Norwegian School of Economics
Bergen, Autumn 2016

An Empirical Analysis of Drivers for Electric Vehicle Adoption:

Evidence from Norway 2010-2014

Mads Fjeld Wold & Sara Ølness

Supervisor: Gunnar Eskeland

Master Thesis, MSc in Economics and Business Administration,

Energy Natural Resources and the Environment,

Economic Analysis

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

We examine how government intervention in the automobile market affected the battery-electric vehicle adoption in the Norwegian counties in the period between 2010 and 2014, and what regional differences influenced the adoption rate. Norway has the world's strongest means of support for electric vehicles and represents a mature market with a significant share of the total car fleet being electric. The government has promoted this growth on the basis that electric vehicles are part of the solution to the climate problem. It postulates that positive externalities from electric vehicle use are not captured by the market, resulting in a market failure, which necessitates government intervention. This paper explores the effects of interventions, such as support for charging-network development and financial incentives, on the development of electric vehicle adoption in the 19 Norwegian counties. We use a panel data approach where econometric methods of fixed effects, random effects and pooled OLS are applied. The period between 2010 and 2014 is covered on a yearly basis in the analysis. The paper contributes to existing literature by studying regions over time. Through pooled OLS, we found charging infrastructure to have the strongest predictive power followed by the economic gain from free passes through toll stations. Reduced rates for EVs on ferries were expected to have a positive effect on EV adoption, but came out with spurious results in this analysis. Time saved by having access to bus lanes did not turn out to have significant influence. Some county-specific features such as coastline and elevation seem to also play a role in the adoption of battery electric vehicles. Our results are interesting as they only partly support existing literature, and supplement it by adding geographic and climatic factors. The paper gives an indication for policy makers of what incentives are efficient in driving forward EV adoption.

Preface

This thesis is written as a part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics and corresponds to one semester of full-time studies. We were two students working on this project during the fall semester of 2016 and it correlates to our two majors: *Energy, Natural Resources and the Environment* and *Economic Analysis*.

Through our work on this project, we have been able to immerse ourselves into an exciting and highly timely topic in a world where climate change problems are becoming increasingly apparent: the adoption of electric vehicles. We chose to write about this topic due to our interest in electric vehicles, public policy and because of our concern for the environment. As two Norwegian students, we are proud to be part of a society that values and encourage environmentally-friendly choices and that has been so successful in promoting them. It has been interesting, insightful and rewarding to explore the Norwegian EV history, examine the role of government and attempting to quantify effects of various factors affecting EV adoption in Norway. Working on this thesis has introduced us to the world of academic writing and taught us how to work independently and structured on such a large and comprehensive project.

We would like to especially thank our supervisor, Professor Gunnar S. Eskeland, for his guidance and support throughout the whole process. He has been a valuable discussion partner and motivated us when the writing process was going slow. We also want to show our gratitude to PhD Research Scholar Shiyu Yan for his support in working with the data set and for his help with econometric theory. We also need to thank the all the people who have provided us with the necessary data required for our analysis. Especially Jan Kristian Jensen and Nina Lysefjord at Norwegian Public Roads Administration have been of tremendous help to us in collecting data on toll stations, ferries and bus lanes.

Bergen, 20th December 2016.

Mads Fjeld Wold

Sara Elisabeth Ølness

Contents

Glossary **7**

Acronyms **8**

1 Introduction **9**

1.1 Research question 11

2 Historical development **12**

2.1 The market phases for electric vehicles in Norway 12

2.2 The role of the government 13

3 Literature review **17**

4 Theoretical background **21**

4.1 Market failure 21

4.2 Modelling demand 24

5 Data **28**

5.1 Building the data set 28

5.1.1 Spatial and time dimension 28

5.1.2 Sales statistics 30

5.1.3 Infrastructure 31

5.1.4 Financial incentives 33

5.1.5 Demographics 35

5.1.6 Geography 37

5.2 Summary statistics 38

5.2.1 Electric vehicles sales share 39

5.2.2 Charging infrastructure 41

5.2.3 Ferry expenses, toll expenses and bus lanes 43

5.3 Correlation analysis 46

6 Empirical framework **52**

6.1 From single cross-sectional models to advanced panel data methods . . 52

6.1.1 Single cross-section 52

6.1.2 Panel data 53

6.1.3 Pooled OLS 55

6.1.4 Fixed effects . . . 56
6.1.5 Random effects . . . 57
6.2 Coefficient of determination . . . 58
6.3 Post regression tests . . . 59
6.3.1 Model selection tests . . . 59
6.3.2 Heteroskedasticity and serial correlation tests . . . 60
6.4 Model specification . . . 62

7 Results **66**
7.1 Regression analysis . . . 66
7.1.1 Analysing the model . . . 69
7.1.2 Results from heteroskedasticity and serial correlation tests . . . 71
7.2 Sensitivity analysis . . . 72
7.2.1 Model without control variables . . . 72
7.2.2 Different measures for population density . . . 74
7.2.3 Combining ferry and toll expenses . . . 77
7.2.4 Substituting year-fixed effects with time trends . . . 79
7.3 Summary of the results . . . 81

8 Discussion **83**
8.1 Discussion of the results . . . 83
8.2 Limitations in the data set and empirical approach . . . 85
8.3 Suggestions for future research . . . 86
8.4 Implications of the study . . . 87

9 Conclusion **91**

Appendices **93**

A Results **94**

Bibliography **98**

List of Figures

2.1 Development of the EV fleet and EV policies in Norway between 1997 and 2013. . . . 14
2.2 Demand as a function of incentive changes in the years between 2000 and 2004. . . . 15

4.1 Negative Externality Causing a Market Failure 22
4.2 Positive Externality Causing a Market Failure 23

5.1 Norwegian counties 29
5.2 Regional development of electric vehicle sales share, Norway 2010-2014. 40
5.3 Development of electric vehicle sales share, Norway 2010-2014. 40
5.4 Share of electric vehicle sales in the extreme cases of Hordalanad and Finnmark, Norway 2010-2014. . . . 41
5.5 Regional development of charging points per capita, Norway 2010-2014. 42
5.6 Development in the sales share of electric vehicles and charging points per capita, Norway 2010-2014. . . . 43
5.7 Development in sales of electric vehicles and the cumulative number of charging points, Norway 2010-2014. . . . 44
5.8 Development in the sales of electric vehicles per capita compared to the total amount of charging points per capita, Norway 2010-2014. 45
5.9 Regional development of toll station expenses per car, Norway 2010-2014. 46
5.10 Regional development of ferry expenses per car, Norway 2010-2014 . . . 47
5.11 Regional development of bus lanes, Norway 2010-2014 47
5.12 Graphical correlation matrix for the dependent variable and the key explanatory variables 49
5.13 Graphical correlation matrix for the dependent variable and demographic variables 50
5.14 Graphical Correlation matrix for the dependent variable and county-fixed control variables 51

7.1 Identifying heteroskedasticity 71

A.1 Fossil fuel and electricity prices 96

List of Tables

5.1 Summary statistics of relevant variables 39
5.2 Yearly means for charging points per capita and relevant variables . . . 43
5.3 Yearly national means for toll and ferry expenses per car 44
5.4 Correlation matrix for all variables. 48

7.1 Nomenclature for regression variables 67
7.2 Regression results for electric vehicle adoption in Norway 68
7.3 Post-regression tests 69
7.4 heteroskedasticity Tests 72
7.5 Regressions results: no control variables. 73
7.6 Regressions results: specifying population density 75
7.7 Regression results: combining ferry and toll expenses 78
7.8 Regressions results: specifying time trends 80

A.1 Test for joint significance of time dummies 94
A.2 Regression results: no time dummies 95
A.3 Wooldridge test for serial correlation 96
A.4 Regression results: urban density 97

Glossary

Battery Electric Vehicle

Vehicle using a battery as its only fuel source.

Hybrid Electric Vehicle

Vehicle using a combination of fossil fuel and electricity as fuel. The electricity is generated as the vehicle is in motion.

Internal Combustion Engine Vehicle

Vehicle using either gasoline or diesel as fuel.

Plug-in Hybrid Electric Vehicle

Vehicle using a combination of fossil fuel and electricity with batteries that can be recharged.

Acronyms

BEV Battery Electric Vehicle.

EV Electric Vehicle.

FE Fixed Effects.

GHG Greenhouse Gas.

GSL Generalised Least Square.

HEV Hybrid Electric Vehicle.

ICEV Internal Combustion Engine Vehicle.

MASL Metres Above Sea Level.

MPC Marginal Private Cost.

MSC Marginal Social Cost.

OLS Ordinary Least Square.

PHEV Plug-in Hybrid Electric Vehicle.

POLS Pooled Ordinary Least Square.

RE Random Effects.

SSB Statistics Norway.

NPRA Norwegian Public Roads Administration.

TØI Institute of Transport Economics.

VKT Vehicle Kilometres Travelled.

WMO World Meteorological Organisation.

YED Income Elasticity of Demand.

1 Introduction

Climate change has been on the political agenda of a majority of nations around the world for an extensive period of time, and countless solutions have been proposed to diminish the problems caused by global warming. In recent years, climate change issues have become exceedingly pressing: global temperature records are being consecutively beaten, wildlife is going extinct en mass, coral reefs are dying and huge masses of people are being displaced from their homes and labelled environmental refugees. In the aftermath of the Paris Agreement of 2015, the debate on what specific national measures each country must undertake to combat climate change has become increasingly relevant as countries are trying to reduce their emission levels in the most efficient way.

Several countries have targeted the transportation sector in their pursuit of lower national emission levels. According to the U.S Environmental Protection Agency (2015), the transportation sector accounted for 26% of the total GHG emissions in the United States in 2014. Light-duty vehicles were responsible for 61% of these emissions. In the EU, the European Commission (2016) reports that around 12% of EU's total CO_2 emissions come from passenger cars. The Norwegian Environmental Agency reveal that emissions from road traffic accounts for 19% of Norway's total emissions (Miljødirektoratet, 2016). These emissions can most easily be cut by reducing the amount of transportation needed. In many developed countries, efforts to increase urbanisation are being made to reduce the overall need for transportation. Improvements in the efficiency of modes of transportation are being undertaken as fossil fuel vehicles are progressively becoming more efficient and their carbon footprint mitigated. By developing a well-functioning public transportation system and making biking a more viable transportation option, many countries are attempting to reduce emissions from road traffic by moving people over to less polluting transportation modes. Encouraging the adoption of zero-emission vehicles is yet another way governments attempt to scale down emissions from private transportation.

The electrification of passenger vehicles has generated a lot of interest over the past years. This has been due to the vehicles' prominence in peoples everyday life and the tremendous technological developments they have undergone over the past years. Improvements in battery technology have enabled Battery Electric Vehicles (BEV) to, on a single charge, drive distances comparable to those ICEVs drive on a full tank. Car manufacturers worldwide are investing large sums into the development of technologies for zero-emission vehicles in order to reduce the carbon foot print of their car fleet. There is a shift towards cars running on alternative fuels such as hydrogen or batteries and hybrids that run on a combination of electricity and fossil fuels. These zero-emission vehicles are being sold in unprecedented numbers, and are becoming increasingly common in countries such as France, Germany, the United States and many more. The development is helped by a range of policies promoting the green transportation shift implemented by the governments in those countries.

In recent years, environmental concerns has been the leading driver behind the spread of electromobility in Norway. In many large Norwegian cities, air quality has reached dangerous levels on cold days during the winter season (NRK, 2016). An example is the city of Bergen where a "seal of smog" is created over the city centre on cold days when the temperature drops to levels where local pollutant problems are attenuated. The Norwegian government has put electric vehicles high on the political agenda as part of the solution to lowering emission levels from the Norwegian transportation sector. Norway has committed itself to reducing the carbon footprint from its transportation sector in order to contribute to the global effort, albeit in a small way, and to combat the detrimental effects of local pollution in cities.

Norway is regarded by many as a success story when it comes to facilitating the adoption of electric vehicles. Compared to other European countries, Norway has had an unparallelled growth in the share of electric vehicles, both hybrids and pure BEVs. In 2015, the market sales share for EVs was between 15% and 20% (Figenbaum and Kolbenstvedt, 2016). A remarkable 69,100 electric cars were registered in Norway at the end of 2015, which constituted 2.6% of the Norwegian car fleet at the time (SSB, 2016i). From 2014 to 2015, the amount of registered electric vehicles grew by an astonishing 79% and from a share of only 1.6%.

Previous literature has found that without external stimulation, EV adoption is limited (Eppstein et al., 2011; Shafiei et al., 2012; IEA, 2013). Specially consumer subsidies has shown to be crucial for making EVs reach the mass market (Hidrue et al., 2011; Eppstein et al., 2011). This paper aims to contribute to existing literature by looking at the development in the Norwegian administrative regions in the time period 2010 to 2014 to investigate if, and to what degree, different consumer incentives have influenced the EV adoption rate. The purpose is to see if the government subsidies fulfil their objective of increasing the number of EV sales. We use panel data approaches, mainly pooled OLS, and explore demographic, geographic and economical aspects of the Norwegian counties.

We find that government intervention is successful in promoting EV sales. Specifically, an increase in BEV sales share by 3.05 percentage points is caused by adding one charging point to the charging infrastructure of a county. Also increased toll expenses turns out to be leading BEV sales, with an increase of 1000 NOK causing an increase in sales by 0.44 percentage points. The results are robust and the estimated coefficients vary only somewhat through a sensitivity analysis. Exemption from ferry fees and access to bus lanes do not prove significant in this analysis. Our results give an indication for policy makers of what incentives are efficient for driving forward EV sales in order to correct for a market failure, and provide foundation for future policy decisions in questions of how to reduce GHG emissions.

1.1 Research question

Based on the preceding orientation we aim to answer the following research question:

> *How did government intervention in the automobile market affect the battery-electric vehicle adoption in the Norwegian counties in the period between 2010 and 2014, and what regional differences influenced the adoption rate?*

The paper does not undertake the effectiveness of national financial incentives, such as the absence of the vehicle purchase tax, as this is not the aim of the paper and needs to be addressed with a different approach. Nor does the paper aim to quantify the effects of other influences that affected all counties in the same manner, such as fluctuations in price of gasoline or the development of the electric vehicle technology. The paper contributes to the existing literature by focusing on Norway and in analysing the development of EV-adoption rates across counties over time.

The remainder of this paper is organised as follows: In section 2 we lay out the historical development of the Norwegian EV-market and describe the government's role in the progress. Section 3 provides a literature review where we describe the academic foundation on which our research is based, and identify our contribution on the topic. In section 4 we put forward and discuss the theoretical background for the analysis. The process of building our data set, together with descriptive statistics and a correlation analysis is presented in section 5. Section 6 outlines the empirical approach of our analysis. The results followed by a sensitivity analysis are presented in section 7. Finally, in section 8 we discuss our findings, shortcomings and implications before we conclude the paper in section 9.

2 Historical development

The Norwegian EV adventure has been long and turbulent with varying degree of intervention from the government. To set the stage for our analysis and connect the past with the present, we portray the history of EV adoption in Norway.

2.1 The market phases for electric vehicles in Norway

Figenbaum and Kolbenstvedt (2013) divide the development into five distinct phases: concept development, test, early market, market introduction and market expansion phase.

The journey began with the concept development phase in the 1970's when prototypes of electric vehicles started being developed in Norway. Norway also imported its first EV during this period (Asphjell et al., 2013). The EV market was at this time promoted as a niche for a selected few interested in electromobility. Environmental concerns were not prioritised by individuals buying the first electric vehicles. Incentives and measures were limited to research funding.

The concept development phase moved over to the test phase around 1990. Now the emphasis was on testing the technology and lowering the barriers to purchasing an electric vehicle. A milestone achieved in this period was the registration of the first electric vehicle in the Norwegian Motor Vehicle Register. The government started introducing incentives for EV adoption: exemption from registration tax (1991), free parking (1993, -1998), reduced annual licence fee (1996), road toll exemptions (1997) and reduced imposed taxable benefit on company cars (1998).

The period between 1999 and 2009 is considered the early market phase. Large firms became active in the Norwegian market, as Ford bought Norwegian manufacturer Think and several wealthy Norwegian investors took an interest in promoting the growing EV trend. The phase was characterised by a volatile demand pattern for EVs, as policy makers further experimented with different incentive options such as bus-lane access and no road tolls. Exemption from the 25%-value-added-tax was introduced in 2001 and from ferry tickets in 2009. The period culminated in the financial crisis in 2008, which left Think Motors in dire straits because it was on the verge of releasing its new generation of think City models.

In 2009, the established automotive manufactures plunged into the struggling Norwegian market, making way for the market introduction phase. Norwegian manufacturers were pushed out of the market by the bigger companies as both Think and Pure Mobility went bankrupt in 2011. The Norwegian market was on the rise with more competition, larger volumes and decreasing prices, attracting consumers showing interest in EVs with technology and attributes that were more similar to their ICEV counterparts. Noteworthy models like the Nissan Leaf and the Mitsubishi I-Miev were introduced to the Norwegian market. These were influential models because they were technologically much more similar to ICEVs and they were priced at a level that made them affordable to people who were not solely motivated by the climate aspect. In 2011, the first publicly available fast chargers went on-line and the charging infrastructure in Norway was on the rise. The rapidly developing of new charging points, and the fact that most of the current incentives were in place combined with steady supply of vehicles from the major manufactures, ensured that barriers to buying an EV had never been lower.

The market expansion phase, which the market is currently in, was entered in 2012 and is characterised by strong demand. Popular brands, such as the Nissan Leaf, have become widely available and additional manufacturers are entering the market, increasing the supply and reducing the prices of EVs. The market is expected to grow in the coming years as EVs are becoming more attractive through increased battery capacity and improved charging infrastructure. A report from the Norwegian transport agencies (Transportetatene, 2016) on the content of the upcoming National Transport Plan states that all new vehicles registered in Norway after 2025 should be zero-emission vehicles. At the same time, the incentives from the government are expected to be reduced as sales volumes increase.

2.2 The role of the government

Throughout all of these phases, the government has played a crucial role in terms of its support, or lack of thereof, for the EV industry. The government went from having little interest in the EV industry and the spread of electric vehicles to having a defining role in making Norway the most EV-friendly country in the world. In later years, a range of policies have been introduced and projects initiated aimed at increasing the share of EVs in the Norwegian car fleet. Figure 2.1, adapted from a report by Fearnley et al. (2015), shows the development of the electric vehicle sales in Norway along with EV policy introductions and other important historical events in the Norwegian EV history.

In the early stages, there was little support from the government to invest in the Norwegian companies that at the time were developing concepts for electric-propulsion

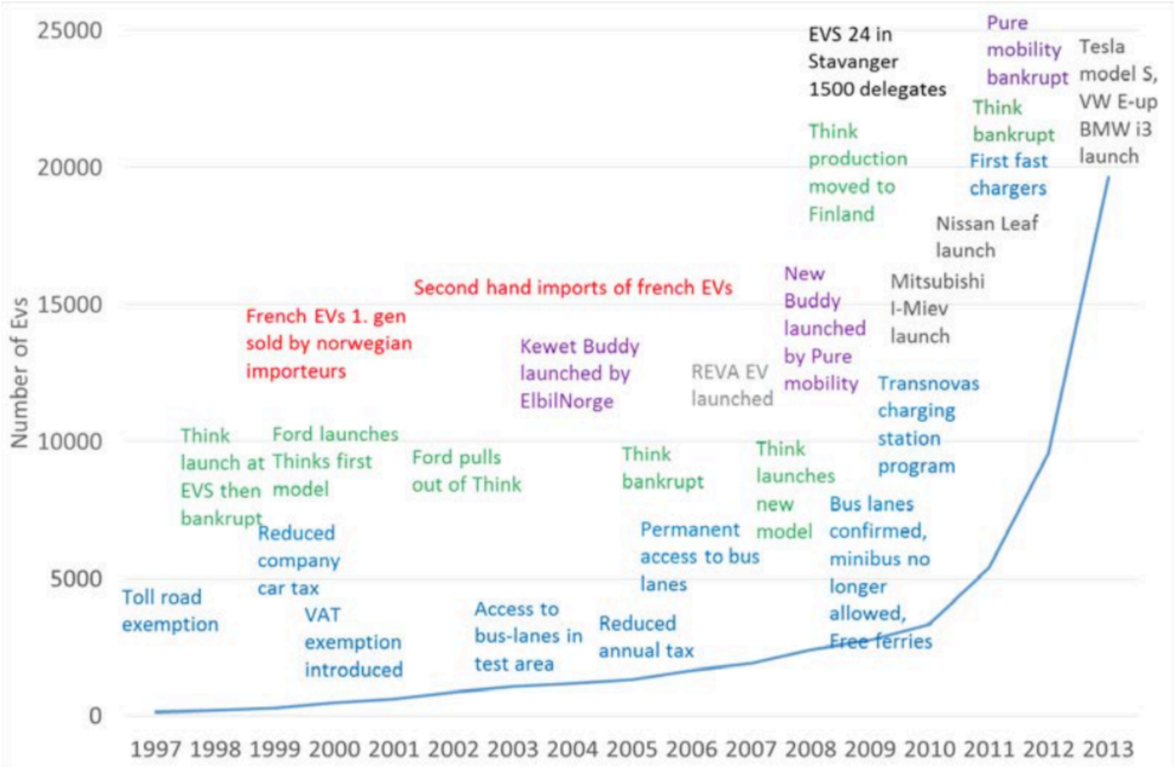

Figure 2.1: Development of the EV fleet and EV policies in Norway between 1997 and 2013. ***Source: Fearnley et al. (2015, fig. 2.2)***

vehicles. The need to find an alternative transportation fuel was strong as the 1973 oil embargo had cut off the oil supply to the western world leading to a spike in oil prices[1]. However, the lack of government intervention led to the companies going bankrupt before large-scale production could be initiated and therefore the Norwegian EV industry missed a golden opportunity to develop into a world-leading industry.

The following periods did not see an increase in government support of the developing EV market in Norway. On the contrary, it actively opposed it by refusing to exempt electric vehicles from the high value based tax on the registration of vehicles, which made it very expensive and practically impossible to buy an electric vehicle in Norway. The environmental group Bellona had to actively challenge the Norwegian legislation before electric vehicles were finally made exempt in 1991 (Figenbaum and Kolbenstvedt, 2013).

In the early market phase the government finally decided to support EV adoption and as a result demand for EVs grew tremendously in this period. Figure 2.2, adapted

[1]In 1973 the members of the Arab Petroleum Exporting Countries instigated an oil embargo in response to the American involvement in the Yom Kippur War (Store Norske Leksikon, 2014).

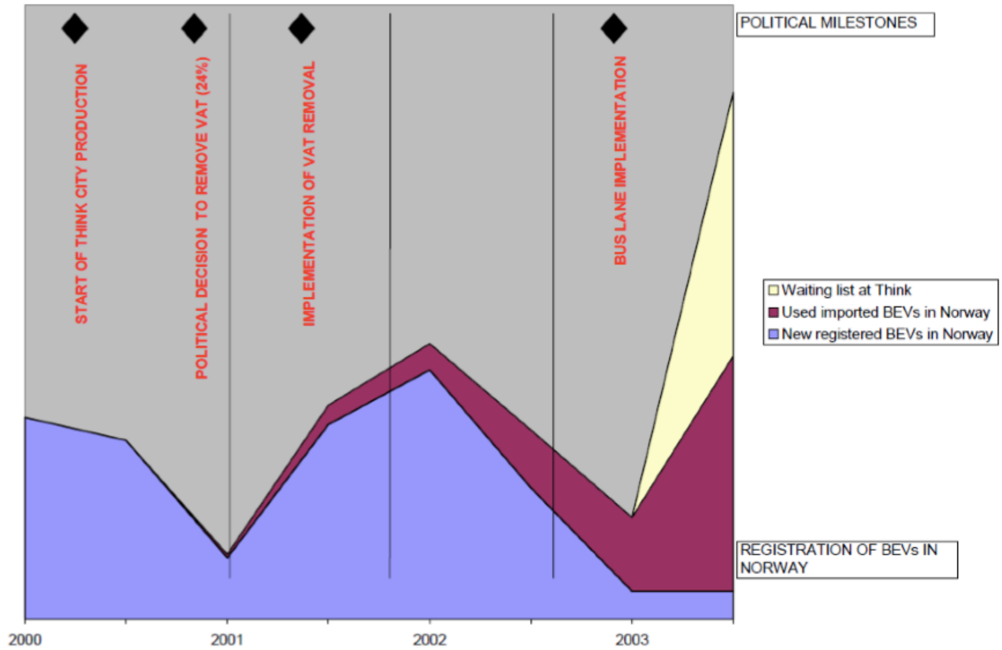

Figure 2.2: Demand as a function of incentive changes in the years between 2000 and 2004. ***Source: Figenbaum and Kolbenstvedt (2013, fig.11)***

from Figenbaum and Kolbenstvedt (2013), show how the growth in number of registrations of EVs closely follow first the implementation of the VAT removal and then the opening of bus lanes for the EVs, clearly indicating the importance of the government's involvement. The government continued to introduce new policy measures and people continued to buy more EVs as the financial incentives soon outweighed the lack in comfort and technology EVs suffered from compared to ICEVs. The government push for EVs was crucial at this stage as the cars were not competitive with ICEVs and could only appeal to those with a special interest in that type of car. This new-found political will to promote the EV industry arose as a result of a wish to establish a sustainable electric car industry in Norway, an opportunity missed in the 1970's. However, the dream of world-leading Norwegian manufacturers had faded away. Entering the market introduction and market expansion phase the political focus shifted towards reducing GHGs rather than pushing forward for a Norwegian-rooted industry. Climate issues became more prominent on the political agenda in Norway. Transnova[2] was established and the project's most important contribution to the Norwegian EV market was its support of charging-infrastructure development across Norway. Through Transnova, the

[2]Transova was a government project established in 2009 that promoted more energy efficient modes of transportation through supporting test projects for new technologies. Enova assumed the responsibilities of Transnova in 2015 and the project was disbanded (Enova, 2009).

government played an active part in developing an extensive charging network across Norway. This development was made possible by an economic stimulation package introduced by the government in 2009 in the wake of the financial crisis (Finanskomiteen, 2008). The public spending also created a closer connection between the energy industry and the EV market as the former became more involved in the development of the charging infrastructure.

