MASTER'S THESIS

Urban, Port & Transport Economics

An empirical analysis of plug-in electric vehicle adoption in Europe

ABSTRACT

Electric vehicles (EVs) can help decrease greenhouse gas emissions and air pollution from passenger cars. This thesis examines factors that influence the adoption of plug-in electric vehicles (PEVs) in Europe. Market shares of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) are analyzed in two separate regressions using a fixed effects method. The dataset covers 26 countries from 2010 to 2016. Variables are identified by reviewing previous literature on EV adoption and include financial incentives, charging infrastructure, fuel price and other socioeconomic factors. The results of the analysis suggest that purchase incentives, charging infrastructure, education and population density determine BEV adoption. Only charging infrastructure has an independent effect on PHEV adoption while incentives are significant in interactions. The effect of fuel price depends on the levels of other variables.

Keywords: electric vehicles, innovation, government incentives, environment

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List of abbreviations

BEV	Battery electric vehicle
EV	Electric vehicle
HEV	Hybrid electric vehicles
ICE	Internal combustion engine
ICEV	Internal combustion engine vehicle
kWh	Kilowatt hour
PEV	Plug-in electric vehicle
PHEV	Plug-in hybrid electric vehicle

1 Introduction

The European Union (EU) has set a target for 2030 to reduce greenhouse gas (GHG) emissions by 40% compared to 1990 levels. Passenger cars account for about 12% of carbon dioxide (CO_2) emissions in Europe (European Comission, 2018). Furthermore, cars are responsible for high concentrations of pollutants in the air of European cities. Both greenhouse gases and air pollution are damaging to the environment and human health. Despite a small decrease of 0.4% in total GHG emissions in the EU in 2016, emissions from the transport sector have increased for three years in a row (European Environment Agency, 2018). Figure 1 compares the trends since 1990 of total GHG emissions and GHG emissions from cars. This shows that total emissions have decreased while emissions from cars have grown, except during the financial crisis aftermath. In order to combat emissions from personal vehicles, new EU legislation commands the average emission achieved by all new cars to be below 95 grams of CO_2 per kilometer by 2021 (European Comission, 2018). This calls for alternative fuel vehicles that emit less greenhouse gases and other pollutants.

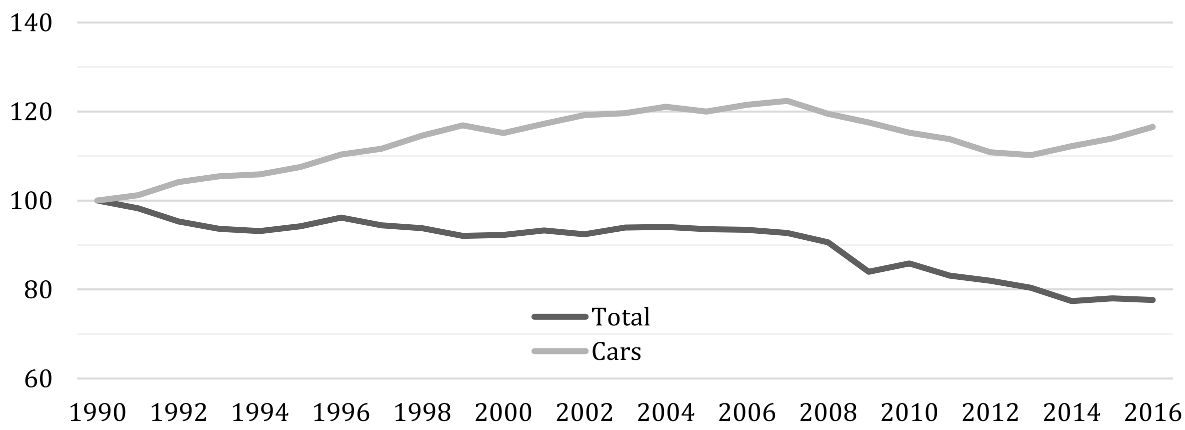

Figure 1 - Greenhouse gas emissions, total and from cars alone, EU-28 (index, 1990=100) (Data: Eurostat)

Electric vehicles (EVs) have the advantage to have lower emissions or be emissions-free in the case of all-electric vehicles, thus providing a possible solution to environmental issues (Vergis & Chen, 2015). However, their adoption still faces barriers such as short driving ranges, long charging times and a high purchase price. As a result, government incentives remain a requirement for EVs to be competitive with conventional vehicles (Hidrue, Parsons, Kempton, & Gardner, 2011). Furthermore, investment in charging infrastructure is required to support the uptake of EVs (European Automobile Manufacturers Association, 2018). EV sales in Europe amounted to about 290 thousand in 2017, which is approximately 2% of total vehicle sales (European Alternative Fuels Observatory, 2018c). There are large differences in the adoption of

EVs between countries, which is shown by the market shares of EVs in 2016, presented in Figure 2. In 2016, most of the countries in Europe had implemented incentives or emission taxes (European Environment Agency, 2018). Hence, the variation in market shares cannot be explained solely by differences in incentives. There are possibly other socioeconomic variables that influence EV market shares. Therefore, in this thesis the factors will be examined that influence the adoption of EVs in Europe.

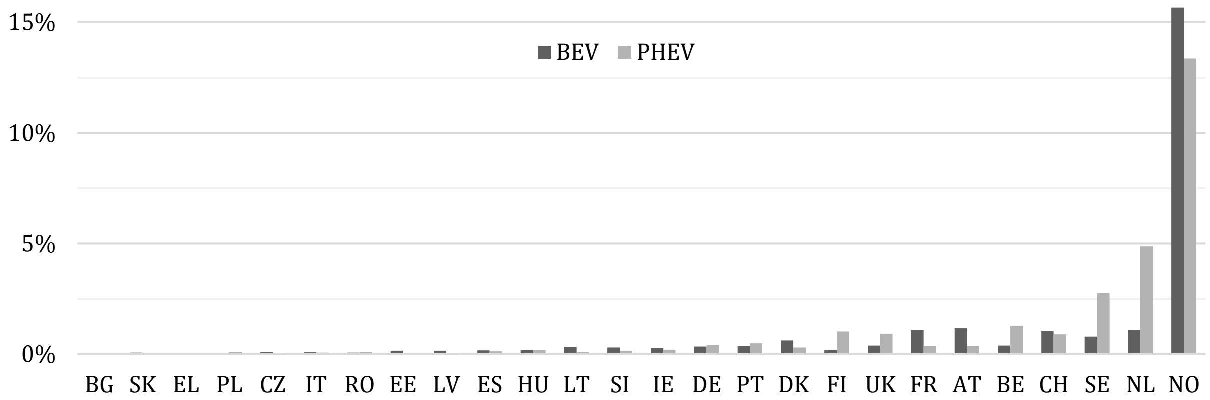

Figure 2 - Electric vehicle market shares by country in 2016 (Data: EAFO, ACEA)

Literature covering the adoption of plug-in electric vehicles (PEVs) and hybrid electric vehicles (HEVs) has increased considerably over the last couple of decades. Several empirical studies focus on the effects of factors such as incentives and fuel prices on HEVs (Beresteanu & Li, 2011; Diamond, 2009; Gallagher & Muehlegger, 2011). Other papers have focused especially on the adoption of PEVs and the relationship with incentives and other socioeconomic factors (Sierzchula, Bakker, Maat, & van Wee, 2014; Vergis & Chen, 2015). Apart from market data studies, there is a variety of research on the attitudes and preferences of consumers towards EVs (Egbue & Long, 2012; Hidrue et al., 2011; Lane & Potter, 2007) and the characteristics of early adopters (Graham-Rowe et al., 2012; Hardman, Shiu, & Steinberger-Wilckens, 2016; Peters & Dütschke, 2014). The research field has broad practical implications. As more countries start to offer incentives to their citizens and begin to establish charging infrastructure networks, academic research can assist governments with empirical evidence. Knowledge of the factors that have the largest impact on EV adoption can help make more informed decisions and possibly lead to more efficient spending of capital.

The research design for this thesis is mainly inspired by previous studies on market shares of HEVs and PEVs. Diamond (2009) focused on HEV adoption in the US and the effect of government incentives. The research concluded that fuel prices have a far stronger effect on HEV market shares than incentives. Gallagher and Muehlegger (2011) also examined US adoption of HEVs and found that both incentives and fuel savings affect adoption. What these papers have in common is that they employ panel data methods, thus analyzing cross-sectional variance as well as time effects. Sierzchula et al. (2014) look particularly at the market shares of PEVs in 30 countries in 2012. Their paper concludes that both incentives and charging infrastructure are important for the rate of adoption. In another study on PEVs, Vergis and Chen (2015) examine adoption in US states in 2013 while separating battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). Their results imply that the factors that influence market shares differ per EV type. The latter two studies only make use of cross-sectional data.

This thesis attempts to combine elements from the four papers mentioned above, using panel data to analyze factors that affect PEV adoption, while separating BEVs and PHEVs to see if there are different factors of influence between the two types. There are no – known – studies at this point which employ panel regression methods in order to analyze PEV adoption. Since their introduction to the market around 2010, more data has become available which now allows for such methods to be used. Europe was chosen as the region of interest because it includes a large number of countries which despite their proximity differ largely in their adoption of EVs, government policy and other socioeconomic factors. The research question of this thesis is as follows:

Which factors determine the adoption of plug-in electric vehicles in Europe?

The thesis examines annual market shares of plug-in electric vehicles (PEVs) in 26 countries in Europe during the 2010-2016 period. Using a fixed effects panel method, the BEV and PHEV market shares will be regressed separately on variables for incentives, charging infrastructure and fuel price, as well as several socioeconomic control variables. The results of the analyses will be compared to see if the market shares of both vehicle types are affected differently by the independent variables.

The next chapter consists of an extensive literature review involving multiple topics regarding innovation and EVs. These topics include theory on innovation in general and the importance of behavioral attitudes towards innovation, the history and development of EVs, and several categories of factors that are identified in the literature as having an impact on EV adoption. The literature review is followed by the chapter on data and methodology, where the different variables and relevant data are introduced, and the regression method used in the analysis is discussed. The results chapter includes two sections were the market shares of BEVs and PHEVs are analyzed separately and ends with a comparison between the results of the vehicle types. The thesis finishes with conclusions and discussion of results, while also referring to possible policy implications, research limitations and suggestions for future research.

2 Literature review

The literature review will present multiple approaches from previous research that can be used to explain the differences in market shares of EVs. Specifically, explanations are to be found for cross-country trends in these market shares but also for differences in adoption between countries. In order to do so, a few theories about the adoption of innovations will be discussed first to get a behavioral insight into why people choose to move to new technologies, and environmental innovations in particular. Next, the development of the EV will first be put into a historic context to show how the technology evolved over time, before distinguishing between several types of EVs and their technical characteristics. Furthermore, the different factors influencing the adoption of EVs will be explored, which is useful when choosing the variables that will be used in the analysis of PEV market shares.

2.1 Theory of innovation

Before examining the factors that influence the adoption of EVs, it is important to consider theories about the adoption of new technologies and what drives the diffusion of innovations in a more general sense. First, the theory about innovation will be discussed, which defines the attributes that determine successful adoption of an innovation and distinguishes between several categories of adopters based on certain characteristics. Thereafter, a couple other behavioral theories that have been used in EV adoption research will be reviewed.

