description: Appendix 2 depicts the summary of results of the Random Effects model, in which we regress the variable ***mktshare*** *on the independent variables displayed in the table. Significance levels are represented by stars, where: 0.01 (***), 0.05 (**), 0.1 (*).*

Appendix 3

mktshare	**coef.**	**Robust SE**	**z**	**p - value**
gasprc	.1806974 **	.0796528	2.27	0.023
lgdp	.1104376	.086812	1.93	0.203
chspkm	.0274271	.0482706	0.35	0.570
sttinc	.0048235	.0275728	0.17	0.861
co2	−.0005137	.0008801	−0.58	0.559
epi	−.0073741	.006015	−1.23	0.220
cons	−.7516585	.4648921	−1.62	0.106

# of observations = 92	$Wald\ chi2(6) = 242.05$
# of groups = 23	$Prob > chi2 = 0.0000$
obs. per group = 4	**overall** $R^2 = 0.4964$

Description: Appendix 3 depicts the summary of results of the Random Effects model, in which we regress the variable ***mktshare*** *on the independent variables displayed in the table. Significance levels are represented by stars, where: 0.01 (***), 0.05 (**), 0.1 (*).*