In the last phase, local governments at the municipal and county level were important contributors to the growing number of EV registrations. Many of them are working on replacing parts of their car fleets with electric vehicles to reduce their carbon footprint. However, as the market is maturing quickly, faster than most have predicted, several counties in Norway have started removing local incentives, such as reduced ferry tolls and access to bus lanes. In Oslo, EVs no longer have unrestricted access to bus lanes as they are creating traffic jams and obstructing the bus routes. Additionally, the Norwegian government is considering minimising the economic incentives for electric vehicles because of the maturity of the market. It is suggested that an expiry date should be set for the various EV tax exemptions. There is a growing political consensus across the political parties that the the government has played its part in the Norwegian EV adventure and that the market is now able to grow on its own without public investments.

With the public incentives disappearing or being partly removed, the Norwegian EV adventure's continued development will depend on how influential the government intervention has been throughout the years, from the early phases up until today, and how important it will be in the future. The climate problem is far from being solved. However, increasing the share of electric vehicles in the Norwegian transportation sector is no longer unanimously considered the responsibility of the government. Some political parties are also questioning the efficiency of the costly government investments. The market seems to be growing on its own and investments might therefore be applied to other parts of the economy where it may have a larger effect on reducing emissions. It is therefore of interest for policy makers to quantify and evaluate the return of earlier investments made in the EV industry. In addition, it is valuable to determine important regional characteristics across Norway that can explain why adoption rates have been high in some regions and identify why these regions might have benefited more from the government intervention than others. This information might help Norwegian legislative bodies, both local and national, wishing to maintain the growth in EV share, assess what incentives should be kept in place and which ones should be replaced by more efficient schemes.

3 Literature review

There has been done much research on electromobility seeking to determine the economical and financial barriers to EV adoption. Some researchers have assessed the effectiveness of national policies by comparing different countries and their EV adoption rates (Sierzchula et al., 2014; Lutsey, 2015), others have looked at regions within a country (Malvik et al., 2013; Mersky et al., 2016). Several reports use consumer surveys to identify characteristics of the typical EV owner as a basis for further analysis (Egbue and Long, 2012; Hackbarth and Madlener, 2013; Fearnley et al., 2015; Figenbaum and Kolbenstvedt, 2015). In this section we go more in depths of the academic foundation that already exists in the field of electric vehicle adoption and place our contribution in the literature.

Previous research that compare national policies and their effectiveness among countries find charging infrastructure to generally be an important driver for BEV sales. In an analysis of 30 electric-vehicle markets around the world, Sierzchula et al. (2014) infer that financial incentives work together with a well-established network of charging stations to promote high EV adoption rates. However, they note that the presence of these two factors do not alone ensure high electric-vehicle adoption rates. The authors point out that financial incentives and charging infrastructure might represent other dynamics that influence EV development. Additionally, they find that characteristics unique to each country explain some of the cross-national variation. This supports the focus we have on cross-county characteristics. Education and income were not found to be significant factors determining EV adoption rates by Sierzchula et al. (2014). However, they argue that this may have been due to EV markets representing a small share of the countries' total car sales. These socioeconomic variables might be better indicators for EV adoption at the county level than they were at the country level. Sierzchula et al. (2014) uses an ordinary least square regression to analyse single cross section of the different EV markets, meaning that they only consider a single year and hence the development of influential factors studied is ignored.

Consistent with the conclusions made by Sierzchula et al. (2014), Lutsey (2015) states that national planning on electric vehicle adoption and development support, such as charging infrastructure, are necessary conditions for a car market to promote EV adoption. The report examines the global transition to zero-emission vehicles, and includes a comprehensive analysis of national policies on EV adoption around the world. The report aims to identify best practises for electric vehicle adoption and encourages increased international cooperation to accelerate the adoption of BEVs. Lutsey repeats the idea of Sierzchula et al. that conditions such as development support (charging infrastructure) are not necessarily sufficient for high EV adoption rates in a country, and that other factors might play important roles in driving the development of the EV car fleet. This is an important point for our analysis as we seek to find the effect of charging infrastructure in our analysis. Lutsey further mentions Norway along with California and the Netherlands as markets where substantial government action plans have been powerful driving forces behind the growth of the EV fleet, resulting in markets where the electric vehicle deployment is ten times the international levels. The report emphasises the importance of an extensive charging network, public and private, in driving EV adoption.

Much of the research on EV adoption has focused on Norway specifically, due to the remarkably high share of electric vehicles in the Norwegian car fleet. Much of the research originates from the institute of transport economics in Norway (TØI) and we have drawn inspiration from these studies in our work. In a TØI report assessing the cost-effectiveness for different EV policies, Fearnley et al. (2015) define free toll roads and access to bus lanes as crucial factors in explaining the EV market development. The report labels fast charging stations and financial support for charging stations as less important factors or only important in some market niches. The authors disregard reduced rates on ferries as a factor influencing EV adoption and deem it a factor which up to 2013 was not important. These labels have emerged from analyses based on stakeholders' stated preferences that might not express the true effect of the incentives. In our analysis we look at actual sales numbers with the aim to address the influence of incentives more objectively. By looking at sales numbers we avoid a common problem in surveys where the stated preferences often deviates from the action taken by the respondents. The report goes on to underline the importance of supply-side improvements in order for the EV market in Norway to grow. This points is echoed in a report by Malvik et al. (2013) where supply-side issues are mentioned as an obstacle to widespread adoption of EVs in Norway prior to 2011/2012. This time period is mentioned specifically as more technologically mature EVs, like the Nissan Leaf, were introduced in the Norwegian market in these years. Malvik et al. state that in Norway the success formula has been a policy mix containing financial incentives combined with with incentives like access to bus lanes, free usages of toll roads and a well-developed charging network.

In a paper analysing electric vehicle sales on a regional scale in Norway, Mersky et al. (2016) only find charging infrastructure and income to have large predictive power for the growth of BEV sales. The authors do not find any evidence of other factors such as access to bus lanes and toll roads to be significant drivers of EV adoption, suggesting that the required incentive mix for successful EV adoption in Norway, suggested by Malvik et al., is not necessarily as extensive as indicated. Mersky et al. underline that the relationship between charging points and EV sales on the regional level is not beyond doubt causal, expanding on the points made by Sierzchula et al. and Lutsey. In our analysis, we hope to be able to better determine the causality by examining the development over time. Mersky et al. analyse the sale of battery-electric vehicles in Norway on a regional and municipal scale where they group the sales statistics for each year, along with other variables, together and set 2012 as the midpoint for the analysis. Using only a single cross section of Norwegian counties and municipalities limits the analysis' ability to assess the development over time. The paper struggles to produce meaningful estimation results on the municipal scale as the data did not provide a sufficient amount of data points; there were not enough sales at this scale to carry out a comprehensive analysis. Seeing as this paper had access to the same sales information as us, this was also an issue for our analysis and prompted us to consider alternative approaches.

Supply-side issues such as the technological inferiority of BEVs in the early stages and how consumers react to this, has been the topic of several research papers. Egbue and Long (2012) find in a survey that technology enthusiasts will only be early adopters of EVs if they find them to be superior in performance to ICEVs. In the years before 2011, the EV models being sold in Norway were inferior to ICEVs and were far from being close substitutes to them. This might have dissuaded technology enthusiasts that were considering buying an EV. Technology enthusiast as early adopters represent an important group as they will often facilitate the dispersion of new technologies by creating the initial demand. Steinhilber et al. (2013) study EV markets in Germany and the UK, and underline how technological shortcomings of EVs act as a barrier to widespread EV adoption. Steinhilber et al. add consumer scepticism as another limiting factor. A product that has yet to be adopted by a large share of early adopters, such as technology enthusiasts, will appear as an uncertain investment and unappealing to a majority of consumers. The study by Steinhilber et al. is based on interviews with stakeholders and evaluate their opinions on various topics concerning EV adoption.

The range limitations of EVs is one aspect that distinguishes them from traditional vehicles and which has made consumers reluctant to purchase EVs. Hackbarth and Madlener (2013) claim that closing the range gap between EVs and other vehicles in the German market, will have a similar effect on EV adoption as policy interventions. They also find that households would be willing to pay considerable amounts for improved driving range. The paper uses survey data from 2011, which was a time period where BEVs were still considerably inferior to ICEVs in technological terms. This might explain why the research found improvements to the BEV characteristics to be so important to the respondents. The technological progress of EVs has been tremendous over the past years and the development can help explain the extreme growth in EV adoption in Norway in recent years. A survey by Figenbaum and Kolbenstvedt (2015) supports this idea by stating that the changes in the EV technology has been a key element promoting diffusion of EVs across Norway. The report outlines how an EV in 2014 is notably different from earlier years: its characteristics more resemble those of ICEVs in terms of price, comfort and safety, among other factors. The fact that more popular brands started selling EVs in Norway is also highlighted as an important element facilitating the diffusion of electric vehicles. This emphasises the importance of taking the historical development into account in our analysis; failing to do so may affect our results considerably.

We bring with us knowledge and inspiration from the presented literature in the decision of what factors to include in our analysis. Charging infrastructure and financial incentives together with a historical technological development appear to be the most important elements to take into consideration. We contribute to existing literature by looking closer at the Norwegian regions over time, and by adding climatic and geographic aspects to our analysis.

4 Theoretical background

Before we move forward with a description of the data gathered for our analysis and the methods applied, it is useful to place the grounds of government incentives for BEV sales in an economic theoretical perspective. In this section we describe market failure and how this is the basis for government intervention in an otherwise simple demand function.

4.1 Market failure

As mentioned in the introduction, many governments are encouraging the adoption of electric vehicles through policy interventions. Such interventions aim to correct a perceived market failure in the private transportation sector. A market failure exists when the allocation of goods or services is such that the social optimum is not reached and it is generally caused by externalities. In the case of electric vehicle adoption, the failure can be described in two ways. Firstly, as a result of the external costs to society from car pollution not being accounted for by the market forces and thus causing a welfare loss due to a negative externality. The rational economic agent will not take into account the negative externalities of driving a polluting car and therefore have a lower perceived cost of doing so compared to the cost incurred by society. Another way of defining this market failure is to attach a positive externality of reduced pollution levels to the use of electric vehicles. The rational economic agent would only consider its own benefit when faced with the choice of buying an electric vehicle and there would hence be a gap between the point where private benefit and social welfare is maximised. The government can attempt to correct the market failure by influencing how the market valuates pollution and abatement to align the incentives of private consumers and society.

To correct the market failure resulting from a negative externality, the external cost to society from ICEV pollution must be internalised. To do this, the authorities can tax the ICEVs either at the point of purchase or by making it more expensive to use them. By taxing vehicles with high emissions and fuels that cause pollution, consumers are forced to take into account the negative environmental side-effects of their activity. A graphical representation of this situation is shown in figure 4.1. In the graph, the x-axis represents the demand for ICEVs while the y-axis represents the price. The marginal social cost (MSC) and the marginal private cost (MPC) curves represent supply. Marginal private benefit (MPB) and marginal social benefit (MSB), which are set equal to each other to simplify the framework, represent demand.

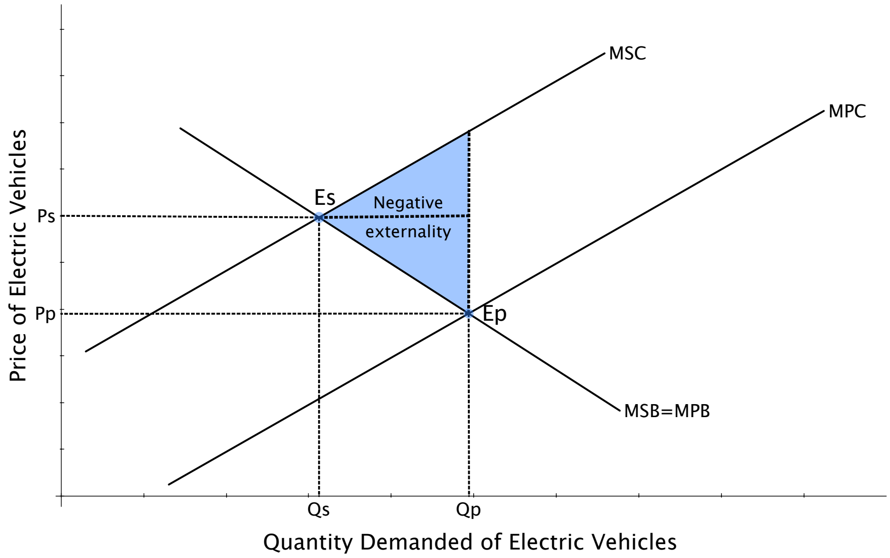

Figure 4.1: Negative Externality Causing a Market Failure

Figure 4.1 shows how a discrepancy between the MSC and MPC, caused by a negative externality, results in a market failure. Without government intervention, the market will demand a quantity Qp of ICEVs as it perceives it to have a price Pp in equilibrium (Ep). In reality however, the negative externality means that the consumption and use of ICEVs have a cost to society such that the real price to society is Ps. It would therefore be optimal to "consume" a quantity of Qs ICEVs in order to maximise the social welfare. Since Qp is larger than Qs, there will be a higher consumption level of ICEVs in the unregulated market equilibrium than what is socially optimal. Taxing the ICEVs would effectively shift the MPC curve to the left towards the MSC curve and the socially optimal point of Es. Reaching this point would require perfect information for the agency setting the tax and is thus very unlikely to be achieved.

A positive externality also results in a market failure by causing the market to under-provide a good or service that has an added social benefit, which the rational agent does not take into account. This market failure is represented in figure 4.2. To simplify the example, the MSC and MPC have been assumed to be equal. The MPB and MSB curves deviate as BEVs are evaluated differently by consumers and society. In this case, the quantity supplied by the market (Qp) is below the social optimal one (Qs) because the private market does not recognise the added benefits of electric vehicles from reduced emissions. We thus end up in a marked equilibrium (Ep) with a demand for electric vehicles below the social optimal equilibrium (Es).

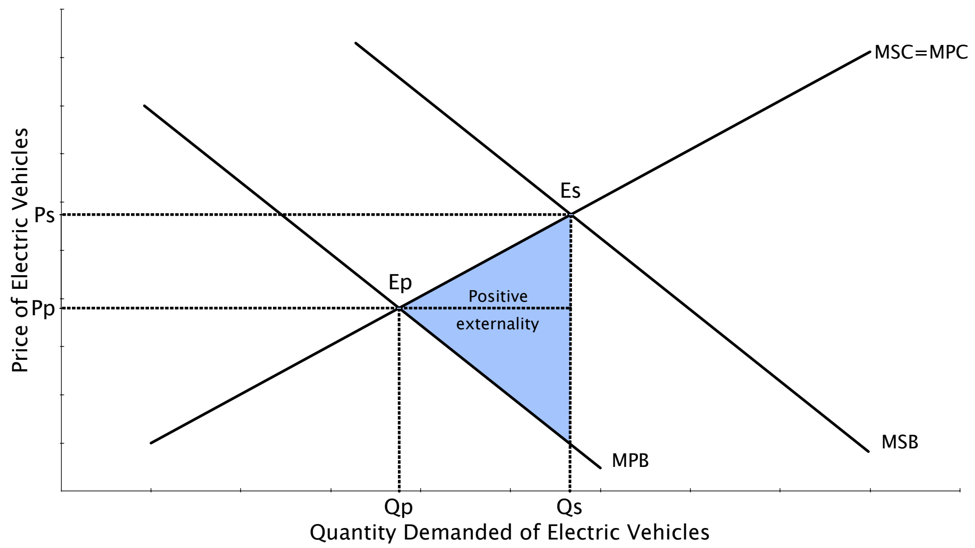

Figure 4.2: Positive Externality Causing a Market Failure

To correct for this failure, the government can shift the MPC or the MPB curve to the right, increasing demand towards the social optimal point. The MPC curve can be shifted by policy interventions that reduce the prices of electric vehicles, either directly through subsidies that make the purchase price lower, or indirectly through toll exemptions, for example. Again, we stress that the social optimal equilibrium (Es) is purely a theoretical one and as such it will be nearly impossible for the government to adjust the market to this point. It is rather a theoretical optimum used to illustrate the intention of the government in implementing policies that increase the adoption of BEVs or reduce the prevalence of ICEVs.

Policy interventions come at a cost to society and can potentially reduce welfare if not implemented efficiently. Subsidising electric vehicles requires funding that can be used in other sectors to increase welfare. When correcting a market failure this trade-off needs to be considered. For the government intervention to increase net welfare, the loss in welfare from the sector where resources are reallocated from should be offset by the gain in welfare from the market where the failure is corrected. In this particular case, the gain in welfare from increasing the share of electric vehicles on Norwegian roads through costly incentives should offset the loss in welfare caused by other sectors losing resources. It is hence of interest to correct the market failure as efficiently as possible, meaning that the resources are used on the means that increase the share of electric vehicles the most. To do this, the factors that have had a large impact on the share of electric vehicles in Norway must be identified. It should be underlined that this paper does not seek to quantify the potential welfare gain from increased BEV sales, nor does it attempt to find the optimal equilibrium point of how many BEVs there should be in the Norwegian car fleet. The aim is to examine what factors have been important for BEV adoption, and whether policy interventions have contributed to reducing the market failure.

4.2 Modelling demand

A fundamental element in answering our research question is to find a proper way to model the demand for battery-electric vehicles. In economic theory the simplest way to model demand is by a function solely depending on income and prices:

$$Q = f(I, \mathbf{P}) \tag{4.1}$$

where Q is demand, f is the function symbol, I represents income. $\mathbf{p}$ represents a vector of prices, for example the price for the good in focus, the nearest substitutes and complementing goods. The equation models how the quantity demanded of electric vehicles will be a function of the income of the consumer and a vector of prices.

When modelling the effects of income and prices on the demand of a good, it is necessary to classify the good in terms of elasticities. We can divide goods into three categories based on income elasticity of demand (YED). A good's YED measures the responsiveness of demand to changes in income, and the three broad categories of goods are:

- **Inferior goods** - Demand falls as income increases: negative YED.
- **Normal goods** - Demand increases as income increases: YED greater than zero.
- **Superior goods** - Demand increases more than proportionally as income rises: YED greater than one. A superior good is a type of normal good.

The characteristics of EVs have varied over time and across models. In the early years before 2011, almost all EV models sold in Norway were inferior to ICEV models in terms of range, safety and comfort - however, it would not be reasonable to label them inferior goods solely based on this observation. They were considerably more expensive than ICEVs in the earlier market phases and one would not expect consumer demand for EVs to increase with reduced income, contradicting the definition of an inferior good. It is improbable that a consumer would choose an EV over an ICEV if faced with reduced income. If income was a strict constraint for consumption, it is likely that a used ICEV would be preferred to a new electric vehicle. It is therefore more accurate to define EVs as a normal good that consumers demand more of as their income rises.

In equation 4.1, this entails a positive relationship between the income variable I and quantity demanded Q.

In addition to being a normal good, EVs can in some situations be considered a superior good. EVs are often purchased as a secondary car for a household due to its limitations compared to ICEVs. Until the household income have reached a level sufficient to justify buying a second or third car, BEVs are not an option. More modern electric vehicles, such as the Tesla model S or X, have comparable driving ranges to ICEVs and some are even technologically superior to ICEVs. Some of these modern EV models are also considered symbols of both status and green virtue, strengthening the argument for defining them as superior goods.

Having labelled EVs as a normal good, we are interested in examining how changes in purchasing power affect the consumer's purchasing pattern. Purchasing power is dependent on both the income and price components in equation 4.1. We are examining government interventions in the EV market that influence the relative prices the consumers face. The government intervenes in the market to increase the demand for BEVs to rectify the before-mentioned market failure. To increase demand, the government can either influence the price of the BEV itself, or the price of fossil-fuel vehicles, which are substitutes for electric cars. Alternatively, it can attempt to influence the price of goods that are complementary to BEVs. Following standard economic theory, demand for electric vehicles will increase with reduced prices or reduced prices for complementary goods. Increased prices of substitutes will increase demand for BEVs.

It is important to accentuate that we are not simply evaluating the sales prices of BEVs, but the total cost a consumer faces when buying and owning an EV. This includes purchase price, fuel prices, prices of substitutes and several other factors. Considering this, the vector $\mathbf{p}$ can be divided into separate price vectors for BEVs, substitutes and complements. An expanded form of equation 4.1 takes on the following form:

$$Q = f(I, \mathbf{P_{BEV}}, \mathbf{P_{ICEV}}, \mathbf{P_{comp}}) \tag{4.2}$$

The vector $\mathbf{P_{BEV}}$ has a negative relationship with quantity demanded, and includes the actual selling price of the electric vehicle along with all other factors affecting the price of buying and owning a BEV. This includes incentives that represent economic benefits that reduce the perceived price: reduced expenses from passing costless through toll stations and free access on ferries. Time saved from access to bus lanes can reasonably be assigned a monetary value as it is conventional to assume that it provides utility to consumers. One could therefore argue that free access to bus lanes reduces the perceived price of BEVs. On the other hand, for some consumers this incentive is perhaps just a convenience factor that can supplement the demand equation as an extra comfort aspect of driving a BEV instead of an ICEV.

Vector $\mathbf{P_{ICEV}}$ from equation 4.2 includes the prices of every type of good that can be considered a substitute to an electric vehicle. This is mainly fossil-fuel based cars, but can also include Hybrid Electric Vehicles (HEV) and Plug-in Electric Vehicles (PHEV). The price vector for substitutes represents a vector containing all the factors affecting the cost of purchasing and owning an ICEV, not just the sales price. The vector has a positive relationship with quantity demanded of electric vehicles. The government can influence the price vector for ICEVs by for example imposing a tax on fuel prices. This will have a positive effect on the quantity demanded of electric vehicles.

The third vector $\mathbf{P_{Comp}}$, represents prices of complementary goods typically used together with electric vehicles, such as public charging stations. Inadequate charging availability infers more range anxiety, which can be interpreted as an increase in the price of the complementary good. The vector is negatively related to quantity demanded as an increase in the price of a complement would reduce the demand for electric vehicles.

Price elasticity of demand measures how responsive the demand for a product is to changes in the products price. Elastic demand would imply that the demand for a product changes proportionately more than the price, while the opposite is true for a product with inelastic demand. In a paper analysing demand and supply in the U.S automobile industry, Berry et al. (1995) find that demand for all car models studied is elastic. The study did not include any electric vehicles, but as they are close substitutes for ICEVs, it is natural to assume that demand for battery electric vehicles is also elastic. Furthermore, as they are such close substitutes, their cross elasticity of demand is likely to be elastic. This implies that government actions affecting the prices of both electric and conventional vehicles will have a large impact on the demand for BEVs, in theory.

Understanding how consumers change their purchasing patterns based on government's incentives requires knowledge of the attributes of the incentivising factors. The psychologist Frederick Herzberg 1959 models a two-factor theory for a work place, which can also be used to describe the market for EVs. Herzberg (1959) states that there are certain factors in a workplace that actively promote satisfaction on the job, he calls such factors motivation factors. Hygiene factors, on the other hand, do not promote satisfaction but cause dissatisfaction if not present. In comparison, there are some factors in the EV market that actively incentivise the purchase of BEVs, such as exemption from the registration tax and toll and ferry fees. Other elements can prevent purchase if not present rather than incentivise it if present. Charging stations and adequate driving range can be argued to be such elements. This argument coincides with the literature mentioned previously which found charging infrastructure to not necessarily be sufficient to drive forward EV adoption alone (Sierzchula et al., 2014). This case can be compared to petrol cars and gas stations: consumers are not likely to demand more ICEVs in the presence of more gas stations, but they certainly would be dissuaded from buying one if there were not a sufficient amount present. Having hygiene factors in place for EVs make them better substitutes for traditional ICEVs. This implies a higher cross elasticity of demand and consequently a higher impact of $\mathbf{p_{ICEV}}$ on the demand for electric vehicles in equation 4.2. Assuming that charging stations is a hygiene factor, the government will only be effective in correcting the market failure by building charging stations up until the point where the consumers perceive the network as sufficiently developed.

Another factor motivating EV purchase, which is not depicted in a simple demand function, is risk aversion. A risk averse individual facing a choice between a one-time certain expense and the same expected, but uncertain expense, will always choose the certain alternative. In the market for passenger cars, EVs have a higher purchase price, but combustion engine vehicles are more expensive to maintain, run on a more expensive fuel, and pay higher fees for parking, tolls and ferries. Some consumers may prefer the higher one-time certain expense. For a family that needs to keep track of their budget and expenses, an EV could be a more reasonable purchase. There are fewer unforeseen maintenance expenses, gasoline prices do not matter and this means that the risk of buying and owning an EV is significantly lower compared to ICEVs. At the same time, ICEVs are more widespread and are therefore considered a safer purchase. In the early periods when BEVs represented a much newer technology with more limitations than ICEVs, they were likely to dissuade risk averse consumers. The relationship between risk aversion and EV sales is not something we aim to model in this paper. It is however worth noting that risk preferences might be an underlying factor affecting a consumers valuation of incentives and consequently the relative price of a BEV.

We aim to expand the simple demand function into a more comprehensive model of the factors influencing the demand for BEVs. We decompose equation 4.1 and include variables that influence the demand for BEVs through the income and price variables. Through this analysis we aim to identify some components of the demand function for battery-electric vehicles, by examining government incentives' effect on relative income and prices across the Norwegian counties.

5 Data

In order to model the effect of government incentives and regional differences on BEV adoption we have constructed a comprehensive panel data set. This section describes this panel data set in three parts. The first part outlines how the data set used in the analysis was built by describing where information was found and presenting the purpose of each variable. The section's second segment presents summary statistics for the data set we built and discusses major trends for our key variables. In the third part of the section we carry out a correlation analysis to get an initial impression of the relationships between the variables.

5.1 Building the data set

The starting point for this analysis is a data set on vehicle sales statistics obtained from the Norwegian Road Federation (OFV). OFV is a politically independent member organisation lobbying for safer and more effective road systems in Norway. The data was obtained through Gunnar S. Eskeland and SNF/CenSES[3].

Additional data was collected from various sources. All monetary values have been adjusted for inflation by using the consumer price index, which was retrieved from SSB (2016g). All demographic data was obtained from SSB's database. Following is a review of the data used and its respective sources.

5.1.1 Spatial and time dimension

Norway is separated into 19 administrative regions also called counties, which represent the first-level geographical division of the country. A map displaying this division is presented in figure 5.1. Our study focuses on this regional separation because there are still too few electrical cars sold per municipality to find significant results at that level. As mentioned earlier, the study by Mersky et al. (2016) found that their municipal models had significantly decreased goodness of fit compared to their county level models. This motivated us to focus on the county level.