2.1.1 Diffusion of innovation

The diffusion of innovation (DOI) theory is frequently used in innovation and eco-innovation research as a way of understanding how potential adopters perceive the characteristics of innovations (Rezvani, Jansson, & Bodin, 2015). The process of spreading of an innovation, such as EV technology, in society is called innovation diffusion. Rogers (2003, p. 11) describes diffusion as ‘the process by which an innovation is communicated through certain channels over time among the members of a social system’. It can be seen as a social change in which the structure and function of a social system is altered. Whether something is an innovation is determined by the ‘perceived newness’ of the idea, practice or object that is considered by an individual (Rogers, 2003). Therefore, is does not matter for how long the innovation has actually existed, as long as one perceives it as new. This is relevant to EVs, since the necessary technology is in fact not so ‘new’, as will be shown in the next section. Rogers (2003) defines five attributes that determine the successful adoption of an innovation: relative advantage, compatibility, complexity, trialability and observability.

Relative advantage is the degree to which the innovation is better than alternatives, in terms of perceived economic benefit, social status, convenience and satisfaction. Examples for EVs are environmental benefits and long-term fuel cost savings. Compatibility refers to whether an innovation is consistent with consumers' experience, values and needs. The presence of charging infrastructure is a way in which EVs could be more compatible with a person's driving experiences and needs (Egbue & Long, 2012). Complexity indicates whether an innovation is difficult to understand and use. EVs might be perceived as more complex by consumers because the technology is different from conventional vehicles. Trialability is the degree to which a new technology can be experienced on a trial basis, thereby decreasing uncertainty. Observability refers to the results of innovations being visible to other consumers (Rogers, 2003). The 'neighbour-effect' has been found to influence the adoption of EVs (Rezvani et al., 2015).

The intention of consumers to adopt a new technology is related to their innovativeness, which is defined by Foxall et al. (1998) as the tendency to buy new products earlier than most other consumers (as cited in Schuitema, Anable, Skippon, & Kinnear, 2013). Innovativeness exists in three main dimensions: instrumental, hedonic and symbolic (Schuitema et al., 2013). Most research on factors influencing EV adoption is focused on instrumental attributes such as purchase price, ownership costs, performance and driving range. Hedonic and symbolic attributes refer to how much pleasure an individual gets from owning an EV and to which extent it complies with his self-identity. Schuitema et al. (2013) showed that instrumental attributes are important but that their direct influence is weaker. Instead, they influence the consumers' hedonic and symbolic attributes. In other words, economic and technical characteristics of an EV influence the way an individual feels about the technology, which in turn determines his level of innovativeness and the intention to adopt it.

2.1.2 Adopter categories

The five categories of adopters identified by Rogers (2003) are innovators, early adopters, early majority, late majority, and laggards. The proportions of the categories usually approach a normal distribution, which means that when presented cumulatively the number of adopters show the typical S-curve. Currently the market shares of PEVs, which can be regarded as the degree of adoption, are mostly below 2.5% in European countries. As can be observed in Figure 3, innovators occupy 2.5% of the market share of an innovation while early adopters take 13.5%. This means that between 2010 and 2016, which is the period of interest, the PEV market was dominated by the first two adopter categories. According to Rogers (2003), the individuals in these categories generally have had more years of education, have a higher socioeconomic status, are more rational and are less risk-averse.

Several studies have attempted to differentiate consumer groups in the EV market based on a variety of characteristics. Peters and Dütschke (2014) examined the factors that are relevant for the adoption of EVs to different consumer groups, as well as the characteristics of those groups. They found that early users of EVs are typically middle-aged men who live with their families in a household that owns multiple vehicles. Besides, early users have a higher willingness-to-pay for an EV. The most important attribute that determines adoption was found to be the perceived compatibility with personal needs. In another research, Hardman, Shiu, and Steinberger-Wilckens (2016) studied adopters of BEVs and obtained compatible results. According to their findings, early adopters have a high income, are highly educated and are mostly male. Furthermore, they owned more cars than the average household and a quarter of them had owned an HEV before purchasing a BEV. These findings correspond with the generalizations about early adopters made by Rogers (2003) and provide a starting point to identify driving factors.

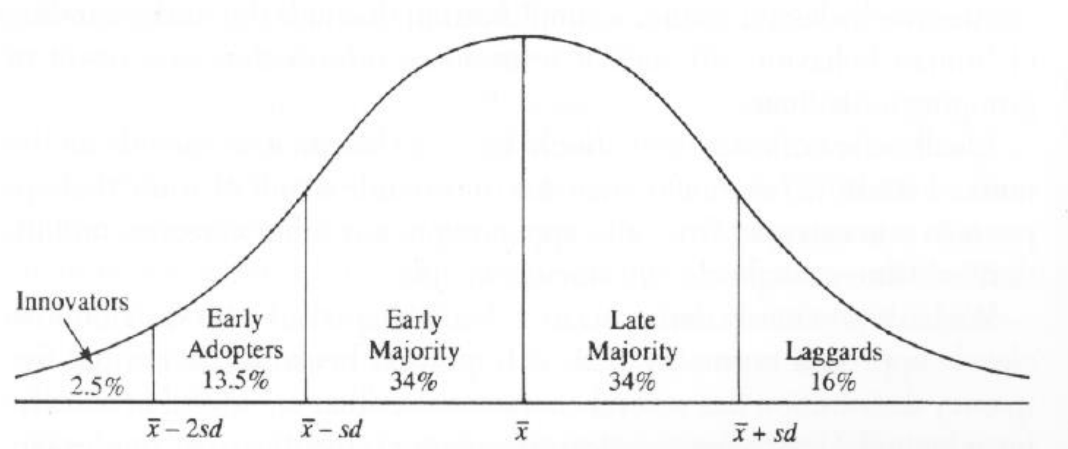

Figure 3 - Adopter categories and their proportions of the market (Rogers, 2003)

2.1.3 Behavioral theory

The adoption of an innovation depends on how it is perceived by individuals based on the aforementioned attributes. In the literature, the purchase and use of an innovation such as an EV is regarded as a behavioral response. Economic incentives are important but alone cannot drive the adoption of such an innovation, since psychological factors such as consumers' attitude towards the innovation matter (Lane & Potter, 2007). Also, because in most markets the adoption of EVs has been in such an early phase, a large part of the previous research focused on behavioral attitudes, for example in revealed-preference studies (Rezvani et al., 2015). Figure 4 provides an overview of the psychological and situational factors that affect car-buyer behavior, which can be used to explain EV adoption as well. Situational factors consist mainly of economic and technological elements, whereas psychological factors involve several aspects from behavioral theories. Two of these theories will be discussed next.

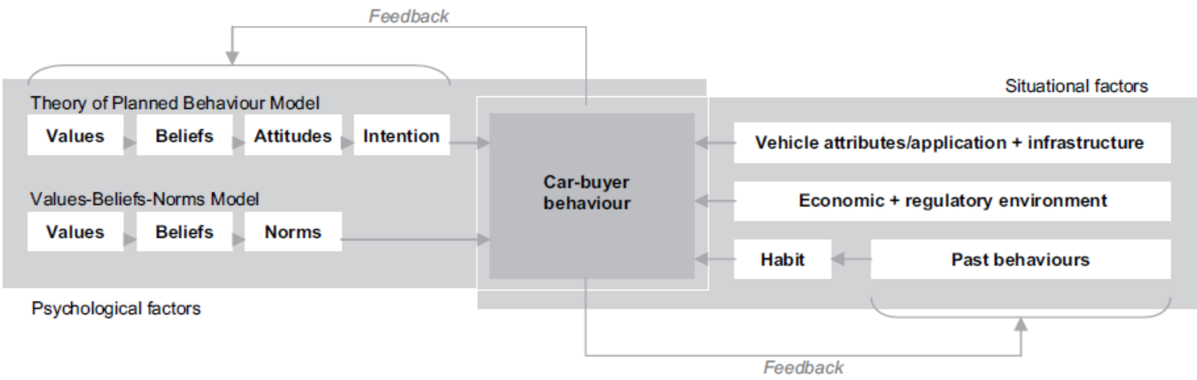

Figure 4 - Different factors that affect car-buyer behavior (Lane & Potter, 2007)

For EVs to be successfully adopted by the public they must not only overcome technological barriers but also social issues. Therefore, public attitudes and preferences for EVs should also be accounted for in the investigation of market shares (Egbue & Long, 2012). One of the most important theories for understanding the attitudes and preferences leading to the adoption decision is the theory of planned behavior (TPB), devised by Ajzen (1991). This theory can be used to predict the intention to perform a certain behavior, in this case buying an EV, from attitudes, subjective norms and perceived behavioral control. Attitudes are based on the consumer's own perception of the innovation, which is influenced by his values and beliefs. Subjective norms depend on the individual's surroundings, such as direct family and friends or the society. Perceived behavioral control depends on whether the individual thinks he can handle the innovation, or if the technology is too difficult for his ability (Ajzen, 1991). The main reasoning of TPB is that the consumer makes a rational decision based on his considering of every alternative (Lane & Potter, 2007).

Whereas TPB can be used to explain pro-environmental behavior from a self-interest perspective, a normative theory such as the value-belief-norm (VBN) theory by Stern (2000) helps to explain pro-environmentalism in the context of concern for the ecosystem and other people (Schuitema et al., 2013). The framework incorporates four categories that determine pro-environmental behavior: contextual forces, attitudinal factors, habit and routine, and personal capabilities. Within the attitudinal factors are the values, beliefs and norms related to the environment. Altogether these form the intention to perform green purchase behavior, but also curtailment, such as reducing energy consumption or car use (Stern, 2000). In EV adoption research the VBN theory has been used to attempt to establish a link between environmental beliefs and awareness of environmental issues, and the intention to adopt an EV (Egbue & Long, 2012; Lane & Potter, 2007).

Although these theories are too complex in their full extent and therefore beyond the scope of this thesis, they are important for understanding the psychological factors that are at play. Additionally, environmentalist attitudes and social norms should not be ignored when analyzing EV adoption. Behavioral attitudes can be helpful to understand the adoption of EVs when economic or technological variables do not suffice. Multiple studies attempted to use behavioral theory in a revealed-preference approach in order to find the relationship between consumer attitudes and EV adoption. However, one problem with this type of research is the 'attitude-action gap', which refers to the phenomenon that often attitudes do not comply with actual behavior (Lane & Potter, 2007). Therefore, with market data now available, using econometric methods could prove to be a good alternative to the behavioral approach, since EV market shares are a better representation of actual adoption than consumer attitudes. Thus far it has been established that an innovation's success is influenced by several attributes and that consumer behavior also plays an important role. Next, the attention is brought to the development of EV technology and the different types of vehicles that exist.

2.2 Development of electric vehicles

2.2.1 Historic perspective

The attention for EVs has gained momentum over the last decades and for this reason the technology might seem like a relatively recent development, but the history of battery-powered vehicles dates back as far as the 19th century. In fact, the first EV was a tricycle presented in 1881 by Mr Trouvé in France, four years before Benz introduced his first internal combustion engine vehicle (ICEV). The first hybrid car was invented by Ferdinand Porsche before 1900 and was expected to have a bright future, however due to cost problems the technology was not picked up again until the 1970s. The period of 1880 to around 1900 is regarded as a 'golden age' for EVs as the extent of usage has not been experienced to this day and most of the technologies invented during this period still form the basis for EV technology today (Høyer, 2008).

After the First World War, EVs started to be dominated by fossil fuel powered vehicles. The stock market bust of 1929 led to the bankruptcy of the majority of EV manufacturers. There was only a spike in production during the Second World War due to fuel shortages and because gasoline and diesel cars were needed for the war effort. In the 1960s, the environmental debate took off, which led to renewed attention for cleaner vehicles. This time the big car manufactures of the world started to be interested as well. However, factors such as range, performance and costs caused difficulties for the development of EVs. The oil crises of the 1970s sparked another wave of interest in vehicles that would lower dependence on foreign oil, but once again the development did not really persist. The 1990s were an intensive period of development for both hybrid and all-electric vehicles. Eventually this led to the introduction of the first mass-produced HEVs on the market around the year 2000 (Høyer, 2008).