[3]SNF (Samfunns- og næringslivsforskning) is the centre for applied research at NHH (SNF, 2016). CenSES (Centre for Sustainable Energy Studies) is a research centre for environmentally friendly energy, and is a collaboration between NTNU, UiO, SINTEF, IFE, NHH, SNF and Høgskulen i Sogn og Fjordane (CenSES, 2016).

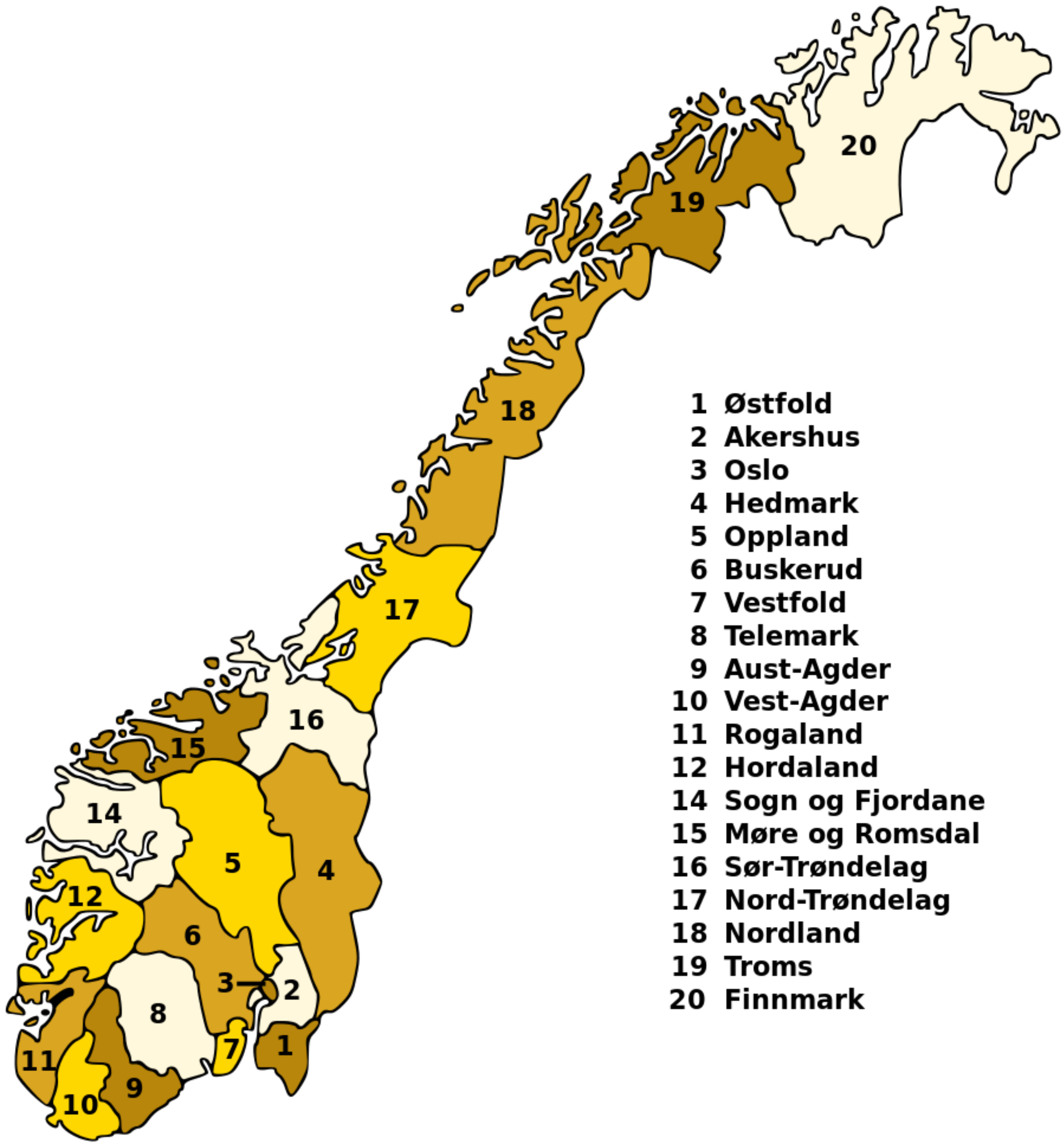

Figure 5.1: Norwegian counties

Reprinted from Norges Fylker, In Wikipedia, n.d., Retrieved October 28, 2016, from *https : //no.wikipedia.org/wiki/Norge_fylker*. ***Reprinted under Creative Commons Attribution ShareAlike.***

There were several reason behind using 2010 to 2014 as the time period for this study, the main one being data availability of key variables. Firstly, sales of electric cars did not reach significant levels regionally in Norway until after 2009/2010. Additionally, data on charging points was not available prior to 2010, meaning that earlier numbers would have had to be extrapolated. Other motives for our choice of time period were of a more theoretical nature. Figenbaum and Kolbenstvedt (2013) describe how 2009-2011 was a period characterised by early market development for EVs in Norway. The purpose of this analysis was to assess drivers in a market approaching maturity in order to correctly identify statistical relationships. A market still in its infancy will have sales statistics influenced by early adopters and innovators, presumably creating a barrier to determining the true influence of the factors studied in this paper. However, the analysis also needed to accurately depict the development in each county and a relatively early market stage was hence needed. Considering this, 2010 was deemed expedient as the initial year as it is the medial year in the early market phase described by Figenbaum and Kolbenstvedt (2013).

5.1.2 Sales statistics

As previously mentioned, sales data was obtained from OFV. The data set contains monthly municipal sales statistics for electric vehicles in Norway between 2006 and 2014. This includes BEVs, HEVs and PHEVs. The data distinguishes between different car models, manufacturers and characteristics such as engine power and transmission type. For us, the most important characteristic was the fuel classification for each vehicle sold, which helped us identify which vehicles were electric. We chose to only look at the sales of pure electric vehicles (BEVs) and not include PHEVs or HEVs in our analysis as they have different incentives for purchase and would disrupt the analysis and interfere with our results.

To model sales of electric vehicles, we first aggregated the sales data for each county so that we obtained the total sales of vehicles, in each year. The total sales included sales of all types of vehicles: PHEVs, BEVs, EVs and ICEVs. We then calculated the total sales of battery electric vehicles in each county for each year. We used information about the fuel type for each vehicle to identify what cars were electric. To obtain the share of electric vehicles sold in each county every year, we divided the total number of cars sold by the number of battery-electric vehicles sold.

To investigate the relationship between BEV sales and the other variables, we chose to specify our dependent variable as the sales share of BEVs. We did this to more accurately model how the demand for electric vehicles is affected by the different explanatory variables; a sales share more closely depicts the demand for electric vehicles relative to the demand for other types of vehicles. Having BEV sales as a share of total sales also allowed us to control for the differences in the sales volumes of vehicles across the counties in Norway.

5.1.3 Infrastructure

The number of charging stations across Norway was obtained from the Norwegian charging point database NOBIL (2016)[4]. The database was accessed through the NOBIL API and contains a list over all the charging stations along with several key characteristics such as location, date registered in the database and power output. The database is operated and maintained by ENOVA, but both private users and commercial operators provide input. The number of charging stations, how many charging points they each have and their database registration dates were used to measure the development in the amount of charging points every year. Information about the status of charging stations was also available from the data set. As of when this study was carried out, none of the charging points were indicated to be inactive and thus the full data base was used. We chose to use the number of charging points as we consider it a better indicator of the charging infrastructure than stations. The total number of charging points in a county was divided by the driving-eligible population to control for differences between the regions. BEV owners can charge their vehicles for free on many of the charging station locations, and in public parking areas with charging possibilities they can also park for free. The possibility of free charging and free parking reduces the operation costs of EVs and would lower the perceived price of EVs in the demand function, which in turn would increase demand, as discussed in the previous section. In a survey, Figenbaum and Kolbenstvedt (2016) find that 11% of the respondents that own a BEV, charge at least once a week at a public charging station. For fast chargers the number was about 10% in 2016. This might not be remarkably high numbers, but as Figenbaum and Kolbenstvedt (2016) point out, charging station availability and visibility are important psychological factors because it reduces range anxiety. This relates to the hygiene factor described in section 4; charging infrastructure is a factor that most likely inhibits widespread EV adoption if not sufficiently developed, while it does not directly induce people to buy an EV.

[4]NOBIL is a cooperation between the public enterprise ENOVA and the Norwegian members organisation for electric vehicles.

When modelling the effect of charging points on the BEV sales share, we deemed it expedient to use the numbers from one year as an explanatory variable for the dependent variable the year after. The NOBIL data base did not contain any information on the charging infrastructure prior to 2010. Considering the fact that most of the real development in charging stations in Norway started in the period 2009-2010 when Transnova supported the development with 50 million NOK (Elbilforening, 2016), we assume that the number of charging points in 2009 were essentially zero.

The charging infrastructure indicator was of special interest in our analysis, partly because we expected it to be very influential in determining EV sales based on previous literature and research done on the subject. We were also interested in the causality problem mentioned by authors such as Mersky et al. and Sierzchula et al. In conclusion, we expect to find a strong and positive relationship between charging points and BEV sales share.

Data on high-occupancy vehicle (HOV) lanes was provided by the Norwegian Public Roads Administration (NPRA), through direct contact. This was the most accurate indicator for lanes designated for public transport they could provide us with. These lanes typically have less traffic than normal lanes, and because electric vehicles are allowed free access to them, there is a potential for saving time in buying an electric vehicle. The length of the HOV lanes, measured in metres, together with their location was used to compute the total length of bus lanes for every county at the end of each year[5]. The length of HOV lanes will be referred to as bus lanes in the rest of our analysis for easy interpretation.

Information on the vehicle kilometres travelled (VKT) per car in a county was collected from SSB (2016). This variable was assumed to have two opposing effects on the dependent variable. First, electric vehicles have shorter range than traditional ICEVs and thus people in a county where cars on average travel long distances annually are less likely to buy a BEV. At the same time, longer distances travelled per vehicle also means higher gasoline expenses and this means higher potential savings from buying an electric vehicle. The vehicles can also be used more frequently for shorter distances and this would suggest a positive relationship between the two.

[5]We did not make any adjustments to this variable although it was discussed whether or not to divide it by the total amount of road in each county. This was not considered helpful to our analysis as a HOV-lane share would not give a realistic picture of potential time saved for BEV drivers.

5.1.4 Financial incentives

To model the expenses for cars travelling on ferries we used data from the NPRA and their ferry database (Norwegian Public Roads Administration, 2016). The database provided us with the yearly number of vehicles travelling with ferries per zone for each county. The variable serves as an indicator of the potential savings from the exemption from ferry fares one could achieve by buying an electric vehicle. Each zone represents a set of fares set by the NPRA and adjusted yearly according to regulations that apply to all government-subsidised ferry stretches in Norway (Norwegian Public Roads Administration, 2015). Those stretches that are not supported by government funding still use this regulation as a guideline when setting their prices. The prices set by the regulations are therefore an accurate indicator of the real expenses of travelling by ferry in Norway. The fares vary based on vehicle type and length, with longer vehicles incurring a higher price. We used the fare for passenger vehicles shorter than 6 metres to calculate the ferry expenses as the majority of all passenger vehicles meet this criteria. The traffic numbers for each zone were multiplied by their respective fares to calculate total yearly ferry costs in each county. It is worth noting that it was not possible to separate the passenger cars from other means of transport in the traffic numbers, hence this factor is likely to be higher than the real number of expenses for passenger cars. However, the total number of vehicles has been used as a factor for all counties and for all years, so the relative difference should be the same. This total was divided by the number of passenger cars in the county to obtain the average ferry-expense per car for each county. Higher ferry-expenses in a county could be interpreted as a decrease in the relative price of an EV compared to an ICEV in the demand-function framework. Based on this, we assume that the relationship between ferry expenses and our dependent variable is positive.

To analyse the impact of toll fee exemption on EV sales, we obtained information on all the toll projects in Norway in the time period 2010-2014 from the NPRA, through direct contact. The intention was to create an indicator for how important toll stations were in a county and get a numeric value for the potential savings one could obtain from reduced toll fares offered to electric vehicles. We expected that high potential savings would induce people to buy BEVs. For each project, the data set contained information on location, number of toll stations, fees per pass and number of passenger vehicle passes. The original data set had information on ferries with toll collection, a variable we have already controlled for with our ferry expenses variable. To avoid problems resulting from double counting of data, we attempted to remove the projects with ferries. Due to the complexity in the way money is collected for some projects, especially those involving bridges, this proved to be a difficult process and all the projects with collection on ferries might not have been identified. Nevertheless, the NPRA estimates that toll revenue from ferries only account for a modest 1% of the total and therefore the discrepancy should not disrupt our analysis significantly. Some projects from the original data set span two counties and thus needed some modification to conform to our analysis. To correct for this, we split the relevant projects into two separate ones, assigning half of the traffic through the cross-county projects to one project allocated to each county. This was the case for Buskerud, Oslo and Akershus located in the eastern part of Norway. In some cases, a singe toll project would be listed with several fares owing to a difference in fares for the toll stations constituting the project. To get a rough estimate of the average fare for those projects we divided the sum of the fares by their number. The total project toll expense was obtained by multiplying the average toll fare by the number of passenger-vehicle passes for each project. The total project expenses were summed up to attain the yearly toll expenses in each county. This sum was divided by the county's car fleet, resulting in a variable describing the average toll expense per car for each county in each year. Ideally, we would have used information on fares and passes for each individual toll station to calculate the real toll expense for each region. Unfortunately, this information was not available to us and thus a rough estimate had to be calculated.

One potential issue with our method of calculating the total cost of toll fees relates the share of electric vehicles passing through the toll stations. Given a large enough share of electric vehicles, our calculated cost would be overestimated on account of the fact that electric vehicles do not pay any fees. The NPRA provided us with the number electric vehicle passes through toll projects from 2011 to 2014. These numbers reveal that, on average, the share is less than 1%. Hence, we find it reasonable to argue that this problem should not create too much anomalies in our case. What we are essentially assuming is that driving an electric vehicle does not induce people to change their driving pattern to the extent that the overall number of passes through toll stations in a county are increased significantly compared to if they drove cars not exempt from the toll fee. It is worth taking notice that Tromsø, the biggest city in the county of Troms, did not have any toll stations in the time period analysed. The city implemented higher petrol gasoline prices instead with the same purpose as toll stations. We do not account for this in our analysis. Furthermore, the data set did not give accurate measures for the fares in Sør-Trøndelag for 2014, as "Miljøpakken" was implemented in Trondheim making the fare system too complex for proper reporting. Consequently, we had to estimate a fare based on an average of the different fares for each toll station in the project, including additional fee for rush-hour passes where applicable, reduced fare for prepayment not included. As for ferry expenses, exemptions from toll fees can be modelled as a relative decrease in price for electric vehicles and in the regression results we expected a positive sign also for this variable.

Ferry and toll fees are two variables that are closely related in our data set. The toll station data we obtained had to be manually checked for cases where a toll project included ferry stretches to avoid double counting. Furthermore, toll and ferry expenses can be considered the same incentive and could potentially be modelled as the same variable in our model.

5.1.5 Demographics

The percent of people over 16 with any kind of university degree was calculated using numbers from SSB (2014a). The education measure includes people with a bachelors or masters degree as well as those with a PhD. This variable was thought to have a positive effect on electric vehicle adoption as individuals with higher education tend to be more receptacle to new technology, and Bjerkan et al. (2016) report findings from a national travel survey where 76% of the EV users have a college or university degree.

In their report, Figenbaum and Kolbenstvedt (2016) present findings from a survey where they find that household characteristics, among them income, affect the purchase of a BEV to a large extent, supporting the choice of using household income levels for this analysis. Median household income (SSB, 2016e), measured in Norwegian Kroner, was used as opposed to mean household income because buying a car is generally thought to be a household decision, not solely dependent on a single person's income level. Furthermore, the distribution of income levels within counties are likely to be skewed, supporting a choice of median over mean income. The variable is adjusted for inflation. The effect on BEV sales share is expected to be positive as we have defined battery electric vehicles as a normal good. Also, if BEVs are mostly bought as car number two (Figenbaum and Kolbenstvedt, 2016), then income would not be of great importance. Therefore, we would expect a coefficient with positive sign, but possibly with low effect.

Population density (SSB, 2016d), measured in people per square kilometre of land area, was an important demographic variable for our analysis as we expected that counties with a high number of inhabitants per square kilometre were more likely to also have a high share of electric vehicle sales. High population density is usually synonymous with urban areas and those are areas where electric vehicles are likely to be popular according to previous research mentioned in section 1. People in urban areas live closer together, mitigating the BEV's range problem, and they are likely to be exposed to other electric vehicles more frequently. We also collected information on the population density in the urban areas (SSB, 2016b) suspecting that this variable might be more appropriate. Population density in the cities was also the variable employed by Sierzchula et al. (2014) when examining incentives for BEV sales.

People per household covers private household and records the average number of people of any age residing in a household (SSB, 2016a). This variable was thought to be interesting based on survey results from Figenbaum and Kolbenstvedt (2016), where they find that the average number of people in a BEV household is significantly higher than that of PHEV and ICEV households. This led us to believe that counties with a higher average number of people per household would have higher EV adoption rates. This variable could also potentially be an indicator for the number of cars in a household, assuming that larger households have a need for more cars. Since BEV owners usually have more than one vehicle at their disposal (Figenbaum and Kolbenstvedt, 2016), this would indicate that households with more cars are more likely to have access to a BEV. That being said, people per household could also serve as an indicator of population density. SSB (2014b) reports that in 2014, single households were mainly located in the large cities. Counties where large cities are located will probably have a lower number of people per household.

Unemployment (SSB, 2016h) was included as a fundamental demographic control variable. It was suspected to have a negative indirect impact on the sale of electric vehicles by affecting the economic environment in a county. Especially the income variable is susceptible to its influence, which might disrupt our analysis. The unemployment rate used was the one recorded in the first month of every year and applies to people between the age of 15 and 74 years.

The population parameter (SSB, 2016c) was used to adjust charging points to make comparisons between counties more accurate. Only the population aged 18 and above was considered as this is the driving-eligible population, and we wanted to adjust for differences in this portion of the population. It could be argued that the population above a certain age is not driving eligible either, but this demographic was assumed to make up a small part of the total population.

Median age was calculated using age statistics from the SSB (SSB, 2016c). Several studies and reports find that owners of electric vehicles are usually younger than the typical car owner. In a report from the Norwegian Institute of Transport Economics

(Figenbaum and Kolbenstvedt, 2016), the authors find a clear age difference between BEV, HEV and ICEV owners, with BEV owners being the youngest. We thus expect the sales share of electric vehicles to be inversely related to the median age.

5.1.6 Geography

To control for differences between regions, we decided to collect data on three geographic and climatic factors: temperature, coastline and elevation.

Temperature was collected from the Norwegian Meteorological Institute's climate database eKlima (2016). Monthly normal values for the mean temperature (measured in Celsius) from the normal period between 1961 and 1990[6] was retrieved from weather stations in each county. The weather station located in each county's most populous area was chosen to obtain temperature values that correspond to the temperature the largest share of each county's population experiences. We suspected the EV adoption to be higher in a county with a higher mean temperature, than in a county that is colder on average. The basis of this expectation is the fact that the batteries in electric vehicles hold less charge when temperatures are low (Yuksel and Michalek, 2015). This means that their range is reduced. Also, in cold climates drivers are more likely to use the heating system, reducing the car's range. Since cold climates exacerbate the range limitation and range anxiety problems of electric vehicles, we suspect temperature to have a positive effect on BEV adoption patterns.

Information on the kilometres of coastline for each county was found in SSB's statistical yearbook from 2013 (SSB, 2013). The variable was meant to account for underlying factors in counties with large coastal regions that could affect the EV adoption rate. One could assume that in such regions, the climate is much harsher and the weather more extreme. This could deter consumers from investing in electric vehicles by increasing range anxiety; people do not want to be stuck out on the road with a flat battery in the middle of a storm. Other underlying factors of coastal counties could be culture and attitudes that differ compared to inland counties with short coastlines. By including this variable, we also hoped to correct for any of these factors that the ferry variable might catch. Ferries are typical for coastal regions and we wanted the variable to only portray the potential savings from reduced ferry fares, not any of the other effects of coastal regions mentioned.

To model a county's elevation, we again used information found in SSBs statistical

[6]The United Nation's World Meteorological Organisation (WMO) requires the calculation of normals every 30 years, with the latest covering the 1961-1990.

yearbook (SSB, 2013). The table contain information on the percent of area within a county that lay at certain altitude categories above sea level. We combined the categories for altitudes 600 MASL and above, giving us an indicator for how large share of a county was elevated at 600 MASL or above. This indicator is meant to catch some of the climate information that the temperature variable might fail to pick up due to its recording of mean temperature from only one single weather station. The idea being that counties with more elevation usually have colder climates. Another effect we wished to control for was increased range problems cars driving through mountains passes might face. The temperature is lower in the mountains and the roads are more prone to closure and slow moving convoys, making range more crucial. We hence believed that counties with a large part of its area above 600 MASL would see a lower rate of EV adoption than counties at lower elevations.

5.2 Summary statistics

A complete overview of the summary statistics for all the variables used in the analysis is provided in table 5.1, it covers all counties and all years used. A more detailed representation of individual counties and years is provided later in this section. Notable variables are those which have zero minimum values as they illustrate the large discrepancies between the counties and over the years. The share of BEV sales, for example, was zero for certain observations while one observation was at a considerable 22%. The variable for charging points per capita has a large standard deviation, indicating large variations in the value of its observations, both over years and counties. Since the variable is strictly growing, it can be inferred from the table that the observations rose from a minimum of 0.02% to just over 0.33% at the end of the period studied.

Median age does not differ much between the counties or across time, as indicated by table 5.1. A median age difference of nine years between the counties with the highest and lowest values across the time period, combined with a standard deviation of barely two years, suggest that counties in Norway are relatively homogeneous in this respect. This suggests that the variable will not be momentous to our analysis and we chose to discard it to keep our model parsimonious.

There are large differences between the counties in terms of the time-invariant variables. All three have large standard deviations and have a wide gap between the minimum and maximum values. This emphasises how different the counties in Norway are in terms of its geographic and climatic features.

The rest of this section will focus on four variables that we expected to be of special

Table 5.1: Summary statistics of relevant variables

	Mean	Standard Deviation	Min	Max
BEV Sales Share	.0346746	.0451209	0	.2275417
Toll Expenses per Car	2542.859	2332.715	0	10980.36
Charging Points per Capita	.0008773	.0006179	.0001968	.0033456
Ferry Expenses per Car	727.3133	1009.617	0	3627.713
Bus Lanes	5059.269	9070.795	0	36927.49
Household Income After Tax	461368.3	33412.62	384806	552000
Commuter Share	.3227684	.1258896	.1237804	.6267096
VKT	12812.31	600.2177	11326	13885
Median Age	39.33684	1.916394	34	43
People per km^2	103.7474	317.3878	2	1488
People per km^2 Urban	1639.414	748.4799	939.3708	4798.939
Population (18+)	203525.2	117736.3	55840	509032
Unemployed	3.003158	.573428	1.8	4.2
Education Level	27.29368	5.695161	21.2	48
Temperature	5.216194	1.747961	1.330769	7.584615
Coastline	5388.158	6234.391	0	26734
Elevation	34.91053	23.78525	0	79.7

importance in our analysis, along with the dependent variable we are investigating: charging infrastructure, ferry expenses, toll expenses and bus lanes.

5.2.1 Electric vehicles sales share

Figure 5.2 shows the regional development in the share of BEV sales of total vehicle sales. The figure further shows that most of the regions' curves are exceptionally steep between 2013 and 2014, indicating that the growth in BEV sales increased significantly almost all over the country between these two years. This rapid development of sales share on a national level in the latter years of the study is illustrated in figure 5.3. Figure 5.2 supports the results from table 5.1 that indicate large variances in the sales between the observations. Many counties have zero, or close to zero sales of BEVs in 2010; some of them never reach substantial numbers. Finnmark, Troms, Hedmark and Oppland have very low numbers in the start of the period and never reach levels

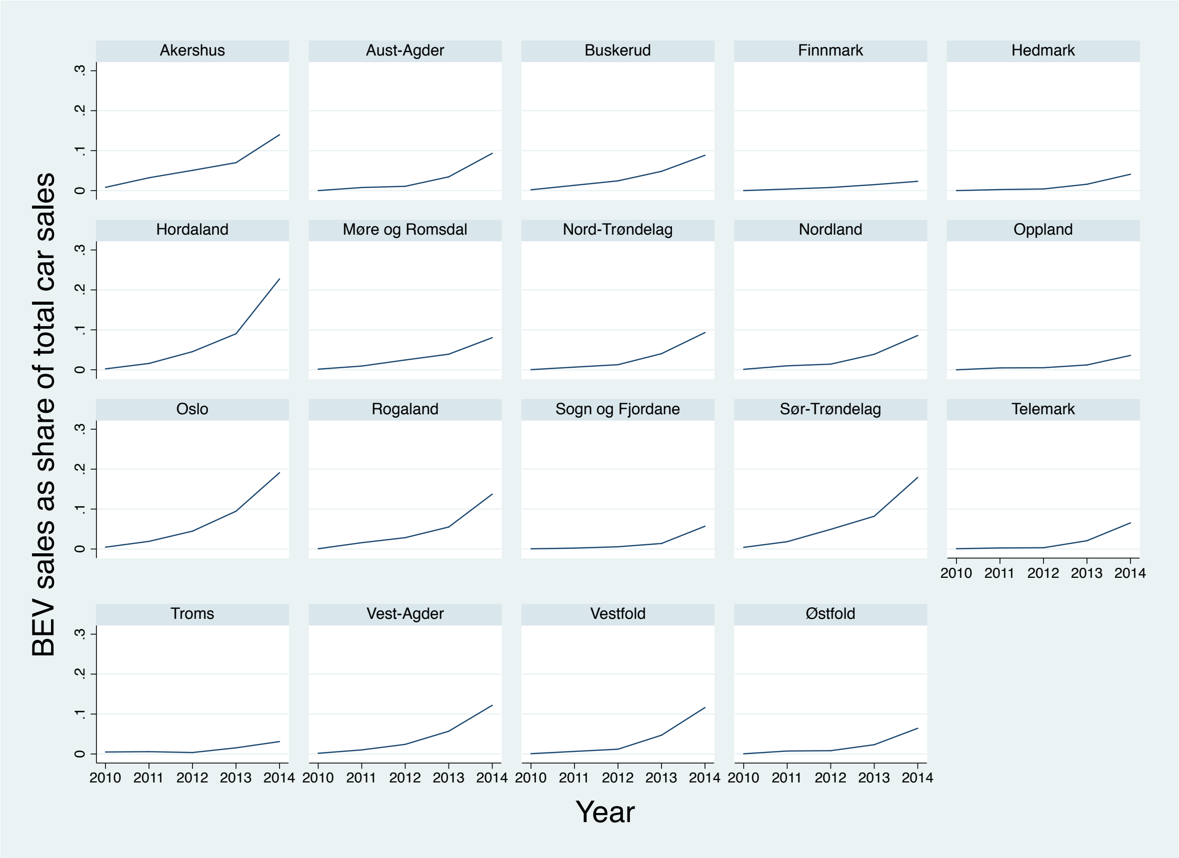

Figure 5.2: Regional development of electric vehicle sales share, Norway 2010-2014.

comparative to that of the other counties. Figure 5.4 compares the two extreme cases of Hordaland and Finnmark, which had the highest and lowest share of BEV sales in 2014, respectively.