What is interesting about this history is that the innovation regarding EVs was not continuous at all. It is striking that most of the technologies were already discovered more than 100 years ago but apart from the first 10 to 20 years the adoption has never gained momentum until today. With serious concerns about global climate change and the dependence on oil, the efforts to develop EVs have now increased (Pollet, Staffell, & Shang, 2012). This suggests that their successful adoption as an innovation depends on more than the issue of technology alone. Environmental considerations are certainly important but alone cannot explain the differences in EV market shares. Hence, it is likely that there are other elements that are crucial in understanding these differences. The question is therefore what factors are causing the adoption of EVs to accelerate at this moment in time.

2.2.2 Types of electric vehicles

There are multiple types of EVs, and it is important for the remainder of this thesis to distinguish between the different types and to indicate which types will be examined. 'Electric vehicle' is a broad concept that has multiple aspects, some of which are beyond the scope of this research due to their complex technical nature. Four main types of EVs can be identified: hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), battery electric vehicle (BEV) and fuel cell electric vehicle (FCEV). The latter is considered to have significant potential in the future but is still in an early stage of development, therefore it will not be discussed further (Çağatay Bayindir, Gözüküçük, & Teke, 2011).

The HEV combines a gasoline or diesel internal combustion engine (ICE) with an additional electric powertrain. This makes it more efficient than ICEVs, because regenerative braking allows for energy to be recovered that would otherwise be lost under braking. It is not possible to charge the battery of an HEV by plugging it into the power grid, which separates it from the PEV. Since the only way in which the battery can be charged is through regenerative braking, it still gets all its energy from fossil fuel (Schuitema et al., 2013). Therefore some scholars do not think of the HEV as a 'true' electric car, and in this thesis this view is embraced (Rezvani et al., 2015; Schuitema et al., 2013). The PHEV is basically an improvement of the HEV, since it too features both an ICE and an electric drivetrain. However, its battery is bigger and can be charged from the power grid. It can be driven using either the ICE or electric propulsion, but its all-electric driving range is shorter than the BEV. (Schuitema et al., 2013). The BEV is propelled solely by an electric motor and therefore receives all its energy from a battery which is charged from the power grid. It has the advantage to be completely emission-free, not require any fossil fuels and operate silently. The battery has a substantially bigger capacity than an HEV's battery, but is considerably more expensive, as will be discussed in the next section (Pollet et al., 2012).

In this research only PEVs, which includes PHEVs and BEVs, will be considered. As mentioned above, PEVs are considered to be 'true' electric cars whereas the HEV often is not. They are also the most recent types to be introduced on the market, whereas the ordinary HEV has been around for a longer period of time. Additionally, in contrast with the HEV, their limited driving range and dependence on charging facilities mean that the barriers to adoption are higher. Most of the research dedicated to PEVs has treated it as a single category, ignoring significant differences between the PHEV and BEV types (Vergis & Chen, 2015). This serves as a motivation for a research design examining factors that influence PEV adoption while exploring differences between PEV types at the same time.

2.2.3 Battery costs

The premium purchase price of an EV compared to conventional vehicles, which is one of the most important barriers to adoption, is mainly caused by the costs of the electric power train, and in particular the battery (Nykvist & Nilsson, 2015). There are two main types of batteries used in EVs: nickel metal hydride (NiMH) and lithium-ion (Li-ion) batteries. NiMH batteries are mostly used in hybrid vehicles in combination with an ordinary gasoline or diesel engine. Li-ion batteries are used as primary energy sources in vehicles that are completely electric. The main differences between the two battery types are production costs and capacity. Li-ion batteries have a higher energy capacity than their NiMH counterpart, but they suffer from high costs as well as concerns about their environmental impact and safety (Pollet et al., 2012).

However, costs of battery packs are declining rapidly, thus increasing the economic viability of EVs. It is assumed that these costs need to dip below $150 per kilowatt hour (kWh) in order for EVs to become cost-competitive with ordinary ICEVs (Nykvist & Nilsson, 2015). Between 2010 and 2016, the costs of battery packs have decreased from around $1000 per kWh to $227 per kWh (McKinsey, 2017). The rapid decline in costs is dedicated to a learning rate of about 6-9%, which is the reduction in costs following a cumulative doubling in production, combined with economies of scale (Nykvist & Nilsson, 2015). Mckinsey (2017) projected the costs of the Li-ion battery to be $190 per kWh by 2020 and suggested the potential for prices to fall below $100 per kWh by 2030. This would mean that battery costs could fall below the threshold of 150$ per kWh in the next decade, thereby causing EVs to become cost-competitive with ICEVs.

2.3 Factors influencing the adoption of electric vehicles

This section focuses on several categories of factors that have been identified in related literature as being associated with the adoption of EVs. These categories include economic, government policy and incentive, environmental, technological, and social and demographic factors. It should be noted that some of the studies that are reviewed focused on HEVs instead of PEVs specifically; therefore results might not directly apply to the latter category. However, since HEVs have been on the market for a longer amount of time, there is substantially more evidence from studies using market data for HEVs.

2.3.1 Economic factors

A major barrier to the adoption of EVs is their purchase price and operational costs, which include service and maintenance. Consumers regard this high purchase price and the long payback time of fuel savings as grounds to reject EVs. This is dedicated to a lack of knowledge among consumers of cost structures and fuel economy. They are reported to put a lot of weight on fuel consumption, which is only part of total operational costs of the vehicle, while possibly ignoring maintenance costs (Lane & Potter, 2007). In a survey by Egbue and Long (2012), cost was ranked second by respondents when asked for their biggest concerns with EVs, with 27% of responses. In the same paper, a comparison was drawn between the lifetime costs of several types of vehicles, including an ICEV, HEV, PHEV and BEV. Considering a fuel price of $3.52 per gallon, which was average at the time of the research, the additional cost to own a PHEV or BEV compared to a ICEV was found to be $16,268 and $12,329 respectively. These figures did not take into account a $7500 tax credit that applied to both vehicles. The difference was caused mainly by the purchase price of the vehicle and the battery replacement costs since the batteries did not last for the entire period that was evaluated. The ICEV had much higher fuel costs but this could not make up for the difference in the other operational costs (Egbue & Long, 2012).

As mentioned, one of the most important considerations for consumers when choosing to buy a green car is fuel savings, which is signaled by the price of fuel. Several studies have incorporated this price in their analyses of EV market shares. Gallagher and Muehlegger (2011) concluded from their analysis of US state-level panel data of HEV sales that the adoption of HEVs is positively correlated with higher prices of fuel. In their model, an increase of $100 in annual fuel savings increases HEV sales by 13%. They explained that this effect is mainly caused by high fuel-economy HEVs. After separating high and low fuel-economy HEVs, an increase of 10% in fuel price results in an 8.6% increase in sales of high fuel-economy HEVs (Gallagher & Muehlegger, 2011). Diamond (2009) conducted a similar research, analyzing the market shares of HEVs in US states. The results of this analysis indicate that fuel price has the largest effect of the variables that were used, even larger than the effect of government incentives. An increase of 10% in fuel price results in a 72-93% increase in HEV market share, varying per car model. The authors reasoned that the price of fuel is a signal for consumers to start considering the benefits of fuel-economy and its cost savings (Diamond, 2009). Apparently, despite consumers having an incomplete view of car ownership costs, a higher price of fuel does serve as an incentive to adopt an HEV.

Related to fuel prices, but not examined as much in relation to EV adoption rates, is the price of electricity. Assuming potential adopters roughly account for the long-term cost benefits of EVs, this means that electricity prices could be of influence because the difference with the gasoline price constitutes the total fuel savings. Vergis and Chin (2015) reported a significant negative correlation between electricity price and BEV market shares. They explained that this makes sense because the additional cost benefit of a lower electricity price could help justify the purchase cost of an EV. In contrast, Sierzchula et al. (2014) found no relationship between electricity prices and EV market shares. However, they used data on both types of PEVs in their model, whereas in the paper by Vergis and Chen the electricity variable was excluded from the PHEV model. This might cause the difference in results since PHEVs rely less on electricity can still rely on a gasoline engine.

The level of welfare in a country or state, usually represented in research by the income per capita, can also affect the adoption of EVs. The high price might make the purchase of an EV unattainable for lower income households, despite the financial benefits of fuel savings. Diamond (2009) obtained mixed evidence to support the existence of this relationship, with the significance of per-capita income varying per HEV model. Hidrue et al. (2011) reported that income reduced the likelihood of individuals being EV owners, against their expectations. Sierzchula et al. (2014) detected no significant coefficient for income in their econometric analysis of EV market shares. However, Merksy et al. (2016) found that income has a significant effect, using evidence from regional data from Norway, but only on a municipal level. The study by Gallagher and Muehlegger (2011) indicated that per-capita income has a significant effect on HEV sales, with a one standard deviation increase in income leading to a 32% increase in sales. Apparently, it depends on model specifications and the type of data used whether income is a significant variable, which results in mixed evidence about the relationship with EV adoption.

2.3.2 Government policy and incentives

Seeing that the relatively high purchase prices of EVs remain as a barrier to their widespread adoption, many governments have started to offer both financial and non-financial incentives to citizens opting for an EV. Before any significant drop in the cost of batteries used in EVs, such subsidies are required in order for these vehicles to find a large market and to be competitive with conventional vehicles (Hidrue et al., 2011). There are multiple types of financial incentives, ranging from instant forms such as purchase subsidies and registration tax benefits, to recurrent forms such as income tax benefits (Yang, Slowik, Lutsey, & Searle, 2016). Apart from financial incentives, some countries offer non-financial incentives for EV ownership like access to bus lanes, free parking and charging infrastructure access. In Europe, differences in incentives between countries are large, with especially Denmark and Norway having high levels of incentives for BEVs and the Netherlands for PHEVs (Mersky et al., 2016).

Examining market shares of PEVs in 30 countries, Sierzchula et al. (2014) found financial incentives to be significant. According to their paper, an increase of $1000 in financial incentives increases the market share of EVs by 0.06%. The authors took caution in establishing this relationship for all countries because descriptive analysis of the data showed a weak relationship between the two. They also pointed at the availability of charging infrastructure as possibly being more important for EV adoption than incentives, considering that the effect of 1 extra charging station per 100,000 inhabitants was twice as large as the effect of $1000 extra in incentives (Sierzchula et al., 2014). Vergis and Chen (2015) also incorporated the existence of incentives in their analysis of US state EV markets, separated into two variables for purchase incentives and other supportive incentives or policies. Both variables were found to be significant but only for PHEVs and not for BEVs. However, the authors used dummy variables for financial incentives whereas other studies have pointed at the importance of the time of receiving a benefit as well as the amount of the incentive (e.g. Gallagher & Muehlegger, 2011). The research of Diamond (2009) yielded contradicting results, with regression coefficients showing no significant impact on HEV market shares. Only fixed effects regression coefficients appear to be significant for monetary incentives, but these have a negative sign, which the authors assumed to be a spurious relationship caused by the phase-out of some incentives while market shares were increasing.