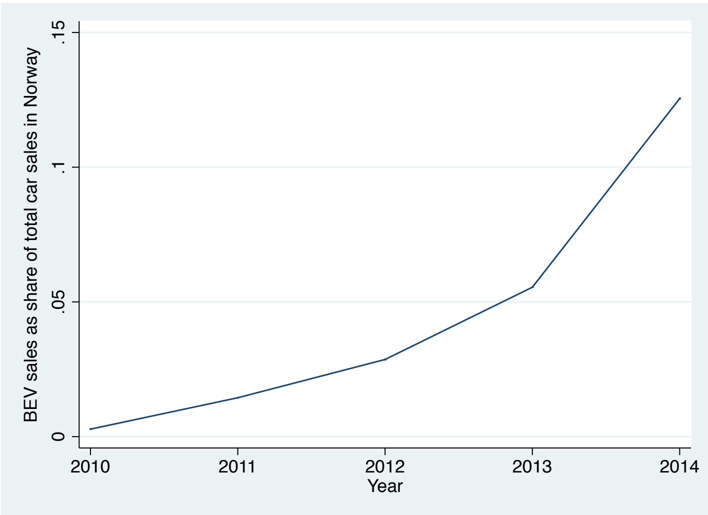

Figure 5.3: Development of electric vehicle sales share, Norway 2010-2014.

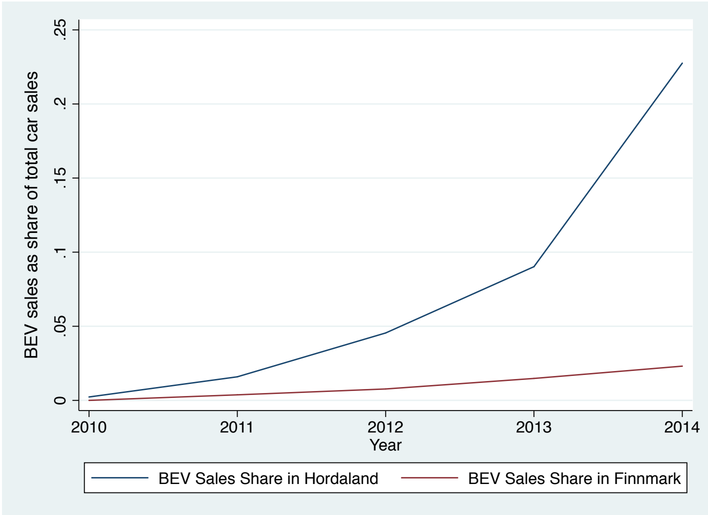

Figure 5.4: Share of electric vehicle sales in the extreme cases of Hordalanad and Finnmark, Norway 2010-2014.

5.2.2 Charging infrastructure

Figure 5.5 shows the development in the number of charging points per driving-eligible capita for the 19 Norwegian counties studied in the time period between 2010 and 2014. The figure gives a good indication of what regions have seen the largest growth in charging points. Regions that stand out are Akershus, Hordaland and Oslo. These three regions started with a relatively high amount of charging points and have higher numbers than any other region by the end of 2014. Vest-Agder is a region with low numbers initially that experiences tremendous growth in the time span between 2010 and 2014. Figure 5.5 shows a trend similar to the one in figure 5.2, counties with a strong growth in charging points per capita also have a steep increase in their BEV sales share. However, counties like Sør-Trøndelag and Vestfold have experienced high growth despite having a relatively low number of charging points per capita.

Table 5.2 shows the yearly development in the mean of charging points per capita together with the driving-eligible population and the share of electric vehicles in the car fleet for all of Norway. The table illustrates the substantial national growth in the mean number of charging points over the years. This growth was especially high between 2013 and 2014 when it rose by almost 30%. The mean growth over the entire period was a considerable 95%. The growth in the mean population has not been as explosive, but still significant as it rose by roughly 6%. The growth in the mean EV share has seen a more exponential growth pattern than charging points per capita with an increase of approximately 183% over the whole period. There seems to be a close relationship between the EV share and charging points per capita in the counties,

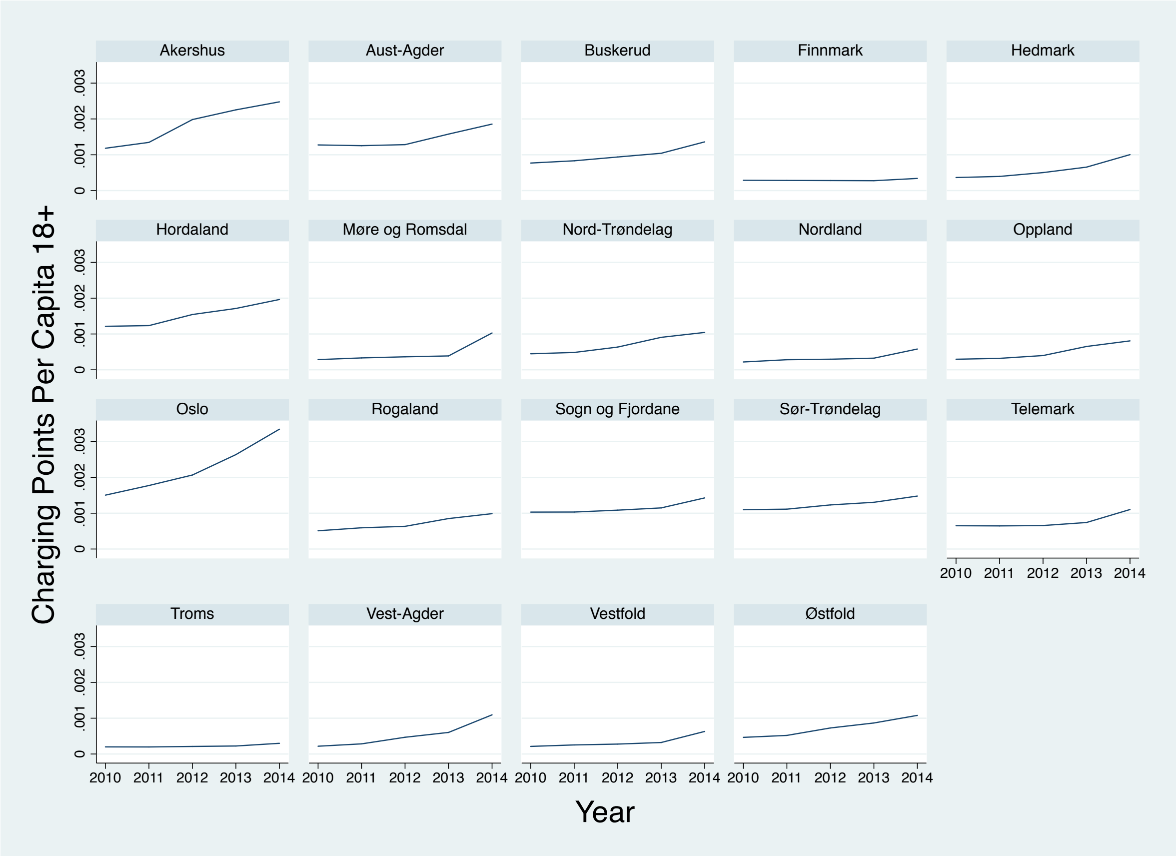

Figure 5.5: Regional development of charging points per capita, Norway 2010-2014.

but from just looking at table 5.2 it is difficult to determine potential causality. The relationship between charging points and BEV sales share will be explored more closely throughout this paper.

As mentioned earlier, the relationship between the BEV sales share and charging points is of special interest in this analysis. Figure 5.6 displays the sales share of electric vehicles in Norway compared to the number of charging points per capita. Each graph has its own axis to better illustrate the development. The number of charging points per capita has seen a steep development throughout the whole period while the sales share for BEVs picked up in the last period between 2013 and 2014.

Figure 5.7 shows how the development in the number of cumulative charging points and the number of electric vehicles sold yearly, without adjusting for anything. This figure restates what the previous figure showed: that the sale of electric vehicles seems to have increased substantially in the latter years while the number of charging points has been consistently growing throughout the time period.

Figure 5.8 shows a histogram of the development of BEV sales and charging points for Norway as a whole. The figure shows an exponential growth in the sales of BEVs

Table 5.2: Yearly means for charging points per capita and relevant variables

	Charging Points per Capita	Population (18+)	EV Share
2010	.0006432	197318.1	.0005901
2011	.0006932	200312.2	.0011223
2012	.0008198	203560.3	.0022973
2013	.0009725	206756.7	.005196
2014	.0012578	209678.7	.0114397

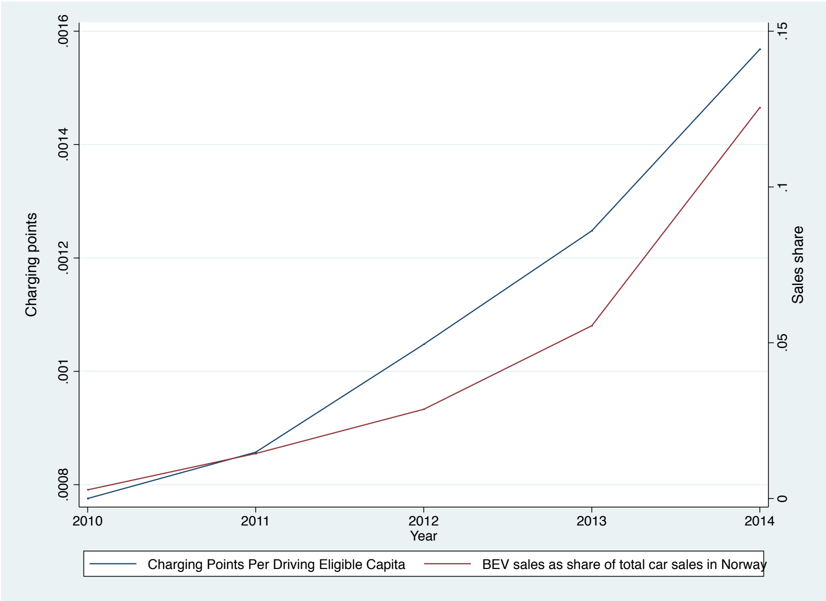

Figure 5.6: Development in the sales share of electric vehicles and charging points per capita, Norway 2010-2014.

along with a steady increase in the total amount of charging points. From the figure one can see how, in per capita terms, the increase in sales of electric vehicles has been substantial in proportion to that of charging points.

5.2.3 Ferry expenses, toll expenses and bus lanes

Table 5.3 shows the mean of ferry and toll expenses per car for all the Norwegian counties. The table is included to give an indication of how the expenses have developed over the years and also to establish a benchmark to which the individual regional values can be compared. It is clear from the table that on a national scale, there are more expenses associated with passing through toll stations than it is travelling with ferries.

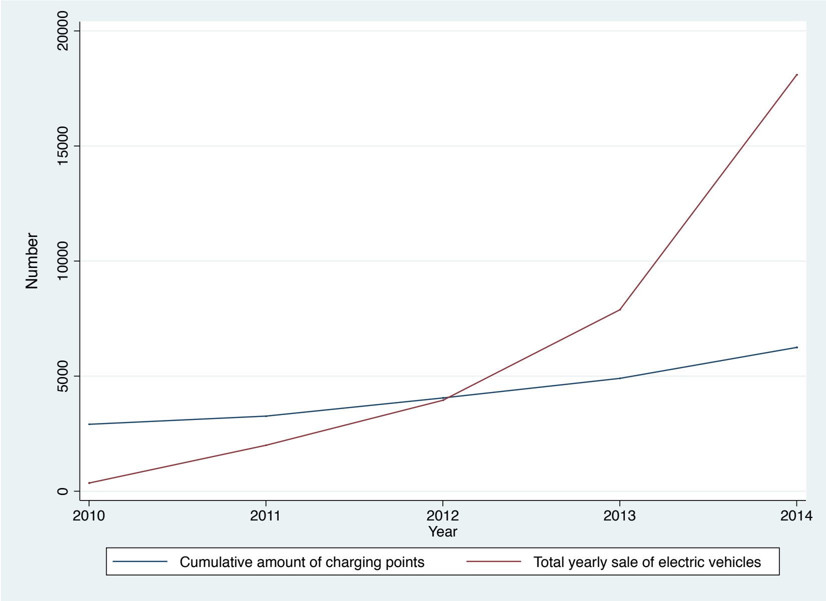

Figure 5.7: Development in sales of electric vehicles and the cumulative number of charging points, Norway 2010-2014.

According to our numbers, the average toll expenses per car has fluctuated to some degree from year to year, but overall it has increased with roughly 200 NOK, or about 7.8% from 2010 to 2014. Ferry expenses has been somewhat more stable, and grew substantially less in the same time period, with 30 NOK per car or 1.3%.

Table 5.3: Yearly national means for toll and ferry expenses per car

	Toll Expenses per Car	Ferry Expenses per Car
2010	2537.86	709.43
2011	2402.89	723.25
2012	2524.36	735.56
2013	2513.04	728.48
2014	2736.15	739.86

Figure 5.9 shows the regional development in toll expenses per car. It emphasises how the importance of toll stations vary among the counties across years. Some notable regions are Akershus, Hordaland, Rogaland and Sør-Trøndelag, which are regions with high toll expenses and high BEV adoption rates, as depicted by figure 5.2. Sør-Trøndelag had the most explosive growth in toll expenses of all the counties, coinciding with its relatively strong growth in BEV sales share. Comparing the figures 5.2 and 5.9, it seems that regions where toll expenses are relatively high, also display volatile

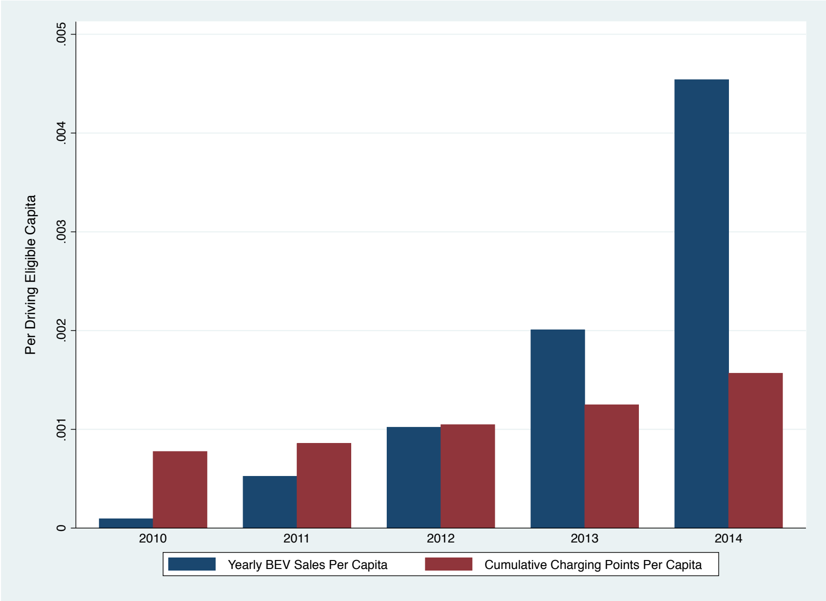

Figure 5.8: Development in the sales of electric vehicles per capita compared to the total amount of charging points per capita, Norway 2010-2014.

changes in the amount of expenses from year to year. In comparison, regions where vehicles pay smaller yearly sums for toll passes show smaller changes across the time period. Several regions have very low toll expenses and these are typically the regions where also BEV sales are low. An extreme case is Telemark where no toll stations were in place over the whole period.

Figure 5.10 illustrates the differences in and development of ferry expenses per car among the regions. 12 of the 19 counties have very low or no expenses at all, meaning that for most of Norway, these expenses are of relative little importance. The regions where ferry travel expenses are high are almost exclusively located on the west coast of Norway. Comparing figures 5.10 and 5.2, it does not seem to be any clear relationship between BEV adoption rates and ferry expenses per car. For example, in the counties of Møre og Romsdal and Sogn og Fjordane, where vehicles pay the highest yearly amounts for ferry travel, the BEV adoption rates are extremely low. At the same time, Rogaland and Hordaland are counties with relative high ferry expenses with considerable amounts of electric vehicles. It does not seem to be substantial changes to expenses in any county in particular, much like the national mean in figure 5.3 suggests.

In Figure 5.11, the regional development of bus lane metres is displayed. A majority of the counties do not appear to have significant amounts of bus lanes, with a few exceptions. Oslo and Akershus are the two counties with most bus lane metres and coincidentally, they are also among the counties with the highest EV adoption rates. It

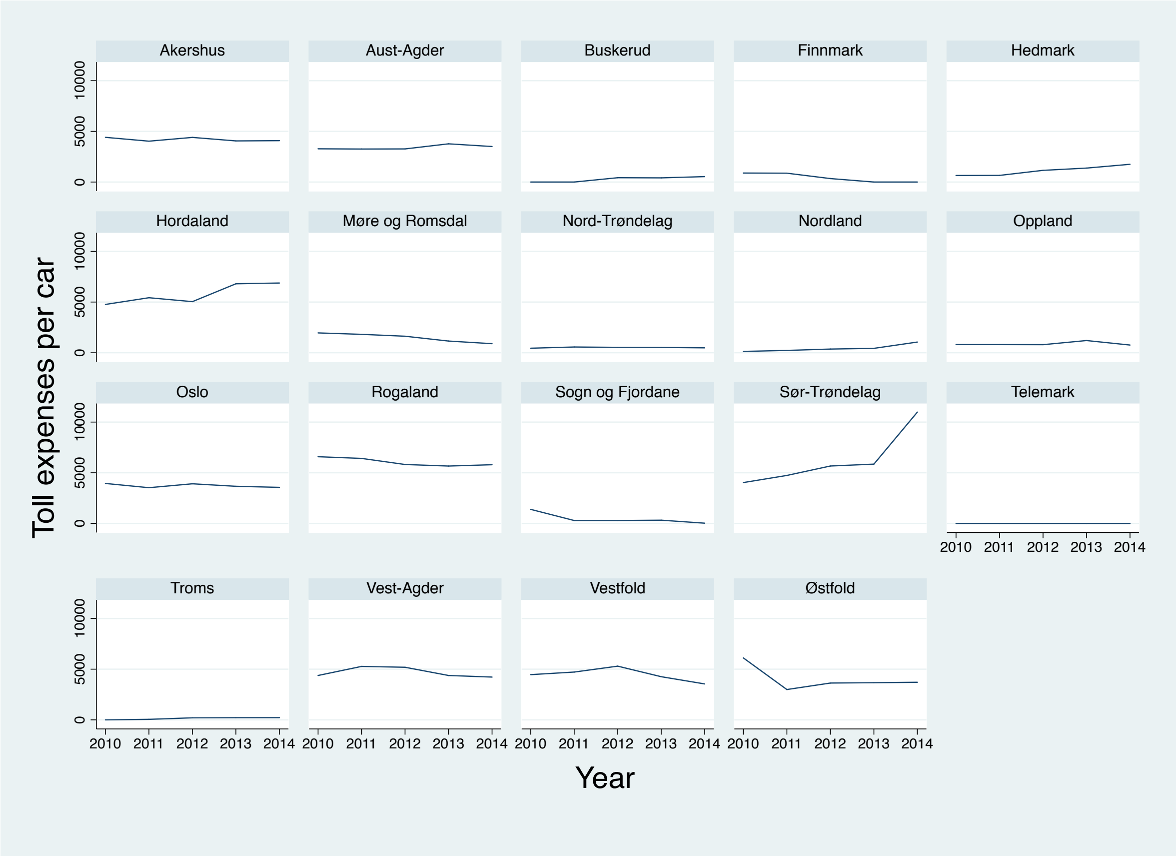

Figure 5.9: Regional development of toll station expenses per car, Norway 2010-2014.

is evident from the figure that the counties with a notable amount of bus lanes are those where major cities are located, which is to be expected. Rogaland is the county that has seen the most notable growth over a one year period while Oslo shows consistent growth over all years. In other regions, it does not seem to have been any apparent growth over the years.

5.3 Correlation analysis

To identify potential problems with the relationship between variables in the data set, we evaluated the correlation between them as well as their correlation with the dependent variable. For this purpose, we used correlation matrices showing the relationship between the variables, both graphical and numerical. The numerical correlation matrix for all variable is shown in table 5.4, it will be referred to in the following paragraphs discussing the correlation for particular variables. However, since the correlation coefficient does not capture nonlinear relationships, it was interesting to also explore the graphical presentations. In these graphs, BEV sales share is on the x-axis, and the explanatory variables are on the y-axis. Individual figures are produced for each

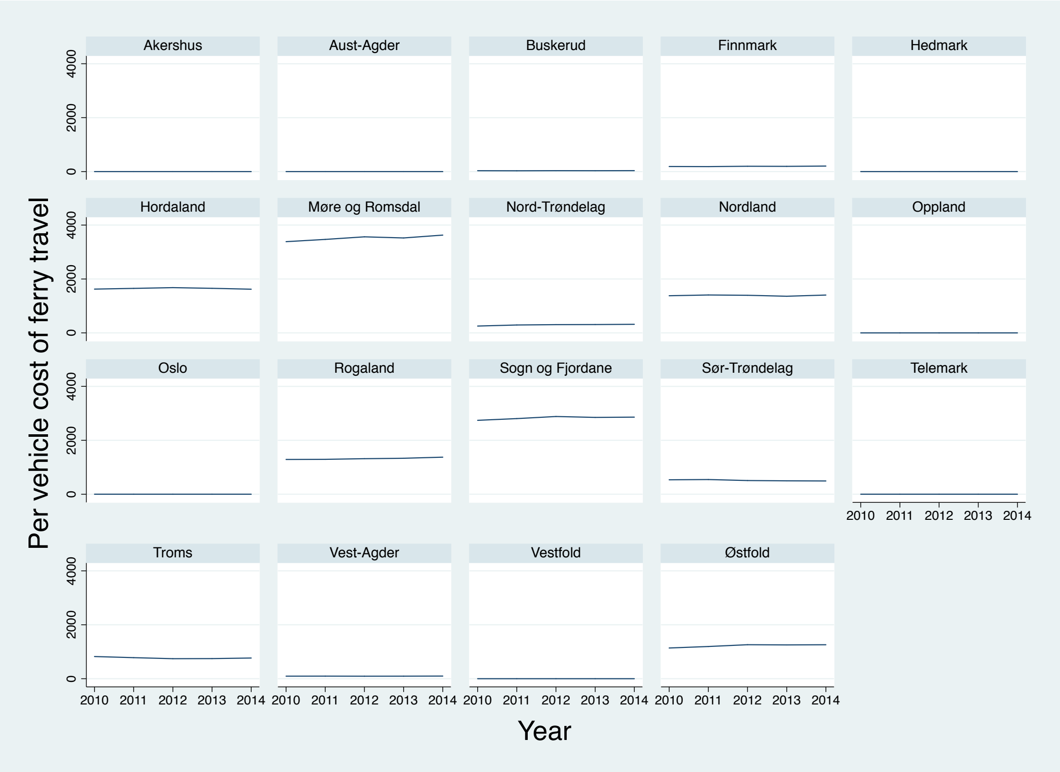

Figure 5.10: Regional development of ferry expenses per car, Norway 2010-2014

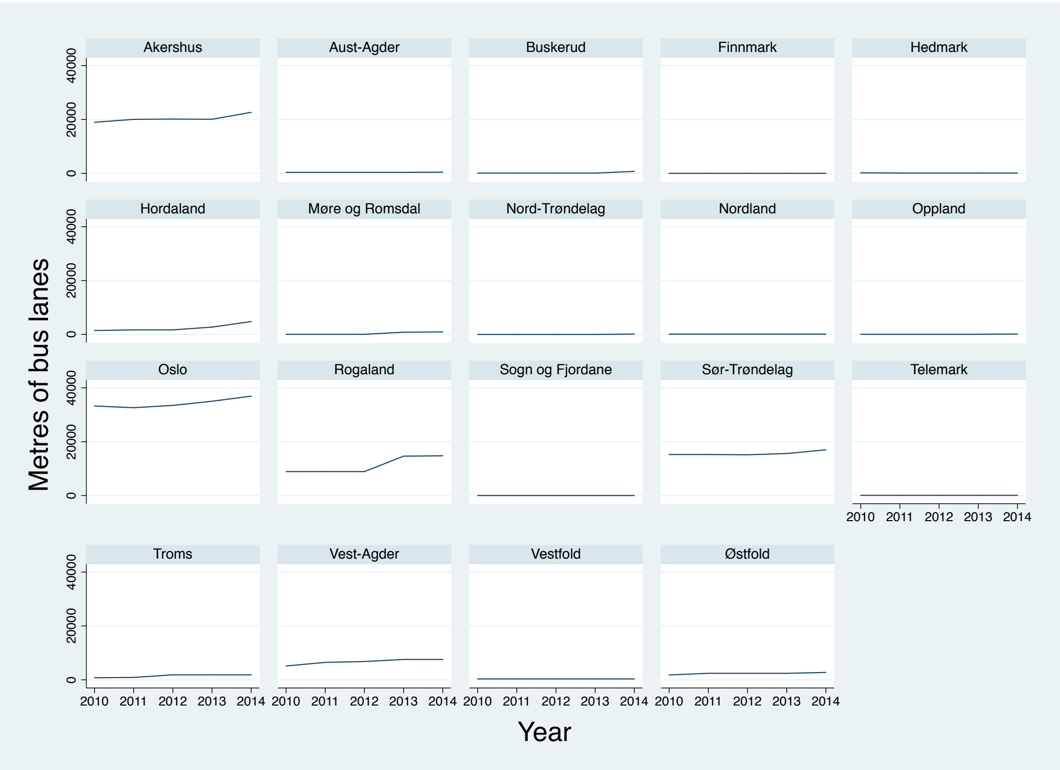

Figure 5.11: Regional development of bus lanes, Norway 2010-2014

group of variables discussed. In the graphs, low correlation values will be displayed as randomly scattered observations while correlations close to one will show a distinct pattern. Variables introduced in this section were deemed relevant either because they were assumed to be important in regards to the dependent variable or because they were considered important control variables. By analysing the correlation matrices, we wanted to identify whether these variables showed indication of being important to our analysis before including them in our regressions. It was also necessary to determine if any of the explanatory variables were significantly correlated with each other, creating problems of multicollinearity that could potentially disrupt our regression results. The choice of boundary to evaluate variables as significantly correlated is not unanimous, but we chose to use the guide suggested by Evans (1996), which previous literature seem to support (Beldjazia and Alatou, 2016; Bendanillo et al., 2016). Evans (1996) consider correlation below 0.40 as " very weak" or "weak", correlation from 0.40 to 0.59 as "moderate", 0.60 to 0.79 as "strong" and above 0.80 as "very strong".