Gallagher and Muehlegger (2011) studied both size and form of government incentives. They considered multiple types of government incentives across US states and their impact on the adoption of HEVs. Their analysis showed a positive and significant coefficient for state tax incentives. An incentive of $1000 is associated with an increase in HEV sales of 5%. This study shows clear differences in effectiveness with regard to the type of incentive and the time at which it is received. A tax waiver, which is an instant incentive, of mean value $1077 leads to an increase in HEV sales three times as high as the increase incurred by the mean income tax credit of $2011, which is a recurrent benefit. This can be explained by the fact that a tax waiver is immediate, automatic, and easy to understand. In contrast, an income tax credit may be discounted by the consumer since the majority of its value lies in the future, while it also takes effort to apply for the credit, making it harder to grasp the benefits (Gallagher & Muehlegger, 2011). Incentives appear to be influential in driving the adoption of EVs. Therefore, they are an important variable to consider in order to explain variation in market shares, because incentives differ per country, while the introduction or phase-out of incentives can explain differences over time. Incentives cannot drive large amounts of sales on their own, nor can they always explain variance in EV adoption. For example, the UK has the same level of incentives as Norway, but adoption rates are considerably lower (Figenbaum, Assum, & Kolbenstvedt, 2015). In order to stimulate a change in the behavior of consumers, two other factors need to be present, which are the availability of charging infrastructure and a positive consumer attitude towards EVs (Lane & Potter, 2007).

2.3.3 Environmental factors

Apart from economic considerations such as fuel savings and monetary incentives, there are obviously large environmental benefits of EVs. PHEVs emit substantially less greenhouse gases while BEVs have no emissions at all. Furthermore, the adoption of EVs reduces air pollution while also resulting in a lower dependence on scarce fossil fuels (Egbue & Long, 2012). EVs are regarded as an eco-friendly innovation, and as mentioned before, their adoption is considered to be caused by pro-environmental behavior (Schuitema et al., 2013). It can be demonstrated with Stern's (2000) value-belief-norm theory that performing pro-environmental behavior is caused by environmental awareness and norms. Therefore, differences in the amount of people with environmentalist beliefs could potentially explain variance in EV adoption between countries, but also within countries since the number of environmentalists could increase over time.

However, whether someone shows pro-environmental behavior or considers himself an environmentalist is difficult to determine without using a survey. In order to tackle this problem, Kahn (2007) used the statistics of memberships of green political parties as a proxy for the amount of environmentalists. The research focused on communities in California and examined whether the proportion of registered Green Party members in a community would influence the transportation choices of households in that area. Environmentalist communities were found to make greener transport choices; they consumed less fossil fuels, made increased use of public transit and bought more HEVs. Gallagher and Muehlegger (2011) found similar results when examining HEV in the US, using membership statistics of the environmental organization Sierra Club as an indicator of a state's environmental awareness. Additionally, they considered the effect of energy security preferences, represented by military participation. The research distinguished between high and low fuel economy HEVs. The results indicate that a one standard deviation increase in Sierra Club membership and military participation results in an increase of HEV sales with high fuel economy with 17% and 11% respectively.

Vergis and Chen (2015) used an index that measures a state's green management abilities and sustainability policies as an indicator of environmentalism in that state. This variable is somewhat different from those used in the papers above, which are more focused on citizens' environmentalism rather than that of the government. The variable was only included in the model for PHEV market shares and was not significant. Sierzchula et al. (2014) used a similar indicator for environmentalism, incorporating the Environmental Performance Index (EPI), which ranks countries based on their environmental regulation and performance. This variable also did not have a significant effect on EV market shares. Although environmentalism seems to be an important factor in the adoption of green vehicles, multiple studies indicate that its impact is smaller than the effect of cost savings and financial incentives. Several survey studies also conclude that environmental benefits are not valued highly by consumers (Graham-Rowe et al., 2012; Lane & Potter, 2007). Supposedly, some consumers are willing to protect the environment and adopt a greener lifestyle by switching to an EV, as long as they are not impacted too much financially by doing so.

The weather in a country could have an impact on the performance of EVs. Extreme temperature can affect the performance of the car and the lifetime of its batteries (Zubaryeva, Thiel, Barbone, & Mercier, 2012). Vergis and Chen (2015) found that the average winter temperature has a significant positive impact on market shares of both BEVs and PHEVs. The authors explained that colder temperatures can decrease the range of EVs by affecting the battery, and because of increased usage of heating inside the car. Since the European continent has considerable differences in climates, it could thus be useful to control for average temperatures in the regression analysis when attempting to explain variation in EV adoption between countries.

2.3.4 Technological factors

The technological differences between EVs and ICEVs result in several advantages and disadvantages of adopting an EV. Advantages of EVs compared to ICEVs as reported by adopters include environmental impact, low running costs and performance (Graham-Rowe et al., 2012; Hidrue et al., 2011; Peters & Dütschke, 2014). Disadvantages include range anxiety, long charging times and high purchase prices (Hidrue et al., 2011). The term 'range anxiety' describes the fear of the driver being stranded by running out of power or driving with a low amount of energy left in the battery (Pearre, Kempton, Guensler, & Elango, 2011). How much these attributes are valued by consumers might depend on the type of adopter. Hardman et al. (2016) attempted to find differences between high and low-end adopters of EVs as to which attributes they valued better or worse than ICEVs. The two adopter categories were determined by the price and features of their vehicles. The high-end adopter group viewed every attribute of their vehicle as better or similar to ICEVs. In contrast, low-end adopters viewed the purchase price, vehicle range and time to refuel as worse than ICEVs. The importance of certain attributes could differ between EV types as well. For example, the problem of range anxiety exists mainly in BEVs when the trip distance is longer than the battery range, since they cannot rely on a complementary gasoline or diesel engine, unlike PHEVs (Egbue & Long, 2012).

Results from Egbue and Long (2012) indicate that battery range is the biggest concern of potential consumers about EVs, chosen by 33% of survey respondents. They attempted to quantify how much range is required to fulfil consumers' transportation needs. The minimum range desired by consumers was 215 miles on average. 32% was interested in ranges of 0-100 miles, 23% preferred ranges of 100-200 miles and 45% wanted over 200 miles as a minimum range. Interestingly, these results did not correspond with respondents' actual reported driving distances, with 87% driving less than 40 miles a day. This means that when considering an EV, consumers possibly overestimate the range that is required for their daily needs. Pearre et al. (2011) found similar results when analyzing data from ICEVs in the US. They concluded that EVs with a limited range would be sufficient for 32% of all drivers, assuming that the cars are charged every night. This would also depend on whether drivers are willing to make six adaptations to their driving behavior, such as taking another vehicle when necessary. Hidrue et al. (2011) conducted a research on consumers' willingness-to-pay (WTP) for certain attributes of EVs and found that increments in driving range have the largest effect on this value. Respondents were willing to pay between $35 and $75 more per extra mile of driving range, at a decreasing rate of return. Charging was ranked second in terms of importance, with WTP increasing by about $425 to $3250 per one hour decrease in charging time.

The development of charging infrastructure is placed highly among the factors necessary for the successful adoption of EVs (Lane & Potter, 2007). An increased amount of charging locations would provide bring more compatibility with current drivers' needs and habits, which is one of the attributes influencing the adoption of an innovation according to the diffusion of innovation theory (Rogers, 2003). ICEVs have the ability to refuel at a large amount of locations, whereas in most countries public charging facilities for EVs are not yet widely available. A number of studies have incorporated the number of charging facilities in a country or state to examine the effect on EV adoption. Vergis and Chen (2015) found that the number of charging outlets per capita in the US is significantly correlated with a state's EV market share, but only for BEVs. This makes sense since PHEVs can switch to an internal combustion engine in the event of an empty battery. Sierzchula et al. (2014) established a similar relationship between charging infrastructure and EV adoption. Following from their regression results, the impact of charging infrastructure is in fact stronger than that of financial incentives. Each additional charging location per 100,000 inhabitants increases the expected market share of EVs by 0.12%.

2.3.5 Social and demographic factors

Multiple studies have recognized education level as an important factor in the adoption of EVs. Individuals with a degree could be more aware of climate change and its implications while also being able to get a more rational view about the costs and benefits of owning an EV. Following this rationale, societies with a larger proportion of higher educated citizens should have relatively higher EV adoption rates. Several papers have pointed at higher education as a characteristic of early EV adopters. Hidrue et al. (2011) determined that the propensity of an individual to purchase an EV increases with youth and education, among other factors. According to Lane and Porter (2007), the market profile for early adopters of low carbon cars is characterized by people who are highly educated, have a high income and live in urban areas. Research on transport choices of Green Party voters in California has shown that individuals who are higher educated are more likely to be an environmentalist (Kahn, 2007). Most of these studies are based on survey data. In cross-sectional studies, the evidence about the relationship between education and EV adoption is mixed. Vergis and Chen (2015) showed that both education is significantly correlated with market shares of BEVs. However, other studies using similar methods report that education is not significant for HEVs (Gallagher & Muehlegger, 2011; Sierzchula et al., 2014).

Another demographic factor that could be related to the adoption of EVs is population density. The advantage of a more urban area is that trips are typically shorter due to proximity of attractions, while charging stations have a higher efficiency in terms of individuals covered (Zubaryeva et al., 2012). On the other hand, one could argue that areas with high population density lack the space needed to park and charge EVs, while also offering more public transportation alternatives. Empirical evidence for the relationship between population density and EV adoption is scarce. Vergis and Chen (2015) is the only known research that reports a significant correlation, while two other studies find no evidence of such a relationship (Javid & Nejat, 2017; Sierzchula et al., 2014).

Finally, variables that are sometimes included in related literature are vehicle density and vehicle distance travelled. A higher vehicle density, which refers to the amount of vehicles per capita, can be an indication of relatively more multi-car households, which might cause higher adoption of EVs (Zubaryeva et al., 2012). The reasoning behind this is that if a household already owns an ICEV, the downsides of owning an EV would be less critical. For instance, longer trips could still be taken using the ICEV. In the research by Sierzchula et al. (2014), no evidence was found for vehicle density to be related with EV market shares. Vehicle distance travelled could be correlated with EV adoption since a higher distance travelled per person can lead to more range anxiety for a certain individual (Zubaryeva et al., 2012). On the other hand, a larger amount of distance travelled implies higher fuel costs and thus more potential benefits of fuel economy. Vergis and Chen (2015) included vehicle distance travelled in their model for PHEV market shares but found that the coefficient was not significant. Diamond (2009) found significant coefficients for average vehicle miles travelled per capita, indicating an increase of 8-15% in HEV share, depending on the vehicle model, when miles travelled increases by 10%. This result might suggest that fuel economy is a more likely explanation than range anxiety, but this is not something that was concluded by the authors.

To summarize, this chapter was aimed at providing an overview of the literature regarding innovation in general, the development of EVs, and factors that drive their adoption. First, several theories were discussed that can be used to explain innovation adoption by using psychological factors. Diffusion of innovation (DOI) theory provides a framework for the analysis of successful innovation adoption, whereas the theory of planned behavior (TPB) can explain adoption behavior. The value-belief-norm (VBN) theory is especially helpful when pro-environmental attitudes drive the intention to adopt innovations. Consumers can be separated into adopter categories based on their innovativeness. The attitude-action gap is a shortcoming of revealed-preference studies which leaves room for market-level adoption analysis.

History shows that in essence, the technology used in EVs has existed for more than a century. Over time, EVs have experienced several comebacks but most times they failed to replace ICEVs. The three main types of EVs that have been identified are HEVs, PHEVs and BEVs. Only PEVs are regarded as 'true' EVs, thus leaving out HEVs. The development of batteries is one of the most important elements for the success of EVs. Costs of battery packs have declined rapidly in recent times, increasing competitiveness relative to conventional vehicles. The scarcity of research into differences between PHEVs and BEVs, especially with panel data, was identified as a research gap.