Table 5.4: Correlation matrix for all variables.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. BEV Sales Share																
2. Charging Points (lagged)	0.65															
3. Charging Points	0.62	0.87														
4. Ferry Expenses per Car	-0.01	-0.08	-0.10													
5. Toll Expense per car	0.41	0.31	0.38	-0.04												
6. Bus Lanes	0.38	0.54	0.68	-0.21	0.49											
7. Household Income	0.41	0.34	0.24	0.28	0.32	0.07										
8. Pop. per km^2	0.22	0.42	0.56	-0.19	0.18	0.80	-0.34									
9. Pop. per km^2 (Cities)	0.42	0.51	0.63	-0.16	0.38	0.89	-0.11	0.93								
10. People per Household	-0.14	-0.19	-0.25	0.43	-0.00	-0.45	0.66	-0.78	-0.65							
11. Unemployment	-0.17	-0.12	-0.06	-0.47	-0.08	-0.02	-0.62	0.24	0.10	-0.48						
12. VKT per Car	-0.46	-0.23	-0.15	-0.59	-0.21	-0.15	-0.37	-0.15	-0.30	-0.00	0.38					
13. Education Level	0.47	0.62	0.75	-0.18	0.46	0.92	0.09	0.83	0.93	-0.51	-0.05	-0.25				
14. Temperature	0.25	0.28	0.36	0.24	0.59	0.19	0.33	0.11	0.20	0.20	-0.07	-0.34	0.23			
15. Elevation	-0.11	-0.10	-0.14	0.20	-0.30	-0.44	-0.06	-0.41	-0.45	0.17	-0.40	-0.10	-0.39	-0.08		
16. Coastline	0.016	-0.18	-0.24	0.50	-0.13	-0.23	0.07	-0.23	-0.15	0.21	-0.17	-0.39	-0.20	-0.09	0.07	

The key factors analysed in this thesis was the effect ferry and toll expenses, charging stations and the amount of bus lanes had on BEV sales share, figure 5.12 displays their correlation matrix as scatter plots. As expected, lagged charging points are highly correlated with the sales share. It has a strong correlation of almost 0.65, making it the strongest correlated variable of the main explanatory variables. Length of bus lanes and toll expenses per car show positive correlation with the share of electric vehicles sold, as expected. The last variable of the four, ferry expenses, has an unexpected negative correlation with the dependent variable, which contradicts our reasoning in the previous subsection. This is probably due to the large discrepancy in prevalence

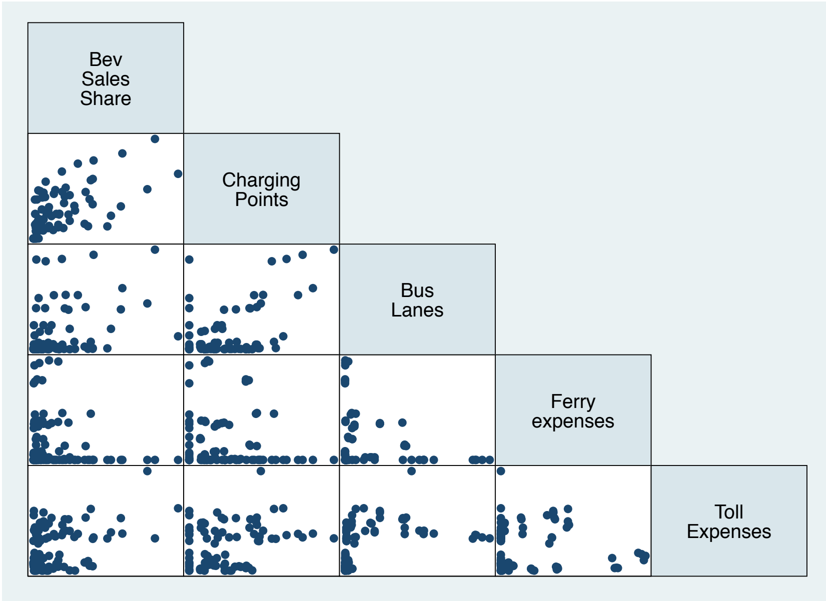

Figure 5.12: Graphical correlation matrix for the dependent variable and the key explanatory variables

of ferries among the counties, amongst other factors, which will be addressed later. From table 5.4, we also see that none of the main explanatory variables have very strong correlation with each other, following the guidelines set by Evans (1996). With a threshold of 0.80, we argue that they will not cause severe multicollinearity problems in our analysis. However, we take notice of the correlation between bus lanes and charging point per capita of 0.68, which is a fairly strong correlation. In table 5.4, we included both the lagged and the normal specification of the charging points per capita variable. The numbers show that the lagged variation has a slightly higher correlation with the dependent variable and lower correlation with most of the other independent variables.

Figure 5.13 illustrate the correlation between the sales share and the demographic variables considered for our analysis. Both the figure and table 5.4 show that all explanatory variables are in accordance with our discussion in section 5.1.5. The correlation between population density in the county, and unemployment are relatively weak while median income and population density are more strongly correlated than the others. As expected, there is a negative correlation between unemployment and median income after tax at almost 0.62, a relationship supported by figure 5.13. This could potentially cause a minor multicollinearity problem in our regression, but considering the variables' role in our analysis, we chose to include them in our models regardless.

Both measures for population density are highly correlated with the bus lanes variable,

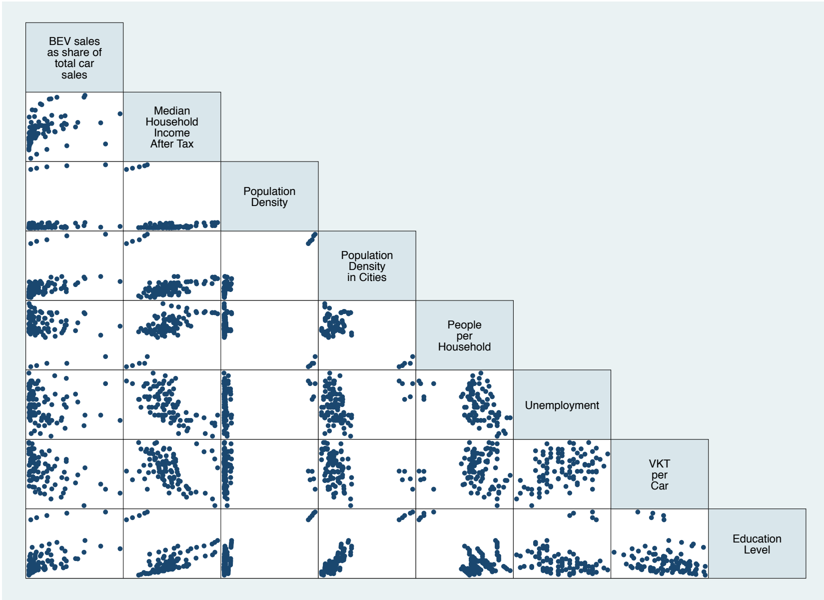

Figure 5.13: Graphical correlation matrix for the dependent variable and demographic variables

making them potential sources of multicollinearity problems that could significantly disrupt our analysis as the bus lanes measure is a key variable. Population density in the cities is more strongly correlated to our dependent variable than population density in the county as a whole, as suspected. However, it is also more strongly correlated to the bus lanes variable. Both measures violate what we would tolerate in terms of multicollinearity.

The figure indicates a relatively clear linear relationships between the dependent variable and vehicle-kilometres per car, which is supported by the negative correlation reported in table 5.4. People per household is negatively correlated with the BEV sales share, contradictory to what was expected. It has a relatively strong correlation with household income, as could be expected. More notably, it has a strong negative correlation with both measures for population density. Education level is moderately correlated with our dependent variable, and has a strong correlation with charging points, bus lanes and population density in cities. For the two latter variables, its correlation is over 0.90. Overall, the correlations analysis of our demographic variables do not imply that they are crucial to our regression model and some even appear to potentially be disrupting.

Figure 5.14 shows correlation matrices for the time-invariant variables included in our analysis to control for county-fixed effects. Looking at the figure, it is hard to determine any clear relationships between any of the variables. Table 5.4 indicates that none of

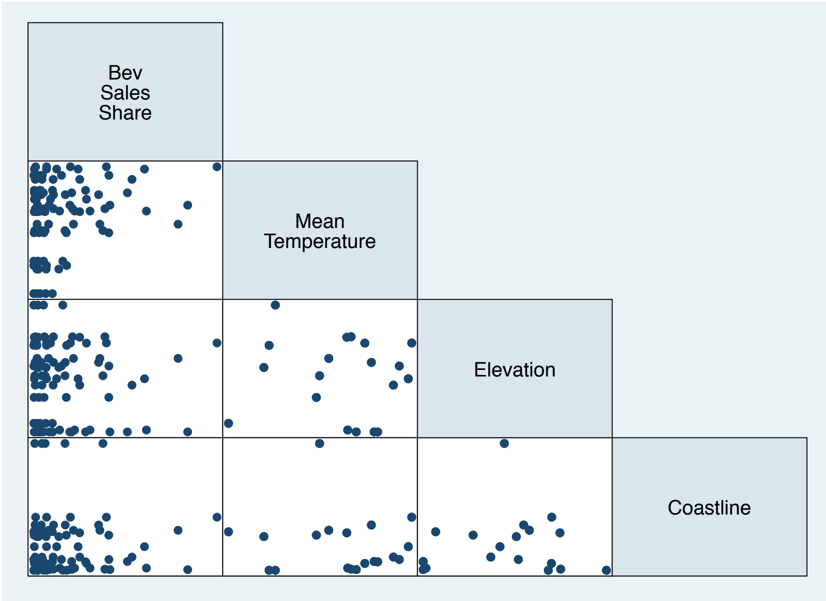

Figure 5.14: Graphical Correlation matrix for the dependent variable and county-fixed control variables

the county-specific variables have strong correlations with the BEV sales share, and that they are generally weakly correlated with the other explanatory variables.

The correlation analysis indicates that our main variables of interest have a substantial relationship with our dependent variable, and that correlation between them should not be significant enough to create severe problems. Some of the demographic variables that we deemed important for our analysis are only somewhat correlated with our dependent variable. Considering that they were mainly included as controls, this is not a troubling result. What can potentially be problematic for our analysis is the significant correlation between the population density indicators and bus lanes. Education level has potentially problematic correlations with several of our explanatory variables. The geographic and climatic indicators are all weakly correlated with the dependent variable. The results from this analysis were carefully considered when specifying our model in section 6.4.

6 Empirical framework

In this section we put forward the empirical framework used to structure the variables described in the previous section, in the attempt to model EV adoption incentives. The first part develops our approach step-by-step, from a single cross section to panel data methods covering random and fixed effects approaches. We then provide details of the post-regressions test employed to assess which approach was best suited for our research question. Together with the panel data framework and the information from the previous section, we finally formalise the model used in our regression analysis.

6.1 From single cross-sectional models to advanced panel data methods

The data set provided by the OFV allowed us to utilise differences over both geographical areas and time to estimate the effect of incentives on EV sales in a panel data analysis. Our short panel covers 19 counties and five years and includes observations for all units over the entire time period, making it a balanced panel. We believed there to be differences across the Norwegian counties, that influence the EV adoption rates. There are differences between the counties both in the development of the dependent and independent variables over time, but also in their initial starting points. In addition there are differences over time within a county. Furthermore, there is some variation that is completely or to a large extent time-invariant. This created a challenge in finding a suitable empirical approach.

In this subsection we go through a sample of model designs based on the framework laid out in Wooldridge (2006) to address our research question concerning the effect of regional incentives and factors on BEV adoption in Norway. We begin by considering the case of a single cross section to explain the benefits of using a panel data approach.

6.1.1 Single cross-section

Single cross-section models only considers a single point in time and it is therefore easier to find all the data needed to perform an analysis using a single cross-sectional model, and it is for many purposes sufficient. Mersky et al. (2016) uses an approach similar to single cross-section in their analysis of EV sales with 2012 as the basis year.

An example of a single cross-sectional model takes the form:

$$y = \beta_0 + \boldsymbol{\beta_j}\mathbf{x_j} + u \tag{6.1}$$

where y is the dependent variable, in our case BEV sales share, β_0 is the intercept, $\boldsymbol{\beta_j}$ is a vector of estimates of the corresponding coefficient of $\mathbf{x_j}$, where $\mathbf{x_j}$ is a vector of all explanatory variables $n, j = 1, 2, ...n$, such as charging points, toll expenses and so on.

It is worth giving the variable u some closer attention as dealing with this term perhaps is the most important component of this econometric analysis. The variable u, called the error term, represents factors other than the included explanatory variables (x) that affect BEV sales share (y). A simple regression analysis effectively treats all factors affecting y other than x as being unobserved. A key assumption in multiple regression analysis is the zero conditional mean assumption, which states that the expected value of the error term equals zero for any values of the explanatory variables. An implication of the zero conditional mean assumption important to this analysis, is that in the population we have to assume that u is uncorrelated with the explanatory variables. If the error term is correlated with one or more of the explanatory variables the model will suffer from omitted variable bias, which results in endogeneity problems.

When analysing the issue at hand with a single cross-sectional model, we would only take advantage of a few data points in order to estimate the relationship between the explanatory variables and BEV sales share. Such a model does not take into account the situation prior to the examined year, nor after. In our case this means that if we regress BEV sales share on charging points only for 2012, and the number of charging points in 2012 depends on the number of charging points in 2011, the model will suffer from omitted variable bias. Using a single cross section disregards much useful information from the other time periods. There are fewer ways to adjust the model, and the cross-sectional study may not provide definite information about cause-and-effect relationships.

6.1.2 Panel data

Using panel data increases the sample size and enables us to reduce multicollinearity problems because we use variation between cross-sections, which are counties in our case, and variation over time. With panel data we can build dynamic models and control for unobserved effects better than in cross-sections. More specifically, in panel data analysis the error term introduced in equation 6.1 can be split into two parts: an idiosyncratic error, or time-varying error (u_{it}) that represents unobserved factors that change over time, and an unobserved effect that is fixed over time (a_i). Equation 6.2 shows a basic regression equation for panel data.

$$y_{it} = \beta_0 + \delta_k \mathbf{T_{kt}} + \boldsymbol{\beta_j} \mathbf{x_{itj}} + a_i + u_{it} \tag{6.2}$$

In equation 6.2 we have also included year dummies represented by the vector $\mathbf{T_{kt}}$ where $k \in [2011, 2014]$ (2010 is omitted as the base year) with the corresponding coefficient estimates δ_k. Subscript t denotes the year, $t \in [2010, 2014]$. If $k = t$, the dummy takes the value of one, and zero otherwise. Year dummies are included to control for unobserved effects that affect our dependent variable and that are present for all counties at the same time, so called macro shocks. The coefficients of the year dummies capture the increase in BEV sales share from one year to another, that is not picked up by the included independent variables. An example is introduction of new models of electric vehicles. We have not presented the coefficients on the year dummies or attempted to analyse them in section 7; our analysis does not aim to quantify and analyse the effect particular years had on the sales of electric vehicles. The time dummies are included to control for shocks so that the effects of our explanatory variables of interest are estimated as accurately as possible.

As we can see, the original error term u from equation 6.1 is now replaced by the two terms a_i and u_{it}. Furthermore, we see by the denotation that a_i is not dependent on t. This term can be considered the unobserved county-fixed effect and represents all factors affecting BEV sales share that do not change over time and that we did not include in the model. All county specific features that do not vary over time are captured by this term, as well as elements that are roughly constant over the five-year period. Examples of such elements are geographical and demographic characteristics of the county not explicitly modelled. Since we believed there were some time-invariant county-specific features that affect BEV adoption, it was beneficial to be able to separate out their effect. If such effects are present, correlated with the explanatory variables and not included in the model, the zero conditional mean assumption is violated and the model suffers from omitted variable bias. For example, in this paper we try to model the incentive effect on BEV adoption from free access to bus lanes. If there are some other time-invariant county specific feature that affect BEV sales and is correlated with the amount of bus lanes in a county, it will create endogeneity problems. The benefit of the panel data is that it enabled us to use the time- and space dimensions of our data set to construct a broader variety of models.

6.1.3 Pooled OLS

The simplest way to address panel data is by using a pooled OLS (POLS) regression model. Using this method we pooled all the years from 2010 to 2014 together, treating all data points as independent observations. In other words, an observation from one county in one year is treated as independent of an observation from the same county in a different year. This provides more data points than the single cross section approach.

In the pooled OLS model we pool the error terms in 6.2 together and end up with the following model:

$$y_{it} = \beta_0 + \delta_k \mathbf{T_{kt}} + \boldsymbol{\beta_j} \mathbf{x_{itj}} + v_{it} \tag{6.3}$$

where $v_{it} = a_i + u_{it}$, which is called the composite error term. This equation is very similar to the one we have in single cross-section models, and with this approach we also meet the same problems as for single cross-section analysis; we need the composite error to be uncorrelated with the explanatory variables for the model to be in line with the zero conditional mean assumption. This means that for our pooled OLS models to estimate the parameters consistently, we had to assume that we managed to include all factors, both the time-variant and the time-constant, that affect BEV sales share. This is a bold assumption that generally does not hold true, but if we manage to control for enough variables, it is easier to trust that the assumption is met and the pooled OLS estimates might be consistent.

A problem with the pooled OLS approach in our case is that the data does not consist of independently sampled observations, and is in fact exhaustive as it represents all the counties in Norway. This means that even if we manage to control for all time-invariant county specific factors, so that the unobserved effect a_i is uncorrelated with all explanatory variables in all time periods, we cannot rule out correlation in the error terms across the different observations in the pooled OLS models. Serial correlation between observations from the same county in different years is likely to occur and since pooled OLS uses the composite error term, which includes the county-specific unobserved error, this model does not fix the problem resulting from omitted variables. An example of this is if unobserved factors, such as environmental awareness in a county, affected BEV sales share in 2010 also affected sales share in 2011. If the serial correlation in the error term is substantial, the pooled OLS standard errors will be incorrect and lead to an incorrectly reported predictive power. This however does not affect the unbiasedness or the consistency of the OLS estimates, only their efficiency.

A key feature with panel data, that distinguishes it from independently pooled cross sectional data is that the same cross-sectional units, in our case counties, are followed over the given time period. This allowed us to control for unobserved characteristics of the counties. Furthermore, using more than one observation per unit, can facilitate causal inference in a better way than a single cross section and independently pooled cross sections. As shown in equation 6.2, panel data provided us with the opportunity to separate out the county-specific time-invariant unobserved effect, a_i. In most applications, the main reason for collecting panel data is to allow for this effect to be correlated with the explanatory variables. The pooled OLS model does not take advantage of this opportunity. To do so, we need to use the fixed effect estimator.

6.1.4 Fixed effects

The fixed effect (FE) estimator allows for the unobserved effect a_i to correlate with our explanatory variables because the fixed effect approach eliminate its bias. This makes the FE model more robust than pooled cross-section.

One way to implement fixed effects is by dummy variable regression. In this model, it is assumed that the unobserved effect, a_i, is a parameter to be estimated for each i. In equation 6.2, a_i is the unknown intercept for each county i that is to be estimated along with the $\boldsymbol{\beta_j}$. The way this intercept is estimated is by including a dummy variable for each county, along with the explanatory variables and year dummies. What is obtained is a time- and county-fixed effects regression model:

$$y_{it} = \beta_0 + \delta_k \mathbf{T_{kt}} + \boldsymbol{\beta_j} \mathbf{x_{itj}} + \mathbf{a_i C_i} + u_{it} \tag{6.4}$$

where $\mathbf{C_i}$ represents a dummy for each county i, and $i = 2, 3...19$ (county 1, Østfold is omitted as the base county) represents the different counties. In the FE approach, a_i is taken out of the error term and we can estimate the model using the OLS estimator without violating the zero conditional mean assumption.

The fixed effect estimation allows for different individual constant terms and we do not need the same strong assumptions as when running cross-sectional pooled OLS with the composite error term. The fixed-effect estimation will control for any county-specific, time-invariant factors influencing BEV sales that are not controlled for directly by the explanatory variables.

The fixed effects estimator is only BLUE under the right set of assumptions, which will not be described here. It is sufficient to underline that for the fixed effects estimator to be unbiased, the idiosyncratic error u_{it} from the panel data model in equation 6.2 should be uncorrelated with each explanatory variable across every year between 2010 and 2014. This means that in our FE model, we had to control for time-varying effects that could potentially be correlated with any explanatory variables.

Since the dummies in equation 6.4 capture all the county-specific time-invariant effects in our data, we are only utilising the variation **within** each county when estimating the coefficients of our explanatory variables. This means that while the FE model fixes some of the problems that we encounter in the pooled OLS model, it also completely neglects the **between** county variation. As Kohler and Kreuter (2012, p. 245) writes:

> One side effect of the features of fixed-effects models is that they cannot be used to investigate time-invariant causes of the dependent variables. Technically, time-invariant characteristics of the individuals are perfectly collinear with the person [or entity] dummies. Substantively, fixed-effects models are designed to study the causes of changes within a person [or entity]. A time-invariant characteristic cannot cause such a change, because it is constant for each person.

In other words, when we used the fixed effect estimator we discarded all the effects time-invariant explanatory variables might have on BEV sales. This means that the time-invariant variables we identified for our analysis, average temperature, kilometres of coastline and elevation, could not be used in the FE approach. Moreover, for the explanatory variables that vary little across time, such as metres of bus lanes, the fixed effect estimator will produce estimators that are imprecise. It would therefore be preferable to also be able to take advantage of the variation between the counties. This leads us to the random effects model.

6.1.5 Random effects

The random effects (RE) model allowed us to analyse the county-specific time-invariant variables' effect on BEV adoption rates. A crucial assumption of the RE model, as for pooled cross-section models, is that that the unobserved effect (a_i) is uncorrelated with each explanatory variable included in our model for all the time periods analysed. Under this assumption, the model in equation 6.2 becomes an RE model. Formally, the assumption is written as follows:

$$Cov(x_{itj}, ai) = 0, \qquad t = 2010, ..., 2014; j = 1, 2, ..., n \tag{6.5}$$

which is a strong assumption. It should be used only if it is believed that the unobserved effect is indeed uncorrelated with the explanatory variables, or if the analysis is attempting to estimate the effect of time-fixed variables.

Under the random effects assumption, coefficients on all our explanatory variables can be consistently estimated, even with only one single cross section of our counties. It is therefore not necessary to use panel data to obtain consistent estimates under this assumption. However, as mentioned earlier, we use panel data to make use of important information from the other time periods. Applying the pooled OLS approach described above would also have led to consistent estimators of the β_j under the RE assumptions, but this estimator is more susceptible to serial correlation problems that needs to be corrected for. This correction renders the POLS estimates less efficient than the RE estimates.

This serial correlation problem is corrected for in the RE approach, and under the right assumptions results in an estimator that is consistent and efficient. This estimator allows for the effects of time-invariant control variables to be measured. In our case, it meant that we could estimate the effects of a county's average temperature, elevation and coastline on the sales of electric vehicles. This is a very useful property of the RE estimator, especially in cases where time-fixed explanatory variables are of principal interest. For our analysis however, this attribute was not of primary concern, but it would nevertheless be beneficial.

Furthermore, the RE estimator allows us to utilise more of the variation in the data set. By taking advantage of between variation we can more accurately estimate the effect of the approximately time-invariant bus lane variable. For this reason, and that the RE estimator produces more efficient results than the FE estimator, we sought to use an RE approach. If we believe that all the explanatory variables we include in our model are uncorrelated with any unobserved county-specific time-invariant effects that might affect the BEV sales share, we can adopt the RE approach and be sure that we have a model with coefficients that are both more efficient than those of the FE approach and at the same time consistent. The reason the RE estimator produces more efficient estimates is because it does not rely on using dummies as explanatory variables, meaning that it uses less degrees of freedom. It gains this efficiency boost by relying on the extra RE assumption. Methods to test whether the RE approach was appropriate for our particular model specification is discussed later in this section.

6.2 Coefficient of determination

Depending on the model specification, different measures for the coefficient of determination (R-squared) is calculated. In a multiple regression model, the R-squared is the proportion of the total sample variation in the dependent variable that is explained by the independent variables (Wooldridge, 2006).

In pooled OLS models we use adjusted R-squared as this measure imposes a penalty for adding additional independent variables, which R-squared does not. For the FE models we have to take into account that we are only utilising the within variation in our variables, hence we apply the within goodness of fit. The RE model utilises both within and between variation in our data set, and we therefore have to consider the overall R-squared in RE models. These three measures of the goodness of fit can not be compared directly, as they explain the portion of total variation in the particular dependent variable in the respective regression, and the functions of the dependent variable in the three model specifications will have different variation to explain. However, the measure of goodness of fit can be used to compare how well one model specification fits the data to another model with the same dependent variable.

6.3 Post regression tests

Various post-regression tests were executed in the process of obtaining the best possible model specification for the data at hand.

6.3.1 Model selection tests

The Hausman test was used to decide between RE and FE models while the common F-test for multiple regressions were used to compare the fit of the different linear models, testing for significance of the coefficients.

The F-test was used to see if there were any reason to control for fixed effects, both unobserved and observed, in our model. The null hypothesis of the test claims that the fixed effects are equal across all the counties, and rejecting this null hypothesis hence means that there is evidence that this difference is not likely to be zero. If the null hypothesis cannot be rejected, there is no evidence for a panel effect and there is no reason to use the less efficient FE estimator, and the POLS estimator is preferred. If the F-test indicates that the fixed effects are non-zero, pooled OLS and random effects will be biased if the unobserved fixed effects are also correlated with any of the included explanatory variables. This condition is tested with the Hausman test.