The factors which were found to be most influential, judging from previous research, are government incentives, charging infrastructure and the price of fuel. Government incentives, especially monetary, are shown to have a large positive effect on EV market shares. Their size and the moment when they are received are important to consider regarding this effect. Charging infrastructure increases compatibility of EVs with drivers' habits and evidence of its influence on EV adoption is compelling. Higher fuel prices increase the need for fuel-economy and result in greater potential fuel savings, and the effect on EV market shares is frequently observed. Each of these variables can be used to explain variation in EV adoption, both between countries as well as over time. Furthermore, the influence of environmentalism seems relatively low and is also difficult to quantify, while technological features of EVs are important but cannot be used to explain variation between countries. Variables such as education, population density and income have resulted in mixed evidence, but are useful as controls for demographic differences between countries. Now that the relevant variables have been identified, the data and methodology for the analysis will be discussed in the next chapter.

3 Data and methodology

This chapter is intended to discuss the data and methodology that was used to answer the research question. First, the countries that are included in the analysis are presented as well as the reason for the selection of these countries. Next, the variables that are used are defined and the methods of collecting the data are pointed out. The section after that is about the econometric method used to analyze the data and gives a rationale for the choice of methods. Finally, the assumptions for ordinary least squares (OLS) are discussed with regards to the panel data as well as sources of potential bias.

3.1 Geography

The research focuses on the countries in the European Union plus Norway and Switzerland. These countries are all part of the European Economic Area (EEA), except for Switzerland, which is included nonetheless because of its location and the fact that its economy and culture are comparable to its EU neighbors. A few countries were excluded because of their small size or remote location from the European mainland, which are Cyprus, Liechtenstein, Luxembourg, Iceland and Malta. For some this was for the reason of shortage of data. Others are suspected to have a scarce availability of PEVs which makes them incomparable. Croatia has only been an EU member since 2013, which results in a lack of data in EU data sources and therefore it was also excluded. Table 1 provides a list of the resulting of 26 countries on the European continent.

Table 1 - Countries included in the analysis

Country name			
Austria	France	Lithuania	Slovenia
Belgium	Germany	Netherlands	Spain
Bulgaria	Greece	Norway	Sweden
Czech Republic	Hungary	Poland	Switzerland
Denmark	Ireland	Portugal	United Kingdom
Estonia	Italy	Romania	
Finland	Latvia	Slovakia	

These countries were chosen primarily because of their inclusion in the EEA, which means that they are covered by most European data services. In contrast, countries in Europe that are outside of this group of countries lack the data that is required for the analysis. All the selected countries are covered by the European Commission's statistics service, Eurostat. This ensures the availability of economic and demographic data for these countries. Furthermore, they are all covered by the data sources of the European Alternative Fuels Observatory (EAFO), which provides a wide range of statistics on PEVs, including vehicle registration figures, charging infrastructure and government incentives.

3.2 Data

This section defines the different variables that are used in the analysis of PEV market shares and the sources of the data. These variables are separated into the same categories as the factors that were identified in the literature review. Table 2 provides an overview of the variables along with descriptions and data sources. For each variable it is explained how it can influence PEV market shares and what the expected result for the effect is.

3.2.1 Market shares

The dependent variable used in this research is the adoption of PEVs. This variable is defined as the annual market share of PEVs as a percentage of total vehicle sales in a country. Since one of the research goals is to examine differences between types of PEVs, this variable is divided into BEV and PHEV market shares. Data on PEV registrations was obtained from the EAFO and the European Automotive Manufactures Association (ACEA). These figures were divided by the annual total number of vehicle registrations per country, which is provided by Eurostat.

3.2.2 Economic variables

This category includes the variables fuel price, electricity price and income. Fuel price is defined as the annual average pump price of gasoline. It is expected to have a positive effect on PEV market shares since higher fuel prices constitute larger potential savings due to decreased fuel consumption resulting from owning an EV. The data is obtained from the World Bank, which unfortunately only supplies these prices for every two years. Since pump gasoline prices are highly correlated with the price of oil, data for the missing years was estimated using the annual average price of Brent oil, collected from Federal Reserve Economic Data (FRED). The data was given in US dollars and was converted to euros using yearly average dollar/euro exchange rates.

The variable electricity price is represented by the annual average electricity price for household consumers, which was obtained from Eurostat. Electricity prices are expected to have a negative effect on PEV market shares because lower prices increase the cost savings caused by switching to an EV. The prices of fuel and electricity were adjusted for inflation using the

Harmonised Index of Consumer Prices (HICP). This index measures price changes of consumer goods and services in the euro area. The variable for income is intended to capture welfare differences between countries. Wealthier countries are assumed to adopt EVs earlier since the consumers can afford to bear the relatively high cost of purchasing such a car. Therefore, a higher income per capita is expected to be positively related to PEV market shares. The variable is measured by real GDP per capita, which was collected from Eurostat.

3.2.3 Government incentive variables

Incentives are measures taken by governments to make it more attractive for citizens to buy and own EVs. These incentives may exist in the form of financial stimuli such as purchase subsidies or tax benefits, or in the form of non-financial benefits such as free or reduced parking or access to priority traffic lanes. Data on non-financial incentives is very limited, especially when it comes to the time of their introduction or changes over time. Furthermore, these incentives are usually offered only in certain regions or major cities of a country. Therefore, non-financial incentives were ignored in the analysis.

Financial incentives exist in a variety of forms and timings. As was concluded from the literature, these factors are all important with respect to the effectiveness of incentives in stimulating EV diffusion. It was also established that immediate subsidies are considered to be more effective than benefits that are received in the future, such as vehicle tax reductions. In most countries, subsidies and tax exemptions are based on a lot of specific vehicle model characteristics such as tailpipe emissions and purchase price. Therefore, precisely quantifying incentives for every country as well as changes over time would be extremely tedious and complex.

Instead, a different approach was used to define this variable. Based on a report on incentive design by the International Council of Clean Transportation (ICCT), financial EV incentives can be divided into four different types: income tax credits, vehicle tax rebates, one-time vehicle tax reductions and annual vehicle tax reductions (Yang et al., 2016, p. 5). Since the moment when the incentive is received is deemed important, two dummy variables were created: a dummy for purchase incentives that are received directly or within limited time after the purchase and a dummy for recurrent incentives that occur annually or monthly. The dummies take on a value of 1 when an incentive is present and 0 otherwise. The information about the presence of financial incentives is based on documents released yearly by the ACEA. Unfortunately, the sources were not detailed enough to distinguish between incentives aimed at BEVs and PHEVs. Therefore, the dummies indicate the presence of incentives for EVs in general.

3.2.4 Environmental variables

This category consists of variables for environmentalism and weather. The degree of environmentalism in a country is one of the most difficult variables to quantify because of the multitude of factors involved. In order to capture environmentalism, literature suggests measures such as government expenditures on environmental measures, the share of renewable energy in total energy generation, or the change in emissions of greenhouse gases (Brunel & Levinson, 2016). However, these are all likely to cause spurious relationships when used in a regression analysis with PEV market shares. The reason is that although they can be a proxy for green policy by governments, the decision of possible adopters of EVs will probably not be directly affected by them because these metrics are not visible to the average consumer. Some quantitative studies regarding alternative fuel vehicles use surveys or indices of environmental performance such as the Environmental Performance Index (EPI) compiled by Yale. This index assigns scores to countries worldwide based on a variety of indicators covering ecosystem vitality and environmental health. Unfortunately, the EPI is not released yearly, and the methodology and data differ per edition, which makes it unsuitable for panel data regression. Nevertheless, the average EPI scores over time are used in interactions with other variables to elicit differences in environmentalism between countries.

Weather is included as a variable to account for the negative impact that cold temperatures can have on the performance of batteries of EVs. Since reduced performance of the battery decreases the attractiveness of an EV, higher temperatures are expected to positively affect PEV market shares. Data on monthly average temperatures per country in degrees Celsius were obtained from the Weatherbase website, which collects climate data from large amounts of weather stations in every country. The average winter temperature was calculated by taking the average of the months December through February. Since average temperatures are the result of measurements from over 30 years, the same values are used for every year in the dataset.

3.2.5 Technological variables

The only technological variable that is included in the analysis is the availability of public charging infrastructure. Other attributes that are specific to EVs such as battery charging times or driving ranges are not included since most vehicles are available across Europe so there would not be any variation to observe. Also, it is not likely that these attributes have changed by a considerable amount over the period that is being examined. Charging infrastructure refers to the amount of publicly accessible charging points. In this case a charging point indicates one outlet that can charge one EV at a time, so there can be multiple charging points at a single station. The presence of charging possibilities reduces range anxiety and increases usability because longer trips are possible. Therefore, higher amounts of charging points are expected to be positively related to PEV market shares.

The EAFO supplies data on charging infrastructure, which is separated into normal and high-power charging. Private or residential charging points are not included in these figures. Normal charging is limited to a maximum charging power of 22 kW, high-power refers to any technologies that have a charging power above 22 kW. Many EVs are not capable of using high power charging technologies, which is also called fast charging. For example, the Nissan Leaf, the most popular BEV in Europe, is only limited to 6.6 kW, and most PHEVs are incapable of using fast charging as well (Hall & Lutsey, 2017). Since the data on PEV registrations does not distinguish between models, charging infrastructure of both the normal and high-power types were combined in one variable. The amounts for each country were corrected for the size of the population.

3.2.6 Social and demographic variables

Education, population density and car density are included as social and demographic variables. The education variable is intended to capture differences in education levels between countries using the proportion of citizens with a degree. More specifically, it is defined by the percentage of the population aged 15-64 who have completed tertiary education, that is a bachelor's degree and higher. Data for this variable was obtained from Eurostat. Higher educated individuals are presumably more knowledgeable about environmental issues while also being more capable of assessing the cost benefits of owning an EV. Therefore, the education level in a country is expected to have a positive relationship with PEV market shares.

Population density is often regarded to be positively related to EV adoption. The idea is that in more densely populated areas attractions are closer, which allows for EVs to be used to take short trips. The variable is defined as the number of inhabitants per square kilometer and the figures are obtained from Eurostat. The variable car density is represented by the number of passenger cars per 1000 inhabitants. The use of an EV as a second car may mitigate some of its downsides. It could be used for shorter trips while still having an ICEV car for longer distances. Therefore, a higher amount of cars relative to population is expected to be positively related to PEV market shares. The data is obtained from Eurostat as well as national statistics services.

Table 2 - List of variables and sources

Variable name	Variable description	Source
Market share (dependent variable)	Annual market shares of BEVs and PHEVs as a percentage of total new vehicle registrations	ACEA, EAFO
Fuel	Average pump price of gasoline	World Bank, FRED
Electricity	Average electricity price for household consumers	Eurostat, national government agencies
Income	Real GDP per capita	Eurostat
Purchase/recurrent incentive	Dummy variables for the presence of purchase and recurrent financial incentives	ACEA, news articles
Environmentalism	Environmental Performance Index (EPI)	Yale University
Weather	Average winter temperature in degrees Celsius	Weatherbase.com
Charging infrastructure	Number of publicly accessible charging points per 100,000 inhabitants	EAFO
Education	Percentage of population aged 15-64 with tertiary education	Eurostat
Population density	Number of inhabitants per square kilometer	Eurostat
Car density	Number of vehicles per 1000 inhabitants	Eurostat, national statistics services

3.2.7 Data inspection and outliers

Now that all variables have been formally defined and discussed it is time to look at the data. First inspection of the data revealed that it is in fact a very balanced panel with few missing values. This indicated that there were no alterations required in order to use the dataset for panel regression purposes. However, the distributions of BEV and PHEV market shares were cause for concern, especially regarding the extremely high values for Norway. In 2012, Norway already had a BEV market share of about 3%, which is higher than any country in every year until 2016. In other years market shares for the country were even higher with roughly 17% in 2015 and 16% in 2016. Therefore, some extra time was spent to investigate what causes these extreme values and whether Norway could be considered an outlier and possibly be left out of the regression. Outliers can be troublesome in regressions because OLS minimizes sum of squares, and large residuals gain a lot of weight in the regression. OLS estimates can be sensitive to the inclusion of one or several observations, especially with small data sets like these. If a member of the population is very different from the rest in some relevant aspect, this can cause outliers (Wooldridge, 2014).

For Norway there certainly seems to be a big difference with the other countries in the dataset when it comes to the maturity of the EV market. Firstly, EV policy in Norway is anchored in its climate policy with government authorities, owner organizations and private companies working together to create the best diffusion circumstances (Figenbaum et al., 2015). This cannot be measured by any of the included variables. Secondly, Norway already had its own BEV industry with Think before any other country, next to having an active user base of 2500 as early as 2009. This probably led to the steep market growth after the large manufacturers started offering their models from 2010 onwards (Figenbaum et al., 2015). This indicates that the Norwegian EV market is in a completely different phase than the other countries, having reached the majority consumer groups, while innovators and early adopters are still predominant in other countries. As a result, the Norwegian EV market shares are likely to be influenced by significantly different factors now that EVs have found a mass market. Since this difference cannot be controlled for using these variables, the choice was made to exclude Norway from the regression analysis.

Table 3 presents the summary statistics for all variables of the 25 remaining countries. The maximum BEV market share was 2.6% which occurred in Estonia in 2012. For PHEVs, the maximum market share was 8.9% and was recorded in the Netherlands in 2015. Most countries had zero PEV market shares in 2010, the same counts for charging infrastructure. The highest value for charging infrastructure was also for the Netherlands, at 157 charging points per 100,000 inhabitants. Fuel prices ranged from €0.97 to €1.87 per liter of gasoline. The mean income per capita for all countries over the respective period was €24,781.

Table 3 - Summary statistics

Variables	N	Mean	Std. dev.	Min.	Max.
BEV market shares	175	0.216	0.370	0	2.61
PHEV market shares	175	0.254	0.912	0	8.86
Purchase incentive	173	0.514	0.501	0	1
Recurrent incentive	172	0.459	0.500	0	1
Charging infrastructure	175	7.690	17.03	0	156.8
Fuel	175	1.386	0.184	0.97	1.87
Income	175	24,781	13,863	5,100	57,900
Education	175	25.82	6.797	11.9	38.4
Population density	175	133.7	109.2	17.60	502.9
Electricity	175	0.178	0.0523	0.0839	0.309
Car density	170	459.8	86.99	214	625
Environmentalism	175	72.86	4.764	60.44	84.68
Weather	175	1.024	4.671	-7.400	11.40

3.3 Methodology

The aim of this thesis is to find out which variables affect the adoption of EVs and examine differences between BEVs and PHEVs. In order to do so, the market shares of either vehicle type will be regressed on the variables described above, in separate analyses. There are two dimensions of effects that are of interest. Firstly, there is the difference in EV adoption between countries that is caused by country-specific variables. Secondly, the difference over time within countries that is caused by the change of those variables. The choice of regression method should be made with special regard to these relationships.

3.3.1 Choice of panel regression method

There might be country-specific and possibly unobserved factors that influence EV adoption, for example local initiatives that drive adoption or a changing public attitude to EVs. Therefore, it is interesting to use an econometric difference model that exploits the time component and accounts for unobserved heterogeneity. This would make it possible to control for effects that are not captured by any of the regression variables. To make use of such a model would require all variables to be varying over time. This means that time-constant variables such as weather and environmentalism cannot be included as variables on their own. Nevertheless, they can be included in interaction terms with other variables to examine partial effects.

When choosing a panel regression method, the choice is likely going to be between either a fixed effects or a random effects model. The difference between the two is that a fixed effects model only exploits within variation, meaning variation that occurs within countries. In contrast, a random effects model is essentially a combination of within and between variation. The use of random effects requires the estimators of the two models to be consistent. In this case, random effects would be more appropriate since its estimators are more efficient (Wooldridge, 2014). To verify which model is more appropriate, the Hausman test is an adequate tool. This method tests the null hypothesis that the coefficients under random and fixed effects are not systematically different from each other (Wooldridge, 2014). The test was conducted using a base model including main and control variables. Judging from the P-value of the output, the null hypothesis can be rejected, which implies that a fixed effects model is more adequate in this case. The fixed effects model that is used is specified below in Equation 1.

$$\begin{aligned} Market\ shares_{vit} &= \alpha_i + \beta_0 + \beta_1 Incentives_{it} + \beta_2 Charging\ infrastructure_{it} + \\ &\beta_3 \log(Fuel)_{it} + \beta_4 \log(Electricity)_{it} + \beta_5 Education_{it} + \\ &\beta_6 Populaton\ density_{it} + \beta_7 \log(Income)_{it} + \beta_8 Car\ density_{it} + u_{it} \end{aligned} \tag{1}$$

The term market shares refers to the dependent variables for either BEVs or PHEVs, which is indicated by *v*. Incentives includes two dummies for the presence of financial incentives. Furthermore, *i* denotes countries while *t* stands for the year. The unobserved, time-constant factors are captured by α_i, whereas u_{it} stands for the idiosyncratic error, representing factors that change over time and affect the dependent variable.

3.3.2 OLS assumptions

Next, it is important to check whether the data complies with the assumptions for the use of OLS regression, which are homoscedasticity, no autocorrelation and normality of residuals. The first assumption was assessed using a modified Wald test for groupwise heteroscedasticity in residuals. The test returned a P-value close to zero, which indicates the presence of heteroskedasticity in the panel. A test for autocorrelation in panel data models written by Drukker (2003) was used after estimating each model. The test results were not significant which means that there is no problem in this area. For each model it was visually assessed if the estimated residuals follow a normal distribution. Histograms of the residuals showed patterns that were close to normality which means that this assumption holds. Because of the heteroscedasticity, robust standard errors were used in the estimation of each model.

3.3.3 Multicollinearity

Not an assumption of OLS, but still an important consideration is the issue of multicollinearity. When independent variables are highly correlated among each other this might cause problems with multiple regression analysis. In particular, it can cause coefficients to be unstable and standard errors to be overestimated. There is no absolute value of correlation between variables that indicates multicollinearity, but idea is that it is 'close' to one (Wooldridge, 2014). A correlation matrix of all independent variables was used to look for any values that could be a sign of possible multicollinearity. The correlation matrix is provided in the appendix. The only variable pair that caught the attention is the log of income and the log of electricity, with a correlation of 0.7. This might warrant some caution while interpreting their coefficients when they are used in the same model. However, because these are both control variables this is not a big problem, since their effects are not the main topic of interest.

3.3.4 Potential bias

It is important to think of factors that could lead to biased estimators and unreliable standard errors. One such factor is the problem of endogeneity. The variable that is most in danger of being endogenous to EV adoption is charging infrastructure. In the regression it is assumed that the number of charging points influences the adoption of EVs and not vice versa. In reality though, it is likely the case that an increase in the number of EVs in a country will also lead to a rise of demand for charging infrastructure, hence causing an endogeneity problem. Additionally, as Gallagher and Muehlegger (2011) already indicated, the policies to stimulate EV adoption might be endogenous to states, or countries in this case. Countries might choose to implement incentives that work best for the local situation. This means that the presence of incentives that are included in this research might depend on other variables.

In this chapter the data and methodology for this thesis were discussed. The reasons for the choice of countries were given and the variables were properly defined while also citing their sources. Furthermore, the choice of regression method was discussed as well as the assumptions for unbiased and consistent estimators in OLS. In the next chapter, the results of the regression analysis will be presented and interpreted.

4 Results

In this chapter the results of the fixed effects models for BEVs and PHEVs are presented. Market shares in 25 countries of both types are regressed on the main variables of interest and several control variables. For each vehicle type multiple models are estimated with different specifications, including quadratic and interaction effects. Each model uses robust standard errors to account for heteroskedasticity. Furthermore, the different effects and their sizes for BEVs and PHEVs are compared in the last section. Since the dependent variables are percentages, effects are indicated as percentage point (pp). All effects discussed are ceteris paribus effects.

4.1 Analysis of BEV market shares

Table 4 presents the fixed effects regression results for BEVs. In the base model (1), BEV market shares are regressed on the main variables of interest. These are purchase and recurrent incentives, charging infrastructure, and the log of fuel price. Model (2) includes all control variables, including the log of income, education, population density, the log of electricity price, and car density. Model (3) incorporates a quadratic effect for charging infrastructure. Car density and the log of electricity price are left out to avoid overfitting the model, and since they are deemed the least important control variables. In the last specification, model (4), the quadratic term is kept while adding an interaction term between purchase incentive and the log of fuel price.

Of the main variables of interest, the coefficients of purchase incentive and charging infrastructure are positive and significant. The introduction of a purchase incentive is estimated to increase BEV market share by 0.12 pp. It is estimated that an increase of 10 charging points per 100,000 inhabitants increases BEV market share by 0.08 pp. No evidence is found that the log of fuel price has an influence on market share in the first two models. Likewise, the coefficients for recurrent incentives show no significant effect. The control variables education and population density display a positive and significant relationship with BEV market share. A one percentage point increase in the proportion of higher educated citizens results in a 0.04 pp increase in BEV market share. This effect is relatively robust to changes in specification across models. It is estimated that an increase in population density of 100 inhabitants per square kilometer increases market share by 1.9 pp. This effect is quite substantial, considering the fact that the 5-95th percentile difference is roughly 350 inhabitants, which constitutes a market share difference of 6.5 pp. However, the effect might be overestimated since in specifications (3) and (4) the coefficients are considerably lower and insignificant.

Table 4 - Fixed effects regression results for BEV market shares

Variables	(1)	(2)	(3)	(4)
Purchase incentive	0.18837***	0.12484**	0.08358	0.39378***
	(0.06138)	(0.05250)	(0.05151)	(0.13044)
Recurrent incentive	-0.05167	-0.07021	-0.06788	-0.10427*
	(0.06086)	(0.05910)	(0.05209)	(0.05476)
Charging infrastructure	0.01015***	0.00756***	0.01768***	0.01837***
	(0.00307)	(0.00164)	(0.00407)	(0.00391)
log Fuel	-0.40283	0.39811	0.43454	0.74593
	(0.44829)	(0.72983)	(0.68878)	(0.76574)
log Income		0.59411	0.35880	0.32304
		(0.51926)	(0.42603)	(0.45244)
Education		0.03843**	0.03324**	0.02915**
		(0.01575)	(0.01192)	(0.01075)
Population density		0.01851***	0.00351	0.00091
		(0.00499)	(0.00715)	(0.00662)
log Electricity		0.07516		
		(0.19649)		
Car density		-0.00066		
		(0.00054)		
Charging infrastructure^2			-0.00007***	-0.00008***
			(0.00002)	(0.00002)
Purchase incentive * log Fuel				-0.96590**
				(0.43771)
Constant	0.19433	-8.93310	-4.94199	-4.20216
	(0.16767)	(6.12207)	(5.01710)	(5.02133)
Observations	172	167	172	172
Number of countries	25	25	25	25
Adjusted R-squared	0.25	0.28	0.33	0.34

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The quadratic effect in model (3) provides an interesting insight into the effect of charging infrastructure on market share. Figure 5 presents a graph of the relationship, showing a curve shaped like an inverted parabola. This implies that the marginal effect on market share is decreasing for each increase in charging infrastructure. At the mean of 8 charging points per 100,000 inhabitants, one extra charging point would increase market share by 0.017 pp. The effect becomes zero at roughly 130 charging points per 100,000 inhabitants, after which it becomes negative. This is relatively close to the maximum value in the dataset of 158. Between the minimum and maximum amounts of charging points in the dataset, the effect decreases by about 0.022 pp. It should be noted that the variable purchase incentive loses its significance in model (3), but this changes again in the next specification.