The Hausman (1978) test assisted in deciding between the RE, FE and POLS estimators[7]. As Wooldridge (2006) explains, the idea behind the Hausman test is that we use

[7]The Hausman test was performed such that the covariance matrices were specified to be based on the estimated disturbance variance from the efficient RE estimator. Doing so is recommended when

the random effects estimates unless the Hausman test rejects the null hypothesis, which states that the unobserved effect a_i is uncorrelated with the explanatory variables. A rejection is taken to mean that the key RE assumption ($\text{Cov}(x_{itj}, a_i) = 0$) is false, and that the FE estimator is preferred because it is still consistent while the RE estimator is not. Failing to reject the Hausman test can mean two things. Firstly, it can mean that the FE and RE estimates are sufficiently close and it is therefore better to use the more efficient RE estimates. Secondly, It can indicate that the sampling variation is so large in the FE estimates that it is difficult to conclude whether differences that are significant on a practical level, are also statistically significant. In the latter case, the data might be lacking enough information to provide precise estimates of the coefficients. We used the results of the Hausman test to check if we managed to find data on all time-invariant individual specific factors that have an effect on the explanatory variables and the dependent variable. If this was the case, the Hausman test would not reject the null-hypothesis, and the interpretation would be that the RE and FE estimates are sufficiently close so that the RE estimates are preferred. The Hausman test was also used to test whether an FE or POLS modelled is preferred.

The Breusch and Pagan Lagrange Multiplier test for random effects were used to examine the statistical significance of the RE model compared to pooled OLS (Breusch and Pagan, 1979). The null hypothesis for this test is that the variance of the unobserved fixed effect in the regression is zero. We use this test to see if the random effect estimation is preferred to pooled OLS. Rejecting the null means that the random effects estimation is preferred because we find evidence of significant differences across units in the data. If the null hypothesis can not be rejected at any reasonable significance level, it means that a panel effect can not be identified, and it is therefore more suitable to run a POLS mode.

6.3.2 Heteroskedasticity and serial correlation tests

In ordinary least squares regressions, one of the main assumptions is homogeneity in the variance of the residuals. To make sure our models gave efficient results, it was important to correct for possible incidents of heteroscedasticity. If the model suffers from heteroscedasticity, the variance of the residuals, i.e. the variance of the predicted y, are not constant given any value of the explanatory variables (Wooldridge, 2006). An example is if the variance of the residuals of the BEV sales share increases with

comparing fixed effects and random effects linear regressions because the estimations are much less likely to produce a non-positive-definite-differenced covariance matrix (StataCorp, 2013).

increased number of charging points. In such a situation, the value of the coefficients in the regression results are still correct, but we cannot trust that we have made the right conclusion of their statistical significance.

In our data set there were few charging points and a low share of BEVs across the whole country in the first year examined. As charging stations can be seen as a hygiene factor for adoption of BEVs, it is reasonable that the sales share is low when the number of charging points are few, making the variance in the residuals small. When more charging stations are built, it makes room for a higher discrepancy in the sales share and number of charging points. Some consumers adopt the new technology, others do not. In other words, the gap between counties with buyers and non-buyers are likely to increase with increased number of charging points. This gave us reasons to worry about heteroskedasticity. Heteroskedasticity can also arise as a result of outliers, which are common regarding new technology, and is also more likely to be present in data sets of modest size, such as the one we employ.

We can use diagrams to illustrate potential heteroskedasticity graphically. If we plot the residuals against the line for the fitted values, the deviations from this line should be the same for all fitted values. Otherwise there will be problems of heteroskedasticity.

Econometric post-regression tests such as Cook-Weisberg and the White-test can also provide information of heteroskedasticity. The Cook-Weisberg test tests the null-hypothesis that the error variance is constant across all observations against the alternative hypothesis that it is not. A rejection of the null is regarded as evidence of heteroskedasticity. A disadvantage of the Cook-Weisberg test is that it only checks for linear forms of the problem. The White-test is a similar, but more general, test that allows for nonlinearities. The test adds several terms to test for more types of heteroskedasticity, and as a result it consumes a lot of degrees of freedom. The White-test is therefore less likely to produce a significant test result than the simpler Cook-Weisberg test.

Our data was grouped into county-clusters, with standard errors assumed to be independent between counties, but correlated within. The default standard errors could then potentially greatly overstate the estimator precision resulting in misleadingly narrow confidence intervals (Colin Cameron and Miller, 2015). If the before-mentioned tests indicate heterogeneity, we can adjust for this problem by using cluster-robust standard errors. Because we have variables aggregated on county-level, clustering at this scale was required. Clustered standard errors allowed the unobservable variables to correlate within the county, and affected the variance estimators. Consequently, the coefficients in our regression tables were rightfully less statistically significant with clustered-robust standard errors where intragroup correlation is allowed. This is especially crucial to do for the POLS estimator considering its aforementioned weaknesses. It is also beneficial for the FE estimator to use cluster-robust standard errors as its estimated standard errors are drastically understated in in the presence of serial correlation, as Bertrand et al. (2004) point out.

Considering how serial correlation could have disrupted our analysis significantly, it was necessary to check if our models suffered from this problem. To check for serial correlation in our panel data models, we implemented a test developed by Wooldridge (2002). The test's null hypothesis states that there is no first-order serial correlation in the model. A significant test statistic indicates serial correlation problems. We computed standard errors for all our models before we tested for serial correlation and then we conferred with the Wooldridge test to see if this was necessary.

6.4 Model specification

We now formulate our final model specification. When formulating our model, we evaluated what functional form and variable specifications would best capture the effects we are trying analyse. The resulting model is displayed in the following equation :

$$\begin{aligned} BEVSalesShare_{it} = {} & \beta_0 + \beta_1(ChargingPointsPercapita_{i(t-1)}) \\ & + \beta_2(FerryExpensesPerCar_{it}) \\ & + \beta_3(TollExpensesPerCar_{it}) + \beta_4(BusLanes_{it}) \\ & + \beta_5(HouseholdIncome_{it}) + \beta_6(PeoplePerHousehold_{it}) \\ & + \beta_7(Unemployment_{it}) + \beta_8(VKT_{it}) \\ & + \beta_9(Temperature_i) + \beta_{10}(Coastline_i) + \beta_{11}(Elevation_i) \\ & + \delta_k T_{kt} + \underbrace{\left[v_{it}\right]}_{POLS/RE} + \underbrace{\left[a_i C_i + u_{it}\right]}_{FE} \end{aligned} \tag{6.6}$$

where either the last or the second last term is included depending on which estimator is used.

In section 5, we mentioned how we chose to use a lagged indicator for charging points per capita to model how consumers would need time to adjust to its development. The charging infrastructure was still in its early stages at the start of the time period studied. We argue that it took people some time to notice that charging stations had been built and to learn where they were so as to feel confident enough to drive around and not be worried about range issues. For our three other key explanatory variables, we contend that this treatment is not necessary. All three factors have been present in all counties long before the time period studied, and therefore we debate that consumers are able to respond to changes in these incentives within a one year period. Consumers are well-aware of these factors, and will have an immediate impact on their demand function for electric vehicles.

The charging station variable was considered a potential source of endogeneity problems in equation 6.6. It can be argued that the number of charging points are in fact a function of the size of the EV fleet, which in turn can be said to be a function of the sales share of electric vehicles. This is a particularly compelling argument if one were to regard the decision of developing charging stations as a business decision. A company profiting from developing the charging infrastructure network, would respond to increased EV sales share and the corresponding increase in the EV fleet, by building more charging stations. Following this line of argument, it is clear that the variable for charging points would create endogeneity problems, severely weakening our analysis as we would be attempting to model vehicles sales share by using a potentially flawed variable as one of our key variables of interest. However, we argue that in the case of Norway, and in the time period studied, developing the charging infrastructure has not solely been a business decision, but has been heavily influenced by policy makers in the national and regional government. Such policy measures are likely to be unaffected by the development of the EV fleet in the short time period over a few years. It is a time-consuming process to implement policy changes and allocate resources to projects, such as in the case for Transnova, and increases in the EV fleet from one year to another are not likely to have been able to influence these decisions. We argue that businesses wishing to build charging stations were entirely dependent on government support as the share of EVs compared to the total car fleet was so low that no projects would be profitable on their own. Additionally, specifying a lagged variable also mitigated potential problems that could have been caused by the charging point indicator being determined by our dependent variable.

The toll and ferry expenditure variables can be argued to be endogenous if EV drivers tend to pass through toll stations and use ferries more than ICEV drivers because they are exempted from fees. It can be argued that if the sales share of electric vehicles were high in one year, this would reduce the expenses of ferry trips and toll station passes in the next year because more drivers are exempt from fees. We propose that this is highly unlikely at a magnitude that would affect these variables considerably. BEVs make up a very small share of sales in the time period studied and an even smaller share of the car fleet in every county[8]. The last key variable, length of bus lanes, is undoubtedly not influenced by the number of BEVs within a county, and we therefore conclude that all our key variables in the analysis satisfy the assumption of exogeneity.

Different functional forms were examined to find the one that represents the relationship we are aiming to model in the best way. A logit transformation of our dependent variable to normalise its distribution and construct a log-level model was considered, but was not found to be appropriate for our analysis. Our dependent variable contains zero values, which need to be adjusted for when doing log transformations and we did not find a method to deal with this that would not compromise our regression framework. Also, we do not have reasons to believe that changes in our explanatory variables were related to *constant* percentage changes in our dependent variable. Particularly for the charging points variable, we suspected that its effect on sales share would be varying, based on our earlier discussion on hygiene factors. We tested and compared the log-level and level-level models and found the latter to have the highest statistical significance. Tests on other transformations of our dependent variable were considered and tested, but were found to neither increase the explanatory power of our model, nor did we find any econometric reasons for doing so.

Several of our explanatory variables were considered log-transformed to create level-log models for our final model specification. This was not found to be a suitable operation for median household income partly based on the comments by Mersky et al. (2016). A log-transformation was neither considered expedient for our other variables based on how we chose to specify them. Their interpretation would not be as straightforward if we were to consider percentage changes in ferry expenses per capita for example, it is more intuitive to evaluate level changes in such a situation. We ran regressions where we log-transformed different sets of our explanatory variables, with and without a log-transformed dependent variable, without getting results of higher statistical significance.

The two measures for population density we collected for our analysis (people per square kilometre in the urban areas of a county and people per square kilometre for the whole county) were both highly correlated with our bus lane variable. We suspected that three of our key variables (bus lanes, toll expenses and charging points) were all indicators of urban areas and because of possible multicollinearity problems, we chose not to include them in our model. However, we investigate the relationships more in detail in the sensitivity analysis.

[8]In 2013, there were 17770 electric vehicles registered in Norway, of a total of 2,5 million passenger vehicles.

The correlation analysis shows that the education variable has strong correlations with two of our key variables and several other variables included in our model. Despite its promising correlation with our dependent variable and the findings in previous literature, we decided to drop the education level indicator altogether from our main model.

In this section, we have presented the framework that allowed us to analyse which of the different models aligned best with our research question. As we believed there to be time-invariant county-fixed effects in our data, the fixed effect and random effect approaches are two procedures that can control for such unobserved heterogeneity. The FE model requires less strict assumptions than the RE model and does not suffer from the same serial correlation problems and omitted variable bias as the POLS approach. We did not put much emphasis on identifying the effect of any time-invariant variables in our analysis, which is one of the main reasons of using RE. We included variables such as temperature and coastline mainly as controls to quantify their impact on our dependent variable. However, our key variables such as ferry expenses and bus lanes do not change considerably over time, and therefore taking advantage of the variation between the counties in an RE or POLS approach would be beneficial to the analysis. Also, the RE model is more efficient than both the POLS and FE approach as it produces more precise results under the right conditions. We had to consider using the POLS model in the event that our data set did not exhibit any panel effects. We needed to conduct tests to check whether it would be statistically justifiable to choose the RE model over the other two. We outlined tests and corrections for problems such as serial correlation and heteroskedasticity.

7 Results

In the two preceding sections we discussed the data gathering process, presented summary statistics and analysed the correlation between our variables. The empirical framework was also put forward, laying the foundation for how we incorporated the data in our regression analysis and tested the various model specifications. We also formulated our regression model. This section will present the regression results from the specified model along with post-regression tests assessing the validity of our results. The section also includes a sensitivity analysis where we specify our model using different explanatory variables.

7.1 Regression analysis

In this subsection, we present the regression results for our main model and analyse them. Heteroskedasticity was controlled for in all models with standard errors clustered on the county level, section 7.1.2 shows the results of the heteroskedasticity test for our model. The R-squared statistics (R^2) reported in each table depends on the estimator used: it represents adjusted R-squared for the POLS models, the within R-squared for the FE models and overall R-squared for the RE models. See section 6 for a discussion on the intuition behind this choice. Table 7.1 recapitulates the variables used in the analysis.

The regression results from our final model specification are presented in table 7.2. The table shows the results from regressions using the FE, POLS and RE approaches. All three were potential estimators for our model, each with strengths and weaknesses, as outlined in section 6. Our initial goal was to use the RE estimator since we have argued that, under the right circumstances, it is preferred over the POLS and FE estimators. We also have two key variables that do not vary much over time: ferry expenses and bus lanes. To justify an RE approach, we included macro factors that vary little over time and time-invariant factors in our final model specification. Many of the most apparent regional differences in Norway are geographically determined and although we did not seek to estimate their effects on BEV sales specifically, we still wanted to control for them in an attempt to justify using the more efficient RE estimator.

To asses which panel data method to use, we ran several post-regression tests on the three models in table 7.2, the outcome of these tests are presented in table 7.3. The F-test yielded a significant test statistic leading to a rejection of the null hypothesis,

Table 7.1: Nomenclature for regression variables

Variable Name	Description	Unit
BEV Sales Share	Share of total vehicle sales that are BEVs	Vehicles
Charging Points per Capita	Number of charging points per driving-eligible capita, from the year before	Charging points
Ferry Expenses per Car	Total expenditure on ferry travel per car	NOK
Toll Expenses per Car	Total expenditure from passing toll stations per car	NOK
Bus Lanes	Length of bus lanes	Metres
Household Income	The median household income after tax in a county	NOK
People per household	Average household size in a county	People
Unemployment	People unemployed in the first month of each year	Percent
VKT per Car	Average distance travelled by a car in a county	Kilometres
Temperature	Average temperature in a county	Celsius
Coastline	Coastline length of a county	Kilometres
Elevation	Share of a county's land area that is 600 MASL or higher	Percent

meaning that there is evidence of non-zero fixed effects in our models. If these fixed effects are also correlated with the explanatory variables, the pooled OLS and RE estimators will be biased. Columns two and three in table 7.3 display the Hausman test results when comparing the POLS model with the FE model, and the RE model with FE model, respectively. The results show that the test statistic is sufficiently small in both cases so that the null hypothesis cannot be rejected at any reasonable significance level. The POLS and RE estimators are therefore preferred over the FE estimator. Left with the choice between the POLS and the RE model, we used the Breusch Pagan Lagrange Multiplier Test to check whether or not there was evidence of a panel effect in our data set. Based on the results from this test, we could not reject the null hypothesis at any reasonable significance level, and the POLS approach was preferred to the RE approach.

We ran post-regression tests on many different model specifications without finding a single case were the RE model was preferred to the POLS one, and we failed to justify the use of a panel data approach for our data set. We suspect that the reason for this was the limited number of observations in our sample, which will be addressed further in section 8.

Based on the post-regression tests conducted, we chose to move forward with analysing the results from the pooled OLS model from table 7.2. We also ran a joint test of whether our included year dummies were jointly equal to zero to assess if it was expedient to use time-fixed effects in our model [9]. The resulting test statistic was significant at the 1% level and we concluded that the year dummies contributed to the explanatory power of the model, supporting our initial assumption.

[9] See results in table A.1 in the appendix.

Table 7.2: Regression results for electric vehicle adoption in Norway

	(1) FE	(2) Pooled OLS	(3) RE
Charging Points per Capita	22.8967**	30.5258***	32.1132***
	(8.00102)	(8.11416)	(7.9079)
Ferry Expenses per Car	-6.72e-06	-8.66e-06*	-9.77e-06*
	(.0000977)	(4.95e-06)	(5.49e-06)
Toll Expense per car	7.80e-06**	4.37e-06***	4.76e-06***
	(3.20e-06)	(1.35e-06)	(1.60e-06)
Bus Lanes	7.63e-06	-1.54e-07	5.40e-08
	(4.70e-06)	(4.65e-07)	(5.67e-07)
Household Income	7.91e-07	-2.04e-07	-3.29e-07*
	(8.04e-07)	(1.89e-07)	(1.99e-07)
People per Household	.373996**	.0111369	.0589577
	(.172849)	(.0728969)	(.0806466)
Unemployment	-.0164949	-.019484***	-.0200461***
	(.0111472)	(.0062127)	(.0073196)
VKT per Car	.0000156	-8.05e-06	-9.92e-06
	(.0000225)	(6.72e-06)	(6.98e-06)
Temperature	0	.0015577	.0010619
	(.)	(.0017141)	(.0018328)
Elevation	0	-.0002001**	-.0002**
	(.)	(.0000745)	(.0000828)
Coastline	0	1.04e-06***	1.04e-06***
	(.)	(2.80e-07)	(3.08e-07)
Constant	-1.39011**	.224045**	.198628*
	(.588312)	(.0993495)	(.117162)
R^2	.900355	.820589	.847497
Year Dummies	Yes	Yes	Yes
Observations	95	95	95

Standard errors in parentheses are clustered on the county level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.3: Post-regression tests

	(1) FE	(2) Pooled OLS	(3) RE
Hausman Test	-	.490828	.505675
Breusch-Pagan Test	-	-	.229093
F-Statistic	4.03448	-	-

7.1.1 Analysing the model

We now turn to analyse the coefficients from the POLS model in table 7.2 with robust standard errors.

The coefficient of lagged charging points is highly significant, both statistically and economically. The results imply that an increase of one charging point per driving-eligible capita one year will result in a 3052 percentage point increase in the share of BEVs sold the next year, holding everything else constant. However, considering that the maximum number of charging points per capita observed in our data set is 0.0033 (see table 5.1), it is more relevant to consider an increase of one charging point per 1000 capita, which infers an increase in BEV sales share of 3.05 percentage points in our model. This is a fairly strong influence and is in line with our assumptions about the effects charging stations have on the EV adoption rate. We observe that compared to the FE estimator, this variable has a higher effect in the POLS approach. We suspect that there might be some time-invariant factors that the FE approach eliminates, and the POLS estimator includes in its estimate.

The coefficient for ferry expenses is statistically significant at the 10% level by a very small margin. Its sign is contradictory to what we argued for in the Data section, but in accordance with what the correlation analysis indicated and our previous stated concerns about this variable. The negative coefficient of 0.00000866 suggests that an increase of 1000 NOK in ferry expenses per car per year, holding everything else constant, will decrease the BEV sales share with 0.00866, or 0.866 percentage points. In the FE model, this coefficient is not statistically significant at a sensible significance level. We will discuss the unexpected coefficient on the ferry variable further in the sensitivity analysis and in section 8.

The coefficient of toll expenses is significant at the highest level and positive in table 7.2. Rising toll expenses will according to our model increase the EV adoption rate, as expected. Interpreting this coefficient in terms of marginal changes is not intuitive, instead we consider changes by 1000 NOK. An increase in toll expenses of 1000 NOK per car from one year to another leads to an increase of 0,00437 in the BEV sales share, or 0.437 percentage points.

The coefficient of the bus lane variable did not turn out significant at any sensible significance level in any of the models from table 7.2, indicating that it is not an influential contributor to EV adoption. People per household does not appear significant in the POLS model, but it seems influential for BEV adoption with the FE approach.

The coefficient of unemployment has a negative sign, as theory predicts, and is significant at the 1% level. The model suggest that decreasing the unemployment rate in the first month of a year with one percentage point will increase the share of BEVs sold by roughly 1.95 percentage points that year, holding all else equal. Median household income after tax on the other hand, does not have the positive effect we expected it to have on a normal good. However, this variable is only significant in the RE model. Vehicle-kilometres per car is not found to have a statistically significant effect on BEV sales share using either of the estimators.

The coefficients of the coastline and elevation variables are significant at the 1% and 5% level, respectively. Our model predicts that counties with a longer coastline have a slightly higher sales share of BEVs, while counties with more of its area at high elevations have a lower BEV sales share. The results for the elevation coefficient correspond with our expectations, while the coefficient of coastlines has a sign opposite of what we argued for in section 5. Theoretically, an increase of one kilometre of coastline is followed by 0.000104 percentage point increase in the BEV sales share, and a county with one percentage point more of its area at elevations of 600 MASL or higher, will have its BEV sales share reduced by 0.02 percentage points. The time-invariant variable temperature does not have a significant coefficient in any of the models. These variables are by design omitted from the FE model due to perfect collinearity.

The goodness of fit described by R-squared (R^2) in the three models in table 7.2 is quite high. An R-squared of 0.82 in the POLS model means that we have managed to explain a considerable portion of the variance in the data set with our model specification. The time dummies account for much of this predictive power[10] as they capture everything that happened a certain year that does not vary across counties. Furthermore, the FE specification has the highest explanatory power in terms of the within R-squared with 90% of the within-county variation being explained by the model.

[10]Excluding the time dummies from our regression leaves us with a model with an R-squared of roughly 0.58. See table A.2 in the appendix.

7.1.2 Results from heteroskedasticity and serial correlation tests

To make sure the assumption of homogeneity in the variance of the residuals in the OLS regressions were not violated, we performed tests for heteroskedasticity. We also checked our panel data for serial correlation to make sure that the efficiency of our POLS and FE estimators were not compromised by correlating error terms.

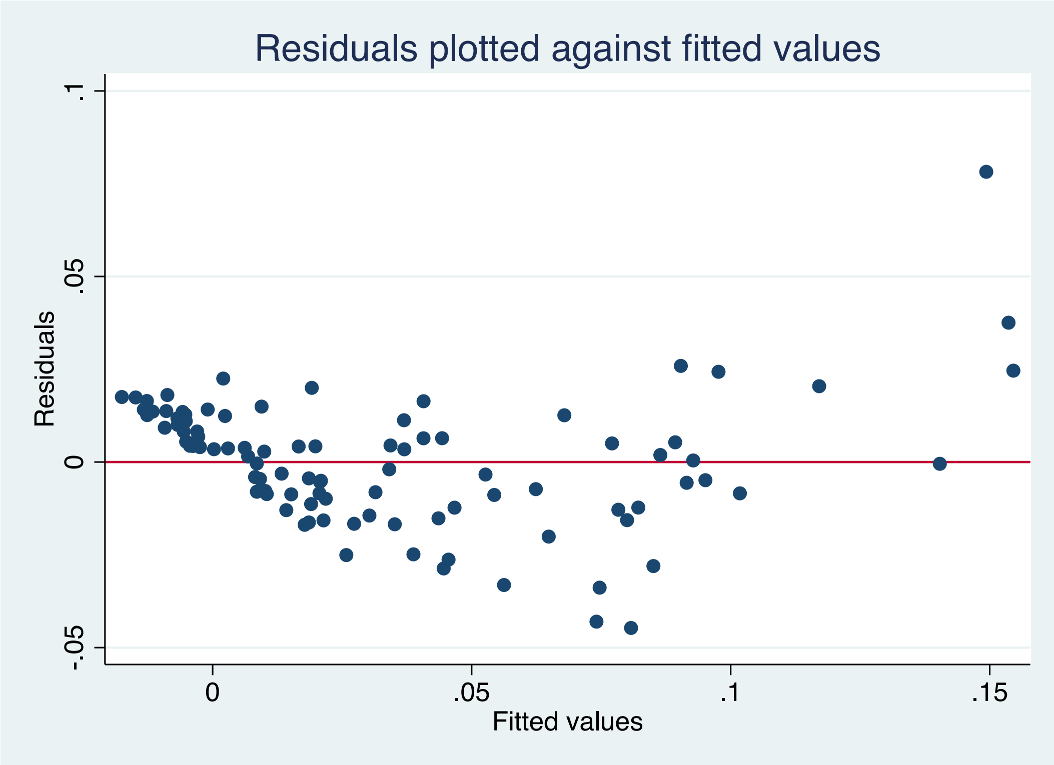

Figure 7.1: Identifying heteroskedasticity

Figure 7.1 shows that the variance in the residuals vary across the fitted values as the band is getting wider with increased fitted values. This is a clear sign of heteroskedasticity. Furthermore, the results of the Cook-Weisberg and the White-test, shown in table 7.4, are contradicting each other. The Cook-Weisberg test statistic and corresponding probability, warrant a rejection of the null hypothesis and thus indicate that the variance of the errors from the regression is dependent on the independent variables. The White-test however does not produce a test statistic that results in a rejection of the null hypothesis of homoskedasticity. This might be due to loss of power from the small sample size and large number of regressors, as discussed in section 6.3.2. We chose to rely on the Cook-Weisberg test in addition to our interpretation of figure 7.1 and concluded that heteroskedasticity was present in our model. We thus found it expedient to correct for this by clustering the standard errors on counties, making them robust.

Table 7.4: heteroskedasticity Tests

	Cook-Weisberg Test	White Test
Chi2	47.42259	95
Probability>Chi2	5.72e-12	.4517351

We also tested our panel data set for serial correlation. This test was rendered highly important as the post-regressions tests pointed to the POLS estimator to be the preferred one, and this particular estimator is especially susceptible to serial serial correlation problems. A significant test result was not obtained by running the Wooldridge test for serial correlation[11] and we failed to reject the null hypothesis, and conclude that there are no evidence of serial correlation in our data set.

7.2 Sensitivity analysis

To test the robustness of our model, and to increase our understanding of the results, we performed a sensitivity analysis. We first specified a model without any control variables to examine if it could be simplified. Then we investigated the relationship between length of bus lanes, population density and people per household more closely. We also ran a regression with toll and ferry expenses combined into one variable. Lastly, we specified a model where we omitted the year dummies and allowed for a time trend.

7.2.1 Model without control variables

The model with no control variables is shown in table 7.5. The coefficients of charging points and toll expenses are still highly significant, although the charging point coefficient is no longer significant at the highest level. The coefficients on both variables have remained relatively similar in magnitude. The effect of charging points is somewhat smaller, meaning that controlling for more macro variables, amplifies the influence of charging points on the BEV sales share in a county. The coefficient of toll expenses increased by 11%, from 0.00000437 to 0.00000492 when omitting the controls. This is not a notable augmentation, but indicates that toll expenses might pick up some of the effect of the other explanatory variables included in our main model. The coefficients of ferry expenses and bus lanes are not significant in this model, but their signs are now positive. This is more in line with what we expected, however, as we control for

[11] Table A.3 in the appendix display the results from the test.

Table 7.5: Regressions results: no control variables.

	(1) FE	(2) Pooled OLS
Charging Points per Capita	29.59***	24.03**
	(8.091)	(8.957)
Ferry Expenses per Car	-0.0000158	1.63e-06
	(0.0000863)	(2.71e-06)
Toll Expense per car	0. 8.33e-06**	4.92e-06***
	(2.90e-06)	(1.37e-06)
Bus Lanes	0.0000116**	3.44e-07
	(4.34e-06)	(4.28e-07)
Constant	-0.0609	-0.0134***
	(0.0663)	(.004613)
R^2	0.886	0.800
Year Dummies	Yes	Yes
Observations	95	95

Standard errors in parentheses are clustered on the county level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

more variables, the effect of these variables turns negative. Again, this suggests that the ferry expense and bus lanes variables are somewhat spurious.

Without any control variables, the post-regression tests unsurprisingly point in direction of the FE model rather than the pooled OLS model. This is because the FE approach controls for time-invariant county-specific effects. In table 7.5 we also included the FE model because it has some interesting results. The charging point and toll expense coefficients are still significant at high levels and they have a larger impact on the BEV sales share when controlling for time-invariant county-specific effects. The coefficient of the ferry expense variable is negative, as in our main model, but is not significant in this case. The coefficient for bus lanes is both positive and significant in this specification. However, since bus lanes do not vary much over time, we suspect that there are time-invariant county-specific factors behind this variable that is omitted by the design of the FE approach that wrongfully augment the bus lanes variable's effect on the dependent variable. This idea is supported by the results in both model (1) and (2) in table 7.2.

7.2.2 Different measures for population density

In the main model, we did not include a measure for population density due to its correlation with bus lanes and because our key variables most likely are urban indicators. Including population density was ultimately deemed unnecessary and disturbing for our results. Initially, we predicted that excluding population density could increase the significance of bus lanes to a significant level, but this was not the case. Instead of population density we included people per household. Without correcting for population density, we could expect that people per household would model the fact that households tend to consist of single people in urban areas, and bigger families outside the cities. This reasoning suggests a negative correlation between people per household and BEV sales share, a relationship shown in table 5.4 in the Data section. However, assuming that the key variables capture the urban effect, the positive sign on the people per household coefficient in table 7.2 is not counter-intuitive. Although not significant in the POLS model, the coefficient of people per household is significant at 5% level in the FE model. This suggests that there might be other time-invariant factors correlating with number of people per household that captures this effect in the POLS and RE models.

In model (1) in table 7.6 we have run the same regression as model (2) in table 7.2 using the POLS approach, and included a variable for number of people per square kilometre in the county to see if this changes our results significantly. The number of people per square kilometre is relatively time-invariant during the time period in question, so a comparison with the FE model is not constructive. The coefficient on the new variable appears with a negative, yet insignificant sign. Its lack of significant effect in our model could suggest that the key variables represent urban areas as argued, and capture much of the same effects as population density.

A notable result from specification (1) is that the sign of the bus lane coefficient has changed to what we expected, although it is still not significant. Ferry expenses retain their negative and significant effect on BEV sales share, but with reduced magnitude. The effect on the other coefficients in the regression of including the population density variable is not noteworthy. Charging points capture even more of the change in BEV sales share in this model, while the impact from increased toll expenses has become slightly smaller, and its coefficient has lost some statistical significance. Unemployment has a larger coefficient in this model specification. The consequence of including population density for the variable for number of people per household is minor. We can see a slight decrease in the size of the coefficient, but it is still far from being significant.

Table 7.6: Regressions results: specifying population density

	(1) Specification 1	(2) Specification 2	(3) Specification 3
Charging Points per Capita	32.4357***	30.4995***	32.4492***
	(8.26112)	(7.98344)	(8.39195)
Ferry Expenses per Car	-8.65e-06*	-8.38e-06*	-8.62e-06*
	(4.96e-06)	(4.56e-06)	(4.64e-06
Toll Expense per car	3.77e-06**	4.36e-06***	3.77e-06**
	(1.65e-06)	(1.32e-06)	(1.62e-06)
Bus Lanes	1.31e-07	-2.00e-07	1.28e-07
	(6.61e-07)	(3.90e-07)	(6.24e-07)
Household Income	-2.73e-07	-1.74e-07**	-2.70e-07**
	(2.05e-07)	(7.22e-08)	(1.26e-07)
People per Household	.0014343		
	(.0742039)		
Population Density	-.0000156		-.0000157
	(.0000166)		(.0000166)
Unemployment	-.021111***	-.0194656***	-.021123***
	(.0065086)	(.0061884)	(.0062984)
VKT per Car	-9.94e-06	-7.51e-06	-9.89e-06*
	(6.29e-06)	(5.44e-06)	(5.25e-06)
Temperature	.0020829	.0015806	.0020902
	(.0020171)	(.0016793)	(.0019232)
Elevation	-.0002653**	-.0001984**	-.0002657**
	(.0000967))	(.0000748)	(.0000965)
Coastline	9.47e-07***	1.04e-06***	9.47e-07***
	(2.70e-07)	(2.74e-07	(2.67e-07)
Constant	.307915***	.228423**	.309179**
	(.120934)	(.0907003)	(.107424))
R^2	.819284	.822751	.821571
Year Dummies	Yes	Yes	Yes
Observations	95	95	95

Standard errors in parentheses are clustered on the county level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Including both people per household and people per square kilometre in the model did not provide much interesting insight. In an attempt to simplify the model, both the measure for people per household and the measure for population density was excluded in model (2) in table 7.6. Comparing the simple model (2) to our main model (2) in table 7.2 reveal that household income is now significant at the 10% level, and has a negative impact on the BEV sales share. It is reasonable to assume that household income is closely related to people per household, and that omitting the latter will wrongfully assign more significance to the former. Their positive relationship is evident in both table 5.4 and figure 5.13 from the correlation analysis section. Fewer people in a household will typically mean that household income is also lower. Therefore, if people per household are not controlled for, the household income variable will capture the negative effect more people in a household have on the BEV sales share. For our model, it is thus essential to control for people per household. The coefficient of the bus lane variable has an increased negative effect on BEV sales, moving further away from our initial expectation that having access to bus lanes should be positive for BEV adoption. The coefficient is still insignificant. The remaining coefficients stay approximately the same compared to model (2) in table 7.2, and they remain at the same levels of significance.

In model (3) in table 7.6, people per square kilometre was added to the model specification. This marginally reduced the effect of toll expenses compared to both the simple model (2) and the main model. The coefficient of bus lanes has turned positive, but remains insignificant in statistical terms. Median household income is significant at the 5% significance level with a negative sign, which speaks against economic theory, given that we define BEVs a normal good. It also contradicts previous research that find income to be a positive determinant of BEV sales. In this model, unemployment captures more of the changes in BEV sales share. Furthermore, the coefficient of kilometres travelled per car is now significant at a 10% significance level, which is not the case in any of the other models considered. This indicates that the number of people per household and kilometres travelled per car might be disrupting each other. Population density might correct for some underlying effects, making vehicle-kilometres travelled significant in the model. People per household evidently plays a role in the significance of VKT. We have stated that the effect of VKT is ambiguous. One could argue that the benefits of driving a BEV are more influential in counties were VKT per car is higher, giving it a greater positive impact in a consumers demand function. On the other hand, it can be argued that higher mileage in a county is an indication of longer distances, making range anxiety more prevalent, having a negative effect on the demand for BEVs.

In model (3) in table 7.6 the latter seems to be the case, presumably because the effects of the first argument is captured in the other variables.

In conclusion, specifying models with different measures of population density and omitting people per household had some interesting implications for our main results. The coefficients of the charging points and toll expenses variables remained significant and of roughly the same magnitude in all models, while the measures for ferry expenses and length of bus lanes did not. The latter two variables change signs and significance in the various model specifications, indicating that they have a spurious influence on BEV sales share. The conclusion we draw from this section is that it is necessary to control for people per household in our model so that the effect of household income is accurately modelled. We also specified a model with population density in the cities as variable. This variable did not generate interesting changes in our results[12]. This supports the argument that our key variables themselves represent urban characteristics.

7.2.3 Combining ferry and toll expenses

Ferry expenses had an unexpected effect in our main model and has changed notably throughout the sensitivity analysis. We also argue that ferry and toll expenses, to a certain extend, represent the same incentive and they therefore complement each other. Several counties where toll station expenditure per car is high have low ferry expenses and vice versa. These factors suggest that a model where ferry and toll expenses are combined could provide interesting results.

Figure 7.7 displays regression results from the original model specification along with a model where ferry and toll expenses have been combined. The combined coefficient is both significant and has the sign expected. Its magnitude is slightly lower than those of the separated coefficients in model (1). Charging points per capita have a slightly smaller coefficient, in terms of both economical and statistical significance. This might be due to the ferry and toll expenses not disrupting each others results to the same extent in model (2) compared to model (1) in table 7.7. Two variables, who were pulling in opposite directions, are combined to one variable, and this variable absorbs some of the influence charging points had on the dependent variable. This might also explain why the coefficients on unemployment and elevation have lost all their significance. The coefficient on coastlines retains its significance but is less influential.

[12]See table A.4 in the appendix for results.

Table 7.7: Regression results: combining ferry and toll expenses

	(1) Separate	(2) Combined
Charging Points per Capita	30.5258***	24.7428**
	(8.11416)	(9.56064)
Total Expenses - Ferry and Toll		3.57e-06**
		(1.58e-06)
Ferry Expenses per Car	-8.66e-06*	
	(4.95e-06)	
Toll Expense per car	4.37e-06***	
	(1.35e-06)	
Bus Lanes	-1.54e-07	1.58e-07
	(4.65e-07)	(5.83e-07)
Household Income	-2.04e-07	1.02e-07
	(1.89e-07)	(2.18e-07)
People per Household	.0111369	-.0744192
	(.0728969)	(.0832412)
Unemployment	-.019484***	-.0102967
	(.0062127)	(.0074416)
VKT per Car	-8.05e-06	5.81e-06
	(6.72e-06)	(6.69e-06)
Temperature	.0015577	.0017683
	(.0017141)	(.0019442)
Elevation	-.0002001**	-.000067
	(.0000745)	(.0001417)
Coastline	1.04e-06***	8.65e-07***
	(2.80e-07)	(2.61e-07)
Constant	.224045**	.0578502
	(.0993495)	(.129943)
R2	.820589	.797181
Year Dummies	Yes	Yes
Observations	95	95

Standard errors in parentheses are clustered on the county level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.4 Substituting year-fixed effects with time trends

We included year-fixed effects in our main model to control for nationwide exogenous shocks occurring in each year, which might have influenced our dependent variable. This is a reliable method of controlling for year-specific events, but it makes the model more complex and uses degrees of freedom. Instead of including time dummies, one could argue that the outside market development affecting BEV sales share in the Norwegian counties follows a simple linear trend. The amounts of BEV models available to Norwegian customers and the amount of dealerships selling them, have progressively increased over the years. Specifying a linear trend instead of year dummies results in a more parsimonious regression model, which is appealing in econometric terms. In table 7.8 we have run a regression with the same explanatory variables as in the POLS estimator from model (2) in table 7.2, but where the year-dummies have been substituted for a year trend. We also ran a model with an exponential trend because it can be argued that the examples of trends mentioned above are exponential, such as the rapid increase in BEV models available in the Norwegian market.

Adding a simple linear time trend to the model drastically decreases the significance and effect that charging points have on BEV sales share in our main model. It appears that the trend absorbs a lot of the effect from the charging point variable. This is to be expected as the number of charging points have continuously increased throughout the time period examined, and the time trend mimics this development to a certain extent. The coefficient of charging points remains significant at a 10% significance level, with roughly half the effect on BEV sales compared to the main model. Toll expenses have a slightly larger impact on BEV sales, while the coefficient of ferry expenses has lost its significance. The length of bus lanes in a county is now significant at the 5% level with the predicted positive sign. Both time-invariant variables that were significant in our main model have lost some significance and magnitude of their coefficients in model (2) in table 7.8. Elevation is no longer statistically significant at any level, and its sign has changed. The time trend variable indicates that the underlying development in moving from one year to another increases the BEV sales share with 2.01 percentage points.

Model (3) in table 7.8 has an exponential time trend included in addition to the linear one. Specifying the model in this manner yields coefficients that are more similar to those in our main model. The coefficient on charging points per capita has the same statistical significance as in the original model, with a slight increase in its magnitude. Ferry expenses is not significant at any level, just as in the model with a simple linear time trend. Toll expenses and the time-invariant variables remain significant and their

Table 7.8: Regressions results: specifying time trends

	(1) Year Dummies	(2) Time Trend	(3) Exponential Time Trend
Charging Points per Capita	30.5258***	15.1137*	32.3286***
	(8.11416)	(7.4401)	(7.38248)
Ferry expenses	-8.66e-06*	-5.51e-06	-8.44e-06
	(4.95e-06)	(4.79e-06)	(5.04e-06)
Toll Expenses	4.37e-06***	5.17e-06**	4.45e-06***
	(1.35e-06)	(1.94e-06)	(1.34e-06)
Bus Lanes	-1.54e-07	1.20e-06**	-2.06e-07
	(4.65e-07)	(5.31e-07)	(4.44e-07)
Household Income	-2.04e-07	-2.58e-07	-1.81e-07
	(1.89e-07)	(2.80e-07)	(2.01e-07)
People Per Household	.0111369	.0999919	.0106936
	(.0728969)	(.0984922)	(.0743638)
Unemployment	-.019484***	.0023502	-.017407***
	(.0062127)	(.0057794)	(.0053492)
VKT per Car	-8.05e-06	-9.43e-06	-9.05e-06
	(6.72e-06)	(8.40e-06)	(6.15e-06)
Mean Temperature	.0015577	.0005139	.0011381
	(.0017141)	(.0016449)	(.0014472)
Elevation	-.0002001**	.0001185	-.0001865**
	(.0000745)	(.0001182)	(.0000785)
Coastline	1.04e-06***	9.02e-07**	1.01e-06***
	(2.80e-07)	(3.81e-07)	(2.70e-07)
Trend		.020586***	-.0475921***
		(.0038757)	(.0094268)
Exponential Trend			.0103529***
			(.0015855)
Constant	.224045**	-.0546582	.26219**
	(.0993495)	(.121118)	(.105112)
R^2	.820589	.694127	.819072
Year Dummies	Yes	No	No
Observations	95	95	95

Standard errors in parentheses clustered on the county level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

coefficients have roughly the same magnitudes, as in the main model (2) from table 7.2.

Substituting year-fixed effects for a linear time trend substantially changed the results of our main model, but adding an exponential term made the two models remarkably similar. Both model modifications provided some interesting insight into our variables. We argue that there have been many changes in the macro environment that do not follow a trend in the time period examined, and that modelling time in this fashion is too simple for our purposes. The technological development for example, even though progressively increasing, has not followed a linear trend. The improvements in the EVs supplied are rather characterised by releases of major new models such as the Tesla model S or Nissan Leaf. Furthermore, the development in the oil and electricity prices does not indicate a trend during the time period studied[13]. We put forward similar arguments for the exponential trend. We find it difficult to justify such a model specification based on our knowledge of the development in nationwide factors that could have affected BEV sales in the period in question. In short, we believe the development to be too complex for either a linear or exponential trend to capture it and argue that using time dummies is a more general and safer choice. However, our arguments can be challenged and the linear time trend model modification show that the effect of charging points on BEV adoption might be smaller than what our main model in table 7.2 suggests. In both models with time trend specification in table 7.8, charging points retains its statistical significance. Toll expenses also remain significant, but might be slightly underestimated in our main model. These two points are encouraging for our analysis because they promote the robustness of two of our key variables. This analysis also reinforces the notion that the effects of ferry expenses and length of bus lanes on BEV sales, if present at all, are difficult to pinpoint.

7.3 Summary of the results

Our results suggest that several of the examined policy instruments have been influential in determining the adoption of battery electric vehicles. The number of charging points the preceding year has the highest effect on BEV sales share for a year. Our analysis predicts that an increase of one charging point per 1000 driving-eligible capita will increase the BEV sales share with 3.05 percentage points the next year, all else equal. Toll expenses were also found to have a prominent effect on BEV sales: an increase of

[13]We retrieved data on household power prices, prices for auto-diesel and prices for car petroleum. Analysing the development in the average fossil fuel price and the average national household power price revealed no clear overall trend for these variables in the time period between 2010 and 2014. See figure A.1 in the appendix.

1000 NOK in toll expenses per car from one year to another would lead to an increase in BEV sales share of 0.437 percentage points. One would expect the ferry expenses to have roughly the same effect as toll expenses - however, this was not the case in our analysis. To the contrary our main model indicates that increased fares on ferries would reduce the BEV sales share. The bus lane variable was not found to have a significant effect on the dependent variable. The fact that two of our four key variables had a significant effect on our dependent variable, along with the expected relationship, is promising for our analysis.

The time-invariant county-specific factors included in the analysis provided some insight into what geographic and climatic differences have prompted BEV adoption in Norway. The results show that coastlines are positive determinants of a county's BEV adoption rate, and that elevation is a negative determinant. Temperature was not found to have a significant effect on the diffusion of electric vehicles, but its coefficient had the expected sign.

In our sensitivity analysis, charging points and toll expenses remained significant and in accordance with our expectation, while the coefficients of ferry expenses and kilometres of bus lanes showed some spurious results. Various model specifications of population density and people per household did not lead to significant changes in the results. Including a linear time trend drastically reduced the effect of charging points and amplified the effect of toll expenses and length of bus lanes. An exponential time trend however, resulted in similar results as our main regression. Combining expenses for ferry travel and toll station passes resulted in a significant and positive variable, which reduced the significance and magnitude of the charging points coefficient.

We conclude that the two key variables charging points and toll expenses have a significant effect on BEV sales share, while the effect of ferry expenses and bus lanes do not prove robust in this analysis. A thorough discussion of our results will follow in the next section.

8 Discussion

The results show that socioeconomic incentives together with climatic and geographic differences have statistical significant effects on the rate of EV adoption in Norway. In this section, we first discuss our results before we consider potential shortcomings in the data set and in the empirical approach that led us to these results. We then propose ideas for future work on the topic and suggest improvements that can be implemented in subsequent research on this topic. Finally, we consider the implications of our study for government policy.

8.1 Discussion of the results

The results from our study are only valid if the explanatory variables are exogenous. In section 6, we argue that the variable for charging points is exogenous from the fact that constructing charging stations mainly is initiated by the government and not a business decision of profit-maximising firms. Furthermore, we lag this variable making it even more robust to endogeneity problems in the model. We also argue that ferry and toll expenditure along with the amount of bus lanes are determined by factors outside our model. For our analysis, we conclude that our key variables satisfy the assumption of exogeneity.

Throughout the robustness tests, charging points and toll expenses remains significant and in accordance with our expectations - which is encouraging for our analysis. The fluctuating results from ferry expenses and bus lanes are troubling. A significant and negative coefficient of ferry expenses is not in line with the conventional economic theory. An increase in ferry fees can be interpreted as an increase in the relative price of ICEVs, the substitute good. This should lead to an increase in demand for BEVs, given that we define BEVs as a normal good. Through the sensitivity analysis we find mixed results for this variable, and we suspect we have not managed to separate out the pure effect of ferry expenses in the modelled variable. As we saw in the summary statistics section, there seems to be a negative relationship between ferry and toll expenses in some regions. It is likely that these two variables operate together in the market to some extent, meaning that the government uses both ferry fees and toll stations to collect money for infrastructure investments and that they are somewhat interchangeable. In the sensitivity analysis, running a model where toll and ferry expenses were combined yielded a significant and positive coefficient. However, the combined variable probably has a significant effect due to the strong positive influence of toll stations we identified in our analysis - and not because combining them created a more accurate indicator. Combining them merely reduced the effect of other variables without adding interpretation value to our results. We argue that keeping the variables separated is more beneficial.

For access to bus lanes to function as an incentive for a potential BEV-buyer, the bus lanes should be located in a congested area. If this is not the case, there would be no benefit of the privilege and the argument that BEV drivers can save time falls apart. We argue that bus lanes are constructed on road stretches with a heavy traffic load by nature, as they are a means of alleviating public transport from congestion problems. The strong correlation between bus lanes and population density supports this argument. Since bus lanes, toll expenses and charging points are all characteristics of urban areas, we have a problem in separating the pure effect of access to bus lanes on BEV adoption. On the other hand, the time spared by having access to bus lanes alone might not be enough to choose a BEV over an ICEV. Adding that charging points might represent a hygiene factor, and that we only found a moderate impact of toll expenses - we suspect that all the key variables operate together in incentivising BEV adoption. Their overlapping effects might prevent us from identifying a significant coefficient of factors that have a smaller impact, like access to bus lanes.

Unemployment was the only demographic factor that was found to be significant in our model. Its large negative impact on BEV sales is in line with what could be expected. Higher unemployment rates means that the purchasing power is lower and consumptions of normal goods, such as the EV, will typically go down. However, the variable varied all through our sensitivity analysis and the coefficient in the main model might be misleading.

Coastlines and elevation were found to have significant effects on the BEV adoption rate, and retained their significance in general through the sensitivity analysis. Our assumptions on the detrimental effects of elevation are supported by the regression results. Mountainous regions are likely to inhibit BEV adoption rates and this conclusion proved to be relatively robust through our sensitivity analysis. The effect of coastlines did not lose its significance in any of the model specifications. The sign of its coefficient was not in accord with the arguments we put forward, and we need to reassess its impact. Our assumptions of coastal regions having more turbulent climate might be wrong. Sør-Trøndelag and Hordaland are two regions with long stretches of coastline, which have the highest average BEV sales share throughout the period. There could be other characteristics of Norwegian counties with long coastlines that encourage BEV adoption, together with the other explanatory variables in our model. Furthermore, dividing regions by counties does not yield large differences in coastline kilometres in Norway. Using a smaller geographic scale with more nuanced regions could provide better estimates.

8.2 Limitations in the data set and empirical approach

As Wooldridge (2006) points out, difficulty in inferring causality can arise when studying data at high levels of aggregation. Initially, we aimed to use the RE approach in our analysis, as it generates more efficient estimates and provides insight into time-invariant explanatory factors - but the post regression tests indicate that we cannot trust its assumptions. The tests unveil contradicting conclusions, suggesting that there are some deficits in our data set.

The most apparent weakness of our study is the limited sample size that we had to operate with. The FE an RE approaches, as most statistical methods, are prone to errors when applied to small samples. The result of our small sample size was an inability to specify an RE model that was preferred to a simple pooled OLS regression framework by the Breusch-Pagan test. Furthermore, the limited sample size is likely to have affected our Hausman test results and led to a rejection of the FE model — not on the basis of the RE and FE estimates being similar — but due to large sampling variations in the FE estimates. The sample size could have been increased by either focusing on a municipal level, where 422 observational units are available, or using more years in the study. We believed, as justified in the Data section, that an analysis on the municipal level would not be suitable due to the lack of reliable data points at this level. We also considered using data from earlier years, but decided that this would not help our analysis for the same reasons. Also, in the period before 2010, the EV market was immature and the true effects of the incentives studied in this thesis would have been difficult to ascertain. Hence, we argue that we have used the most fitting approach based on the data available at the time of writing.

The data we have employed to model toll and ferry expenses have some vulnerabilities. The toll expense variable is computed from information on toll projects, not on the specific toll station. We had to make adjustments to get a measure of the total expense for car drivers passing through toll stations within each county, which might not reflect the true value. Furthermore, this variable is not corrected for the number of EV passes, meaning that we wrongfully include free passes when calculating total toll expenses. We reiterate that the number of EVs that passed through toll stations was negligible and thus should not interfere notably with the variable. Some toll projects that were financed by ferry stretches are likely to constitute a marginal part of the calculated toll expenses, potentially making it overestimated compared to the real expenses. We attempted to identify and remove the cases where a toll project included ferry stretches, and were informed by the NPRA that the influence of ferry trips was minimal in the data set for toll projects. Ferry expenses are more likely to be impacted by the overlapping data sets, the noise probably constitutes a larger share of the information from the ferry data. This might help explain why we had difficulties determining an effect of ferry expenses in our analysis.

An additional shortcoming in the ferry variable is that it includes traffic numbers for heavy transport and tourism. On certain ferry stretches, traffic mainly consist of cargo transport and tourism[14]. This does not raise incentives for BEV demand among the private car drivers, creating noise in the ferry-variable and causing us to overestimate the potential savings per car.

8.3 Suggestions for future research

Our analysis covers a crucial period in the Norwegian EV adoption timeline, but does not include the most recent years. We used data ranging from the early market stages to when the market was reaching maturity, allowing us to capture the effect of the main drivers of EV adoption over a period when EV sales went from being marginal to experiencing explosive growth. Having access to BEV sales numbers for 2015 and 2016 would significantly have strengthened the analysis, as those two years constitute crucial maturity period of the marked and also mark a turn in the political climate around government incentives for BEVs. Many local governments have started to phase out some of the BEV incentives such as free access to bus lanes and reduced ferry rates. In the 2017 state budget, the Norwegian government promotes a green shift and aims at growing the share of emission-free cars in the coming years (Ministry of Finance, 2016). At the same time, they are scaling back on some of the incentives for electric vehicles, such as exemption from toll fees. It will therefore be interesting to undertake a similar analysis as ours in the coming years.

Having access to sales numbers from more recent years could also potentially enable a municipal analysis. Municipalities have more distinct features compared to counties as they represent a more detailed regional division. This makes it possible to study effects

[14]Especially ferry stretches between the northern islands are exposed to tourism (Mimir, 2006; Bodø NU, 2015).

of factors that might not vary much on the county level, such as the median age. A municipal analysis would be more comprehensive and flexible than a county-level one.

A more sophisticated spatial analysis based on the municipality level could also contribute to determining regional drivers of EV adoption. The low sales numbers in individual municipalities could be circumvented by aggregating municipalities based on geographic or socioeconomic similarities, in essence creating a customised regional division. This allows for a more flexible analysis, providing more detailed results. Saarenpää et al. (2013) undertakes such a study for Finland, where they analyse the adoption of hybrid electric vehicles in demographically distinct areas constructed. A similar research approach can also be applied to Norway.