Model (4) shows a significant interaction effect between purchase incentive and the log of fuel price. This implies that the partial effect of a purchase incentive on market share depends on the fuel price level. The negative coefficient for the interaction indicates that a higher fuel price reduces the impact of a purchase incentive, which is the opposite of what was expected. At the mean fuel price of €1.39, the effect of the introduction of a purchase incentive increases market share by 0.26 pp. At the minimum fuel price of €0.97, the partial effect is 0.41 pp, while at the maximum price of €1.87 the effect is 0.13 pp, which is a substantial difference. The negative relationship can be attributed to the large drop in the oil price from 2014 to 2016, during which it was more than halved. As a result, fuel prices show a downward trend in the dataset, while for market shares the opposite is true.

The interaction between purchase incentive and the log of fuel price is the only combined term that is found to be significant for BEV market shares. Beside the main variables, interactions with weather and environmentalism are considered as well but these do not yield any significant results. For each model an alternative specification is estimated with the inclusion of time dummy variables. The results for the models including time dummies can be found in the appendix. The dummies appear to affect the significance of the coefficients for purchase incentive in model (2) and education in models (2) and (4). This might indicate that these effects could actually be caused by time effects. However, since the dummies are insignificant in both cases this is not certain.

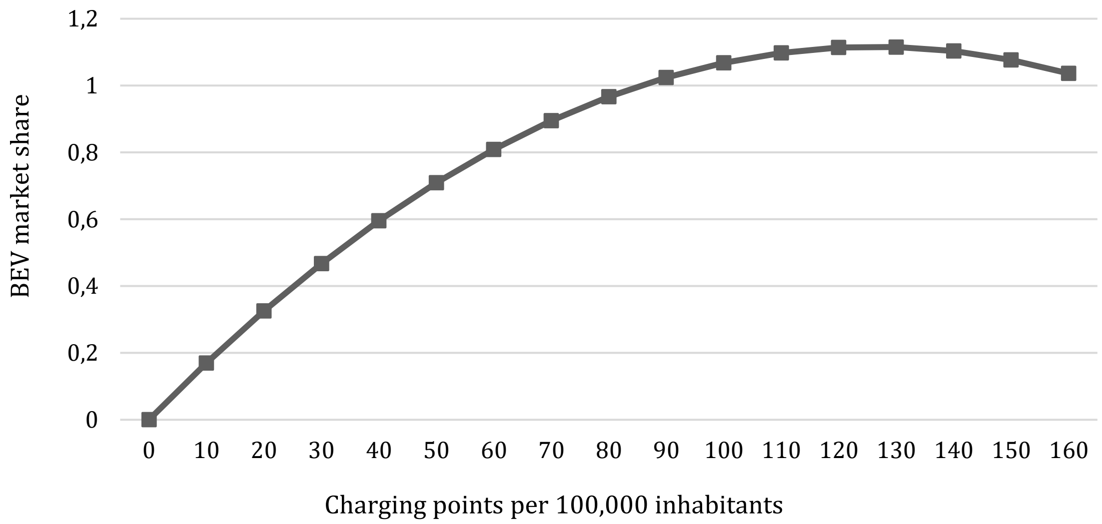

Figure 5 - Relationship between charging infrastructure and BEV market share

Table 5 - Fixed effects regression results for PHEV market shares

Variables	(1)	(2)	(3)	(4)	(5)
Purchase incentive	-0.02730	0.00414	0.38459**	0.01436	0.09649
	(0.09749)	(0.10618)	(0.17962)	(0.11650)	(0.09522)
Recurrent incentive	0.25783	0.29539	-0.73435***	0.10440	0.12131
	(0.23677)	(0.24672)	(0.21698)	(0.11389)	(0.22273)
Charging infrastructure	0.03541***	0.03335***	0.02073***	-0.03625	0.00342
	(0.00388)	(0.00162)	(0.00675)	(0.03460)	(0.00539)
log Fuel	0.27637	-0.25979	-0.42633	-1.74061**	-0.35554
	(0.56654)	(0.52035)	(0.38056)	(0.71371)	(0.44373)
log Income		-0.99691**	-0.08397	-0.64519*	-0.72227
		(0.47557)	(0.57116)	(0.35028)	(0.50630)
Education		-0.00787			
		(0.02019)			
Population density		0.03620	0.01042		
		(0.04647)	(0.03345)		
log Electricity		-0.38710			
		(0.39191)			
Car density		-0.00107			
		(0.00074)			
Purchase incentive * Population density			-0.00269**		
			(0.00107)		
Recurrent incentive * Population density			0.00680***		
			(0.00227)		
Charging infrastructure * log Fuel				0.18310**	
				(0.08241)	
Purchase incentive * Charging infrastructure					0.01010*
					(0.00564)
Recurrent incentive * Charging infrastructure					0.02576***
					(0.00369)
Constant	-0.20934	5.03163	-0.52274	6.95728*	7.22380
	(0.28747)	(6.96645)	(9.89163)	(3.50770)	(4.95949)
Observations	172	167	172	172	172
Number of countries	25	25	25	25	25
Adjusted R-squared	0.50	0.51	0.63	0.61	0.55

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2 Analysis of PHEV market shares

Table 5 presents the fixed effects regression results for PHEV market shares. Model (1) includes the main variables of interest, whereas model (2) also includes all control variables. These first two specifications are the same as for BEVs, which allows for convenient comparison of the effects. In model (3), two interaction terms are considered between purchase and recurrent incentives, and population density. Several variables that are insignificant in the previous model are excluded from this point on, except the ones used in interactions. Model (4) incorporates an interaction term between charging infrastructure and the log of fuel. Finally, in model (5), two interaction terms are included between purchase and recurrent incentives, and charging infrastructure.

Charging infrastructure is the only variable with a significant coefficient out of the main variables of interest. It is estimated that an increase of 10 charging points per 100,000 inhabitants increase PHEV market share by 0.33 pp. This result is robust against the addition of control variables. There are no signs of relationships between incentives or the log of fuel price and market share in the base models. The log of income is the only significant control variable, however the negative sign of the coefficient was not expected beforehand. The coefficient implies that PHEV market share decreases with 0.01 pp following a one percent increase in GDP per capita. This seems counter-intuitive, since wealthier countries are expected to have higher EV adoption. Two explanations for this result are proposed. First, it could be caused by multicollinearity since the log of income was shown to have a relatively high level of correlation with the log of electricity price, which could cause an unexpected sign. Second, the European debt crisis that occurred during this period caused stagnant or negative GDP growth, affecting less wealthy countries more severely. These countries possibly had higher absolute GDP per capita growth during the recovery, relative to wealthier countries. Since fixed effects makes use of differences, this would explain the negative relationship that is found here.

The interactions terms between purchase and recurrent incentives and population density in model (3) are both significant, while the two primary coefficients for incentives become significant as well. As can be deduced from the signs of the coefficients, the partial effects move in opposite directions, which is surprising. At the mean population density, the introduction of a purchase incentive increases PHEV market share by 0.02 pp, while for a recurrent incentive the partial effect is 0.18 pp. At the 5th percentile of population density, the partial effect of a purchase incentive is 0.34 pp whereas for a recurrent incentive it is -0.62 pp. At the 95th percentile, the partial effects of purchase and recurrent incentives are -0.62 pp and 1.8 pp respectively. These results are unexpected, and it is ambiguous why the effects would depend on population density in opposite directions.

The interaction term in model (4) between charging infrastructure and the log of fuel price reveals a significant interaction effect. It is estimated that in a country that has no charging infrastructure, a one percent increase in fuel price leads to a decrease in PHEV market share of 0.02 pp. At the mean amount of 8 charging points of per 100,000 inhabitants, the partial effect is 0.003 pp. But at the maximum value of 158, a one percent rise in fuel price increases market share by 0.27 pp. This result implies that fuel price does affect PHEV market share but only when sufficient charging infrastructure is present.

In the final model (5), the interaction term of recurrent incentive with charging infrastructure is significant, but for purchase incentive this not the case. At the mean of 8 charging points per 100,000 inhabitants, the introduction of a recurrent incentive increases PHEV market share by 0.33 pp. When there is zero charging infrastructure, the partial effect is 0.12 pp. At the maximum amount of 158 charging points per 100,000 inhabitants, the partial effect of a recurrent incentive on market share is 4.19 pp, which is remarkably high. This indicates that the impact of a recurrent incentive increases considerably with higher amounts of charging points.

Again, all the models are also estimated with time dummy variables, for which the results are given in the appendix. In none of the models the inclusion of time dummies causes any material changes to the significance of the coefficients. Lastly, interactions effects are considered between the main variables and weather or environmentalism, but none of these provide significant interaction coefficients.

4.3 Comparison of results between PEV types

Now the results of the fixed effects regressions for BEVs and PHEVs will be compared. The differences in significance and signs of variables between both analyses provide some interesting insights. Both BEV and PHEV market shares are positively influenced by charging infrastructure. The effects are also robust across every specification in both analyses. Furthermore, in the BEV analysis a quadratic effect is found for charging infrastructure. This term is not significant when it is included in the PHEV model. The effect of charging infrastructure seems to be larger for PHEVs, with 0.033 per charging point versus 0.008 for BEVs, even when considering that the range of PHEV market shares is more than three times as large. Based on the quadratic effect on BEVs, the difference is smaller, with a marginal effect of 0.017 at the mean level of charging points.

The significance of the financial incentives dummies differs substantially between the two PEV types. For BEVs, purchase incentives are positively related to market share, also after including control variables. In the analysis of PHEV market shares, there is no evidence of a relationship with incentives without using interactions. However, after interacting incentives with the variables for population density and charging infrastructure, it appears that their effects depends on these variables. There is no proof of a significant unconditional effect of the fuel price on BEV or PHEV market share. Nonetheless, the significant interaction term between purchase incentive and fuel price in the BEV regression indicates a partial effect. For PHEVs, the effect of fuel price seems to depend on the availability of charging infrastructure.

The control variables do not show any significant relationship with PHEV market shares, apart from income, which shows an unexpected sign. However, for BEV market shares, population density and education level are found to have a positive relationship. The coefficient for population density does not seem to be robust against different specifications of the model. For education the opposite is true, since the coefficient shows hardly any change across different models. The variables electricity price and car density do not appear to be significant in any of the models for both EV types. Finally, there is a clear difference in adjusted R-squared. For PHEVs these are roughly twice as high as for BEV models, which indicates that the explanatory power of the regressions is bigger.

To summarize this chapter, several variables are found to be important when attempting to explain BEV and PHEV market shares. The effect of charging infrastructure is without doubt the most compelling when considering both vehicle types. Purchase incentives are an important factor for BEV market share while education and population density are significant control variables. The effect of incentives on PHEV market share appears to be dependent on levels of population density as well as charging infrastructure. Fuel price only shows conditional effects in both analyses. In the next chapter, conclusions are formed with regard to the research question, and the results are discussed further. A discussion of the policy implications and suggestions for further research completes the chapter.

5 Conclusion and discussion

5.1 Conclusion

EVs are considered as a solution to the issue of negative environmental consequences of personal transportation. Therefore, their adoption and the knowledge of the different factors that influence the diffusion process are essential in order to decrease greenhouse gas emissions and the dependence on fossil fuels worldwide. This thesis was aimed at explaining the variation in PEV adoption in Europe between countries and over time. Additionally, the difference in driving factors between two types of vehicles, BEVs and PHEVs, was a main topic of interest. The research question was as follows:

Which factors determine the adoption of plug-in electric vehicles in Europe?

In order to answer the research question, multiple fixed effects regression models were estimated using panel data of BEV and PHEV market shares covering 26 countries over the 2010-2016 period. Using related literature and professional reports, several categories of factors were identified that are found to be important in PEV adoption. These variables were used to conduct two separate analyses of the two PEV types. The variables of particular interest were financial incentives, charging infrastructure and fuel price.

The results imply that charging infrastructure is one of the most important factors that drive the adoption of PEVs. Purchase incentives influence BEV market share in particular, whereas for PHEVs the effect of financial incentives is dependent on other factors such as population density. Education and population density are significant control variables that explain variation in BEV market share, while these do not appear to be related to PHEV market share. The effect of fuel price on the adoption of PEVs was found to be dependent on the availability of charging infrastructure and the existence of purchase incentives.

5.2 Discussion of results

The significant relationship between PEV market shares and purchase incentives is in agreement with the overall view that incentives support the successful adoption of EVs. This result also corroborates findings from previous literature (Gallagher & Muehlegger, 2011; Sierzchula et al., 2014). As long as the purchase price of PEVs remains at a premium compared to ICEVs, purchase incentives can close the gap to make them price-competitive. The fact that the variable for recurrent incentives was not independently significant in both regressions leads to another important conclusion. It suggests that the time when monetary incentives are received relative to the moment of purchase is crucial with respect to their effectiveness on PEV adoption. Credit that is received directly or within limited time after the purchase seems to be more effective. Moreover, it is in line with findings from other studies which suggest that consumers are myopic when it comes to financial incentives and heavily discount benefits that are received in the future (Diamond, 2009; Gallagher & Muehlegger, 2011).

The evidence of a relationship between incentives and market shares was less conclusive for PHEVs than in the case of BEVs. The interactions with population density were significant but the opposite partial effects between incentive types are difficult to interpret. Still, the partial effect of a recurrent incentive depending on charging infrastructure was very large, ranging from 0.12 pp to 4.19 pp. There are signs in the results that purchase incentives are more effective for BEVs while recurrent incentives work better with PHEVs, but this is stated with caution. The differences in significant incentives could be caused by the fact that the variables for incentives were based on the presence of EV incentives in general. Since governments generally favor BEVs more in their incentive policy, as they have better environmental performance, this could explain the more ambiguous relationship of purchase incentives with PHEV adoption.

The regression results underline the importance of charging infrastructure for the adoption of PEVs. This variable showed significant positive coefficients across all models for both PEV types. This is also in agreement with previous research on PEVs (Sierzchula et al., 2014; Vergis & Chen, 2015). Charging opportunities away from home are essential in taking away the range anxiety that exists with consumers. Referring back to Roger's (2003) diffusion of innovation theory, it also increases the compatibility of owning an PEV with current drivers' habits of refueling on the road, thereby lowering the barrier to adoption. The quadratic relationship between charging infrastructure and BEV market shares is especially interesting. It implies that the marginal effect of extra charging positions decreases at higher cumulative amounts.

In contrast with expectations, no evidence was found of an independent relationship of PEV market shares with fuel price. However, a significant interaction effect between purchase incentives and fuel price was found for BEVs, while for PHEVs the effect of fuel price seems to depend on the presence of charging infrastructure. The fact that fuel price does not always have an impact, suggests that the signaling effect of fuel prices is not strong enough to drive PEV adoption. This could be viewed as being congruent with the idea of myopic consumers, and the high implicit discount rate found in previous research (Gallagher & Muehlegger, 2011). If consumers are in fact myopic in their calculation of total car costs, this would explain why implied fuel savings are not as decisive as purchase incentives. The lack of correlation could be caused by the use of annual averages of fuel prices, since these might fail to capture the effect of changes and volatility during the year. It could also be caused by the downward trend in fuel prices during this particular period.

5.3 Policy implications

The results have some important practical implications. First, they imply that governments do well to offer incentives to consumers in order to boost PEV adoption, as long as purchase prices are above par compared to conventional vehicles. Furthermore, the findings suggest that instant incentives are more effective than benefits that are received in the future. Since a considerable number of governments in Europe make use of income tax waivers and fuel taxes instead of purchase incentives, this might be an important thing to consider.

Second, the importance of stimulating investment in charging infrastructure is underlined by the results. Especially considering that an additional 20 charging points per 100,00 inhabitants is estimated to have a larger effect on BEV adoption than offering a countrywide purchase incentive. The results also suggest that the effect of charging infrastructure decreases with larger amounts of positions. This finding can be relevant for countries that already have relatively many charging points and are still looking to expand PEV adoption.

Third, the influence of fuel prices on the effectiveness of both charging infrastructure and purchase incentives is relevant. Even though national governments do not have as much control over the fuel price, apart from setting taxes, it indicates that its impact should be taken into account. Since extra charging points appear to be more effective when fuel prices are high then this should be recognized in decision-making.

5.4 Limitations and suggestions for further research

One of the limitations of this research is the small sample size, which is caused by the length of the time period. This makes the results more susceptible to short-term trends in variables. Higher frequency data such as biannual or quarterly statistics could give a better picture of the effect of changes in certain variables, like in the case of fuel prices. The use of dummies to distinguish between purchase and recurrent incentives proved to be adequate for this analysis. However, more effort could be spend on quantifying incentives for each country. This would give more insight into how consumers take into account the size of purchase incentives or how they discount recurrent incentives. Additionally, separating BEV and PHEV incentives, which was not done in this thesis, could yield more information about differences in incentive effectiveness between the two types. Extending this type of research to other regions such as the US or China would be an opportunity to see if the relationships identified here also apply to those parts of the world.

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Appendix

Table A1 - Correlations between the independent variables

Variables	Purchase incentive	Recurrent incentive	Charging inf.	log Fuel	log Income	Education	Population density	log Electricity	Car density
Purchase incentive	1								
Recurrent incentive	0.177	1							
Charging inf.	0.271	0.170	1						
log Fuel	0.231	0.230	0.090	1					
log income	0.370	0.331	0.345	0.522	1				
Education	0.258	-0.061	0.302	0.027	0.527	1			
Population density	0.187	0.303	0.430	0.434	0.397	0.078	1		
log Electricity	0.195	0.399	0.179	0.494	0.702	0.181	0.351	1	
Car density	-0.115	0.193	0.129	0.198	0.508	0.292	0.183	0.287	1

Table A2 - BEV fixed effects regression results, including time dummies

Variables	(1)	(2)	(3)	(4)
Purchase incentive	0.09966**	0.08756*	0.07201	0.39301***
	(0.03996)	(0.04383)	(0.04783)	(0.12350)
Recurrent incentive	-0.09635*	-0.08548	-0.06480	-0.11185*
	(0.04787)	(0.05507)	(0.05066)	(0.05496)
Charging infrastructure	0.00793***	0.00676***	0.01702***	0.01695***
	(0.00206)	(0.00150)	(0.00382)	(0.00356)
log Fuel	0.78515	1.10631	0.67822	1.03177
	(0.56930)	(0.83414)	(0.63392)	(0.68434)
log Income		0.56021	0.37092	0.29463
		(0.57056)	(0.48171)	(0.49769)
Education		0.01813	0.02970**	0.01957*
		(0.01251)	(0.01395)	(0.01134)
Population density		0.01775***	0.00372	0.00148
		(0.00470)	(0.00653)	(0.00625)
log Electricity		-0.08446		
		(0.22143)		
Car density		-0.00075		
		(0.00069)		
Charging infrastructure^2			-0.00007***	-0.00007***
			(0.00002)	(0.00002)
Purchase incentive *				-1.01991**
log Fuel				(0.44923)
Year=2012	0.07385	0.03504	0.01470	0.04053
	(0.09209)	(0.08073)	(0.06557)	(0.07938)
Year=2013	0.06339*	0.03059	-0.05012	-0.01293
	(0.03465)	(0.03874)	(0.03793)	(0.03276)
Year=2014	0.28987***	0.25013*	0.10801	0.14773
	(0.10141)	(0.12497)	(0.09016)	(0.09491)
Year=2015	0.32390**	0.26116	0.07450	0.12934
	(0.11596)	(0.16539)	(0.12962)	(0.12416)
Year=2016	0.33893***	0.24104	0.03932	0.09855
	(0.09497)	(0.14140)	(0.10000)	(0.09672)
Constant	-0.25403	-8.51972	-5.09510	-3.87536
	(0.21576)	(6.49790)	(5.50821)	(5.41284)
Observations	172	167	172	172
Number of countries	25	25	25	25
Adjusted R-squared	0.30	0.30	0.32	0.34

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3 - PHEV fixed effects regression results, including time dummies

Variables	(1)	(2)	(3)	(4)	(5)
Purchase incentive	0.01160	0.02978	0.42202**	0.02493	0.07616
	(0.12010)	(0.11908)	(0.18876)	(0.11544)	(0.09596)
Recurrent incentive	0.32400	0.34764	-0.74215***	0.08666	0.12127
	(0.25516)	(0.27554)	(0.21744)	(0.12047)	(0.25675)
Charging infrastructure	0.03795***	0.03505***	0.02018**	-0.04028	0.00209
	(0.00290)	(0.00182)	(0.00733)	(0.03765)	(0.00779)
log Fuel	-1.54805*	-2.41414	-0.51640	-2.01007**	-0.41437
	(0.76937)	(1.47021)	(0.65244)	(0.80153)	(0.70504)
log Income		-1.12354**	-0.23159	-0.88461*	-0.93944
		(0.53637)	(0.42053)	(0.47610)	(0.68302)
Education		-0.00931			
		(0.03031)			
Population density		0.04002	0.00958		
		(0.04768)	(0.03330)		
log Electricity		-0.03657			
		(0.50856)			
Car density		-0.00123			
		(0.00084)			
Purchase incentive *			-0.00274**		
Population density			(0.00113)		
Recurrent incentive *			0.00696***		
Population density			(0.00230)		
Charging infrastructure *				0.19159**	
log Fuel				(0.08677)	
Purchase incentive *					0.00976
Charging infrastructure					(0.00682)
Recurrent incentive *					0.02688***
Charging infrastructure					(0.00515)
Year=2012	0.03645	0.12153	-0.03284	0.04703	0.01967
	(0.07440)	(0.11355)	(0.04639)	(0.03949)	(0.07207)
Year=2013	0.01110	0.07425	-0.06251	0.03384	0.07418
	(0.11655)	(0.13117)	(0.04330)	(0.12186)	(0.13101)
Year=2014	-0.25011***	-0.24761	-0.14722	-0.13148	-0.01397
	(0.08717)	(0.17015)	(0.10441)	(0.08858)	(0.07700)
Year=2015	-0.16219	-0.12428	0.07280	0.06852	0.20125
	(0.12482)	(0.13181)	(0.18170)	(0.24726)	(0.16472)
Year=2016	-0.55086*	-0.55119	-0.04307	0.04204	-0.01838
	(0.28190)	(0.42833)	(0.17352)	(0.24298)	(0.25129)
Constant	0.42932*	7.24477	1.09661	9.42553*	9.38037
	(0.23638)	(6.46856)	(7.96967)	(4.80014)	(6.83531)
Observations	172	167	172	172	172
Number of countries	25	25	25	25	25
Adjusted R-squared	0.51	0.52	0.63	0.61	0.55

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1