Through our work, we identified and gathered information on many important drivers for BEV adoption - but there are without a doubt many other significant factors that have been omitted from our analysis. We wanted to include the number of public parking spots in each county, but were unable to retrieve data of sufficient quality. There is probably a strong link between public parking spots and the amount of charging points. Many local governments have combined the two so that people can charge their electric vehicles while parked. With information on public parking, one could separate the effects of charging infrastructure and parking availability on the electric vehicle sales share. These two effects might have been merged in the charging points variable in our analysis. Risk aversion, as mentioned in section 4.2, might impose changes in the real demand function for BEVs. Looking into how the consumer perceive the relative prices of a BEV and ICEV, based on differences in the known and expected expenses of the two, could be an interesting platform for future research on the topic.

Our analysis focuses on a time period where the EV was technologically evolving from a limited mode of transportation into a well-functioning vehicle. It is therefore not suitable for describing the role of the incentives in a mature market. As ICEVs and BEVs become closer substitutes, it is reasonable to assume that incentives to promote BEVs become less important. In the future it will thus become more relevant to investigate what drivers retain the EV fleet, rather than what drivers promoted the growth in the past.

8.4 Implications of the study

According to our results, the government push for developing a network of charging stations has had an important impact on increasing the share of BEVs in the Norwegian car fleet. The investments made by the government in this area have been successful in promoting their goal of reducing emissions from the transportation sector. Previous research are mostly in unison on the importance of charging infrastructure (Malvik et al., 2013; Sierzchula et al., 2014; Lutsey, 2015; Mersky et al., 2016). However, our analysis indicate a somewhat smaller implication of an additional charging unit than previous research. Sierzchula et al. (2014) find that, holding all other factors constant, each additional charging *station* per 100,000 residents would increase a country's EV market share by 0.12%. With slightly different measure, we find that increasing the infrastructure with a single charging *point* per 100,000 driving-eligible residents, would lead to an increase in BEV *sales* share by 0.00305 percentage points. That being said, we argue that there is a difference in our explanatory variables of whether they actively incentivise purchase of BEVs, or rather are needed as hygiene factors. Undoubtedly, EVs will have no future without charging stations. It is critical that charging points are available, however to what extent building more charging stations will drive forward demand for EVs is questionable, especially in a maturing market. The effect of access to bus lanes and exemption from ferry expenses show mixed results in existing literature. We can not find evidence of these factors being important driving forces for BEV adoption, everything else kept constant. Contrary to the research done by Mersky et al. (2016), we do not find evidence of income being an important driver for BEV adoption. Further challenging Mersky et al.'s results, we find toll expenses to be an important factor in determining BEV sales using our empirical approach.

Supplementary to what has been found in previous research, we find evidence that geographical characteristics of a county influence how susceptible residents are to shifting their means of transport to BEVs. To our knowledge this as not been investigated earlier. We find that counties with longer coastlines and less area at high elevation, are more likely to have a higher BEV sales share. In short, mountainous regions will need stronger incentives to promote BEV adoption than coastal areas with fewer mountains. These factors can be interpreted as measures for harsh environment and cold climate, elements that amplify range anxiety among BEV drivers. The first observation is therefore contradicting what we expected, but the impact of more area at higher MASL seems reasonable.

By allowing electric vehicles reduced rates on ferries and access to bus lanes, the government has tried to make it more appealing to buy an electric vehicle, but not without a cost. These activities were subsidies by the government in order to correct a perceived market failure. Potential income from ferry travels is forgone, and the traffic in bus lanes have increased to an extent where public transport is inhibited in some areas. The fact that there is little evidence that these incentives have had a significant effect on the adoption of electric vehicles in Norway, suggest that the subsidies have not been successful in correcting the market failure and reducing the emissions from the transportation sector. This in turn implies that the subsidies could have been used in other, more efficient ways for the same purpose.

The income that was foregone by exempting EVs from toll fees had a positive effect on the BEV adoption rate according to our study. The government's investment into this incentive has successfully promoted their goal of reducing the market failure arising from consumers not incorporating the perceived positive externality on the environment from BEV adoption. Whether increasing the BEV sales share in Norway actually solves the climate change problem is a different question. The funds foregone could have been used in other sectors of the economy, potentially mitigating pollution problems in a more efficient manner. There is an ongoing debate of how efficient electric cars actually are in reducing climate problems (Eskeland, 2012; Holtsmark, 2012; Huo et al., 2015), but this is beyond the scope of this paper.

All things considered, we support existing literature that it is more probable that the ensemble of socioeconomic incentives function together with a well-developed network of charging stations to promote high EV adoption rates. We argue that government intervention in the market for electric vehicles was beneficial to increase the BEV sales share in the years between 2010 and 2014. It was important to reduce the perceived market failure and provide incentives for the majority of consumers beyond the early adopters, by reducing the relative prices of EVs compared to ICEVs. However, times are changing and electric vehicles are becoming a significant part of the car fleet. We are past the threshold of EVs being of lesser functionality than ICEVs, the technology has come far and the industry might not need as much help from the government as in the early years of production. Many EVs are also becoming less expensive, making them available to a larger market segment. There are reasons to discuss whether reducing the government's cost to subsidies for BEV adoption might be beneficial. Even though our results speaks of some significant impact, today the means might be employed in other ways with greater impact.

Whether our results are applicable for the Norwegian government in the coming years depends on how we define our sample and population. In terms of Norway in the years 2010 to 2014, our sample is exhaustive covering all counties. The sample examined is the same as the population. If we consider the regions in the time period 2010-2014 as a sample of the same regions over a larger time period, the population is not exhaustive. We can then draw some parallels beyond the regions and the time periods we studied.

However, whether the counties in previous years are representative for the future is debatable. The situation in Norway in 2010, regarding the market for electric vehicles, was quite different from the current one. Comparing the development that has been, to a development in the coming years is difficult with completely different starting points. As argued, it is unlikely that the substantial effect of the first set of charging points will persist through another decade. Access to bus lanes becomes less compelling as the EV fleet grows bigger and the bus lanes fill up. Furthermore, even though the effects of financial incentives on the consumer might be present also in the future, the circumstances that formed the basis for maintaining those incentives up until now, have changed drastically. The aim in the early market phase and market introduction phase was to kick-start the EV market in Norway, to get the early adopters on board and dissolve consumer scepticism so as to build a self-sufficient EV-market. As the market is entering an expansion phase, one can postulate that the objective for the government in the future has to shift towards sustaining growth and the evoked EV-adoption rates with other means than those needed for the pioneer purchases.

The climate change issues is a global concern, and it would be rewarding if our findings could guide international policy makers in countries with emerging EV-markets. To do so, we need to argue that the Norwegian counties represent a random sample for regions in the world[15]. To define the Norwegian counties as a part of a bigger worldwide population, the foundations of the regions would have to be the same. Taking into account the different political systems, law enforcement, culture and geographical characteristics, this is highly unlikely. On the other hand, as proposed for future research, aggregating regions based on characteristics could provide a basis for comparisons where our Norwegian-founded analysis can be combined with research on a global scale.

[15] The POLS framework considers data points as independent observations, and enables comparisons beyond the sample. The FE approach does not allow for this.

9 Conclusion

Through this study we have aimed to answer the research question *"How did government intervention in the automobile market affect the battery-electric vehicle adoption in the Norwegian counties in the period between 2010 and 2014, and what regional differences influenced the adoption rate?"*. The analysis focuses on factors determining sales that differ between the Norwegian counties.

We used data on vehicle sales in Norway from 2010 to 2014 and concentrated on the development of sales in battery electric vehicles compared to sales of other types of passenger cars. Information on a plethora of potentially influential factors and control elements were gathered, resulting in a comprehensive panel data set. To capture both time-varying and time-constant drivers, we used a pooled OLS approach, as tests found no evidence of a significant panel effect in our data.

Our results suggest that charging infrastructure has been essential for driving forward BEV sales together with exemption from road tolls. According to our estimates, an additional charging point per 1000 driving-eligible person will be followed by an increase in BEV sales share of 3.05 percentage points, holding all other factors constant. An increase in the toll expense the average car driver faces of 1000 NOK per year, would cause an increase in BEV sales share of 0.44 percentage points. The results remain stable through various model specifications and robustness tests, with modest changes in magnitude. The effect of exempting BEVs from ferry fees and giving them access to bus lanes did not prove robust in this analysis.

This paper contributes to prior research on the development of electromobility by focusing on a single country over time. We argue that we with strong confidence can conclude on the causal relationship between the examined factors and BEV adoption, due to the added time aspect. An effect that previous research have struggled to confirm. For current policy makers in Norway, our study shows that the government intervention has been important in encouraging a substantial EV fleet in Norway. Withdrawing the incentives might have serious consequences for the future development of EV sales. However, we argue that the circumstances in the market today are considerably different than in the years examined; it is debatable whether the counties in 2010 to 2014 is a representative sample for the counties in the future. In order to apply this paper's findings to policy decisions in others countries, a similar assumption would have to be made. It is a strong assumption to state that the Norwegian counties in the period from 2010 to 2014 is representative for regions in other countries, but parallels can certainly be drawn. Building a solid charging infrastructure network is momentous for promoting EV sales, and together with socioeconomic incentives - especially alleviations in road tolls - the government has potential to drive forward widespread electric vehicle adoption.

Appendices

A Results

Table A.1: Test for joint significance of time dummies

	(1) F Statistic	(2) Probability > F
F-test	12.59	0.0000

Table A.2: Regression results: no time dummies

	(1) FE	(2) Pooled OLS	(3) RE
Charging Points per Capita	13.0433	35.4346***	35.4346***
	(9.61845)	(9.02788)	(9.02788)
Ferry Expenses per Car	.0000671	-7.45e-06	-7.45e-06
	(.0000972)	(6.69e-06)	(6.69e-06)
Toll Expense per car	.0000102**	4.66e-06**	4.66e-06**
	(3.68e-06)	(2.11e-06)	(2.11e-06)
Bus Lanes	.0000149**	-7.66e-07**	-7.66e-07**
	(6.70e-06)	(3.49e-07)	(3.49e-07)
Household Income	4.69e-08	4.67e-07*	4.67e-07*
	(5.73e-07)	(2.44e-07)	(2.44e-07)
People per Household	.104382	-.104597	-.104597
	(.267819)	(.0910356)	(.0910356)
Unemployment	.022436*	.004592	.004592
	(.0117007)	(.0106102)	(.0106102)
Vehicle-Kilometres per Car	-.0000789**	-.0000253**	-.0000253**
	(.0000284)	(.0000105)	(.0000105)
Temperature	0	-.003043	-.003043
	(.)	(.002861)	(.002861)
Elevation	0	.0000203	.0000203
	(.)	(.0001808)	(.0001808)
Coastline	0	5.15e-07	5.15e-07
	(.)	(3.44e-07)	(3.44e-07)
Constant	.564433	.351111***	.351111***
	(.864541)	(.0666961)	(.0666961)
R2	.793941	.578687	.627989
Year Dummies	No	No	No
Observations	95	95	95

Standard errors in parentheses are clustered on the county level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Wooldridge test for serial correlation

	(1)	(2)
	F Statistic	Probability > F
F-test	2.137	0.1610

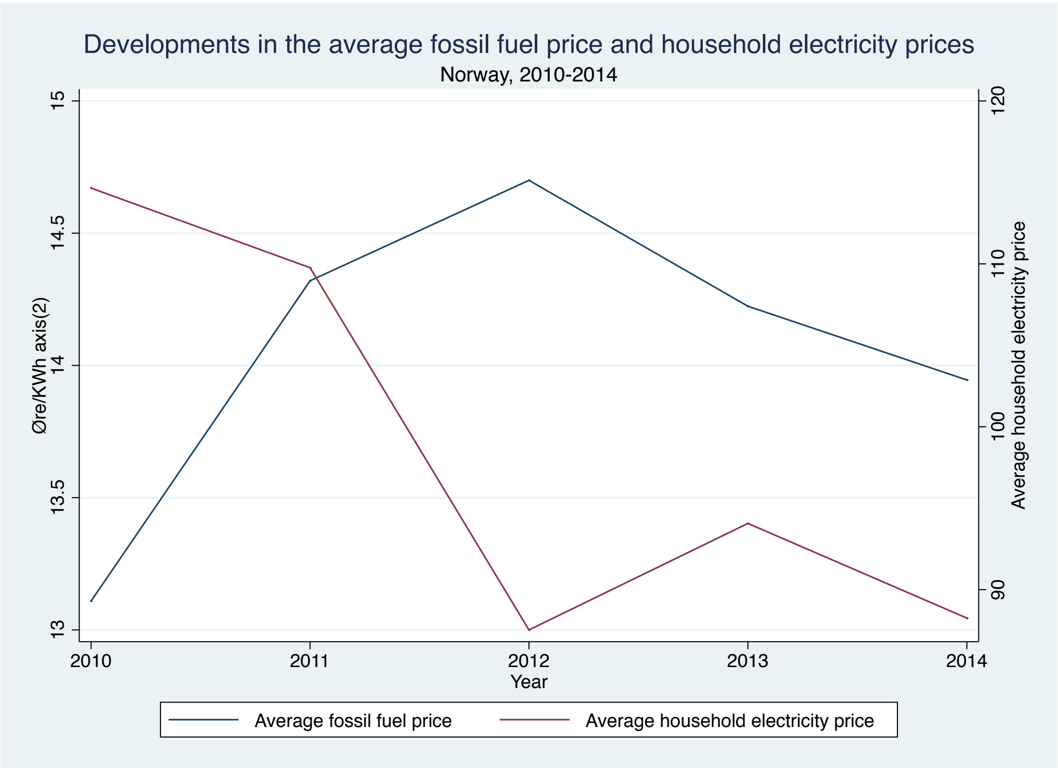

Figure A.1: Fossil fuel and electricity prices

Table A.4: Regression results: urban density

	(1) FE	(2) Pooled OLS	(3) RE
Charging Points	20.9758*	30.218***	31.9315***
	(11.1033)	(8.46713)	(8.57854)
Ferry expenses	-5.91e-06	-8.58e-06*	-9.91e-06*
	(.0000963)	(4.86e-06)	(5.62e-06)
Toll Expenses	7.61e-06**	4.43e-06***	4.93e-06***
	(3.37e-06)	(1.42e-06)	(1.76e-06)
Bus Lanes	7.68e-06	-2.32e-07	1.71e-08
	(4.64e-06)	(6.70e-07)	(9.26e-07)
Household Income	7.39e-07	-1.95e-07	-3.47e-07
	(8.24e-07)	(1.99e-07)	(2.19e-07)
People per Household	.29746	.0144874	.0751371
	(.190462)	(.0778366)	(.0907547)
Population Density in Cities	.0000496	1.69e-06	2.21e-06
	(.0001079)	(.0000109)	(.0000155)
Unemployment	-.0125245	-.0190272**	-.0196489**
	(.0137021)	(.0071797)	(.0090668)
VKT per Car	.0000134	-7.55e-06	-9.58e-06
	(.000024)	(7.11e-06)	(7.81e-06)
Mean Temperature	0	.0014528	.0008182
	(.)	(.0017963)	(.0020529)
Elevation	0	-.0001856	-.0001794
	(.)	(.0001243)	(.0001578)
Coastline	0	1.04e-06***	1.04e-06***
	(.)	(2.78e-07)	(3.20e-07)
Constant	-1.25444**	.20227	.16149
	(.583946)	(.179234)	(.237751)
R2	.900892	.818334	.846551
Year Dummies	Yes	Yes	Yes
Observations	95	95	95

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Bibliography

Asphjell, A., Ø. Asphjell and H.H. Kvisle (2013). *Elbil på Norsk*.

Beldjazia, A and D Alatou (2016). 'Precipitation variability on the massif Forest of Mahouna (North Eastern-Algeria) from 1986 to 2010'. In: *International Journal of Management Sciences and Business Research ISSN* 5.3, pp. 2226–8235.

Bendanillo, Fidel E. et al. (2016). 'Species Composition, Abundance and Distribution of Seawater Bugs (Order Hemiptera: Class Insecta) in Badian, Cebu, Philippines'. In: *Journal of Aquatic Science, Vol. 4, 2016, Pages 1-10* 4.1, pp. 1–10.

Berry, Steven T., James Levinsohn and Ariel Pakes (1995). 'Automobile Prices in Market Equilibrium'. In: *Econometrica* 63.4, pp. 841–890.

Bertrand, Marianne, Esther Duflo and Sendhil Mullainathan (2004). 'How much should we trust differences-in-differences estimates?*'. In: *The Quarterly Journal of Economics* 119.1, pp. 249–275.

Bjerkan, Kristin Ystmark, Tom E. Nørbech and Marianne Elvsaas Nordtømme (2016). 'Incentives for promoting Battery Electric Vehicle (BEV) adoption in Norway'. In: *Transportation Research Part D: Transport and Environment* 43, pp. 169–180.

Bodø NU (2015). *95 prosent av de reisende på Moskenes-ferga var turister*. URL: http://bodonu.no/95-prosent-av-de-reisende-pa-moskenes-ferga-var-turister (visited on 17/12/2016).

Breusch, T.S. and A.R. Pagan (1979). 'A simple test for heteroscedasticity and random coefficient variation'. In: *Econometrica: Journal of the Econometric Society* 47.5, pp. 1287–1294.

CenSES (2016). *Centre for Sustainable Energy Studies (CenSES)*. URL: www.ntnu.no/censes (visited on 17/12/2016).

Colin Cameron, A. and Douglas L. Miller (2015). 'A Practitioner's Guide to Cluster-Robust Inference'. In: *Journal of Human Resources* 50.2, pp. 317–372.

Egbue, Ona and Suzanna Long (2012). 'Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions'. In: *Energy Policy* 48.2012, pp. 717–729.

Elbilforening, Norsk (2016). *Ladestasjoner.no*. URL: http://www.ladestasjoner.no/nyheter/65-3-746-ladepunkt-for-elbiler-i-norge (visited on 10/12/2016).

Enova (2009). *Nye oppgaver til Enova*. URL: https://www.enova.no/finansiering/naring/aktuelt/nye-oppgaver-til-enova/250/1929/ (visited on 01/12/2016).

Eppstein, Margaret J. et al. (2011). 'An agent-based model to study market penetration of plug-in hybrid electric vehicles'. In: *Energy Policy* 39.6, pp. 3789–3802.

Eskeland, Gunnar S (2012). 'Elbil og plugghybrid : Hvilke utslipp er våre ?' In: *Samfunnsøkonomen* 7.

European Commission (2016). *Reducing CO2 emissions from passenger cars - European Commission*. URL: http://ec.europa.eu/clima/policies/transport/vehicles/cars_en (visited on 27/09/2016).

Evans, J D (1996). *Straightforward Statistics for the Behavioral Sciences*. Brooks/Cole Publishing Company.

Fearnley, Nils et al. (2015). *E-vehicle policies and incentives - assessment and recommendations*.

Figenbaum, Erik and Marika Kolbenstvedt (2013). *Electromobility in Norway-experiences and opportunities with Electric Vehicles*. 1281/2013.

– (2016). *Learning from Norwegian Battery Electric and Plug-in Hybrid Vehicle Users*. TØI, p. 9.

– (2015). *Pathways to electromobility - perspectives based on Norwegian experiences*.

Finanskomiteen (2008). *Innst. S. nr. 139*.

Hackbarth, André and Reinhard Madlener (2013). 'Consumer preferences for alternative fuel vehicles: A discrete choice analysis'. In: *Transportation Research Part D: Transport and Environment* 25, pp. 5–17.

Hausman, James (1978). 'Specification Tests In Econometrics'. In: *Econometrica* 46.6, pp. 1251–1271.

Herzberg, Frederick. (1959). *The motivation to work*. 2nd ed. New York [etc.]: Wiley, p. 157.

Hidrue, Michael K. et al. (2011). 'Willingness to pay for electric vehicles and their attributes'. In: *Resource and Energy Economics* 33.3, pp. 686–705.

Holtsmark, Bjart (2012). 'Elbilpolitikken – virker den etter hensikten ?' In: *Samfunnsøkonomen* 5, pp. 4–11.

Huo, Hong et al. (2015). 'Life-cycle assessment of greenhouse gas and air emissions of electric vehicles : A comparison between China and the U . S .' In: *Atmospheric Environment* 108, pp. 107–116.

IEA (2013). *GLOBAL EV OUTLOOK Understanding the Electric Vehicle Landscape to 2020.*

Kohler, Ulrich and Frauke Kreuter (2012). *Data Analysis Using Stata*. 3rd, p. 378.

Lutsey, Nic (2015). *Transition to a global zero-emission vehicle fleet: A collaborative agenda for governments.*

Malvik, Håvard Vaggen, Ole Henrik Hannisdahl and Guro Bøe Wensaas (2013). 'The future is electric ! The EV revolution in Norway – explanations and lessons learned'. In: pp. 995–1005.

Mersky, Avi Chaim et al. (2016). 'Effectiveness of incentives on electric vehicle adoption in Norway'. In: *Transportation Research Part D: Transport and Environment* 46, pp. 56–68.

Miljødirektoratet (2016). *Klimagassutslipp fra veitrafikk*. URL: http://www.miljostatus.no/tema/klima/norske-klimagassutslipp/utslipp-av-klimagasser-fra-transport/klimagassutslipp-fra-veitrafikk/ (visited on 15/11/2016).

Mimir (2006). *Den veibaserte turismens bevegelsesmønster i nordre Nordland og Sør-Troms.*

Ministry of Finance (2016). *Prop. 1 S - Proposisjon til Stortinget.*

NOBIL (2016). *NOBIL API*. URL: http://info.nobil.no/index.php/api (visited on 27/09/2016).

Norwegian Meteorological Institute (2016). *eKlima*. URL: http://sharki.oslo.dnmi.no/portal/page?_pageid=73,39035,73_39049&_dad=portal&_schema=PORTAL (visited on 15/11/2016).

Norwegian Public Roads Administration (2015). *Riksregulativ for ferjetakster*. Norwegian Public Roads Administration. URL: http://fdb.triona.no/contact.xhtml (visited on 02/09/2016).
– (2016). *Sonefordeling*. URL: http://fdb.triona.no/ (visited on 02/09/2016).

NRK (2016). *Høy luftforurensing i flere norske byer tirsdag*. (Visited on 09/11/2016).

Saarenpää, Jukka, Mikko Kolehmainen and Harri Niska (2013). 'Geodemographic analysis and estimation of early plug-in hybrid electric vehicle adoption'. In: *Applied Energy* 107, pp. 456–464.

Shafiei, Ehsan et al. (2012). 'An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland'. In: *Technological Forecasting and Social Change* 79.9, pp. 1638–1653.

Sierzchula, William et al. (2014). 'The influence of financial incentives and other socio-economic factors on electric vehicle adoption'. In: *Energy Policy* 68, pp. 183–194.

SNF (2016). *SNF - Samfunns- og næringslivsforsking AS*. URL: www.snf.no (visited on 17/12/2016).

SSB (2014a). *Befolkningens Utdanningsnivå*. URL: https://www.ssb.no/statistikkbanken/selecttable/hovedtabellHjem.asp?KortNavnWeb=utniv&CMSSubjectArea=utdanning&checked=true (visited on 15/08/2016).

– (2014b). *Familier og Husholdninger*. URL: https://www.ssb.no/befolkning/statistikker/familie/aar/2014-12-12 (visited on 15/12/2016).

– (2016a). *Familier og Husholdninger*. URL: https://www.ssb.no/statistikkbanken/selecttable/hovedtabellHjem.asp?KortNavnWeb=familie&CMSSubjectArea=befolkning&checked=true (visited on 10/10/2016).

– (2016b). *Folkemendge og areal i tettsteder*. URL: https://www.ssb.no/statistikkbanken/selecttable/hovedtabellHjem.asp?KortNavnWeb=beftett&CMSSubjectArea=befolkning&checked=true (visited on 20/10/2016).

– (2016c). *Folkemengde, etter kjønn og ettårig alder*. URL: https://www.ssb.no/statistikkbanken/selecttable/hovedtabellHjem.asp?KortNavnWeb=folkemengde&checked=true (visited on 03/10/2016).

– (2016d). *Folkemengde og areal*. URL: https://www.ssb.no/statistikkbanken/selecttable/hovedtabellHjem.asp?KortNavnWeb=folkemengde&CMSSubjectArea=befolkning&checked=true (visited on 03/10/2016).

– (2016e). *Inntekt etter skatt, etter husholdningstype*. URL: https://www.ssb.no/statistikkbanken/selecttable/hovedtabellHjem.asp?KortNavnWeb=ifhus&CMSSubjectArea=inntekt-og-forbruk&checked=true (visited on 03/10/2016).

– (2016f). *Kjørelengder*. URL: https://www.ssb.no/statistikkbanken/selecttable/hovedtabellHjem.asp?KortNavnWeb=klreg&CMSSubjectArea=transport-og-reiseliv&checked=true (visited on 25/10/2016).

– (2016g). *Konsumprisindeksen - SSB*. URL: https://www.ssb.no/kpi (visited on 03/10/2016).

SSB (2016h). *Registrerte arbeidsledige 15-74 år, etter alder (prosent)*. URL: https://www.ssb.no/statistikkbanken/selecttable/hovedtabellHjem.asp?KortNavnWeb=regledig&CMSSubjectArea=arbeid-og-lonn&checked=true (visited on 03/10/2016).

– (2016i). *Registrerte kjøretøy*. URL: https://www.ssb.no/transport-og-reiseliv/statistikker/bilreg/aar/2016-03-30 (visited on 05/12/2016).

– (2013). *Statistisk Årbok 2013*.

StataCorp (2013). *Stata User's Guide*. Vol. Statistica.

Steinhilber, Simone, Peter Wells and Samarthia Thankappan (2013). 'Socio-technical inertia: Understanding the barriers to electric vehicles'. In: *Energy Policy* 60, pp. 531–539.

Store Norske Leksikon (2014). *Oljekrisen 1973–74*. URL: https://snl.no/oljekrisen_1973 (visited on 01/12/2016).

Transportetatene (2016). *Grunnlagsdokument Nasjonal transportplan 2018-2029*.

U.S Environmental Protection Agency (2015). *Fast Facts U.S Transportation Greenhouse Gas Emissions 1990-2012*.

Wooldridge, Jeffrey M (2002). *Econometric Analysis of Cross Section and Panel Data*.

– (2006). *Introductory Econometrics - A Modern Apporach*, p. 865.

Yuksel, Tugce and Jeremy J. Michalek (2015). 'Effects of regional temperature on electric vehicle efficiency, range, and emissions in the united states'. In: *Environmental Science and Technology* 49.6, pp. 3974–3980.