



# **An Empirical Analysis of Toll Road Exemption as a Determinant for Electric Vehicle Adoption:**

*Norway as a Case Study 2010-2015*

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## Abstract

Rising greenhouse gases (GHG) are posing a series of threat to the physical and economical livelihood of individuals living around the globe. The biggest source of world GHG emission is energy production and consumption activities, which makes the diffusion of energy-sustainable transport innovation to be very crucial. One example of such innovations, which has potential to reduce GHG emission, is electric vehicles (EV). However, despite its potential to address the global warming concern, EV adoption has been very limited without stimulation from external factors: such as strict emission regulation, financial incentives and rising fuel prices. In this regard, the Norwegian government has employed a wide range of incentive packages for promoting the purchase and use of electric vehicles including EV toll exemption. However, currently many people (including many politicians) would consider the market to being close to maturity and therefore expect the government incentives to be removed or updated. With this background, we assess whether the Norwegian EV toll road exemption is significant in promoting EV sales. To accomplish this, we mainly use monthly data on EV sales, toll cost and toll traffic and apply panel data regression method with city, year and month fixed effects. The time range of our analysis is 2010–2015. Our results show that EV toll exemption is insignificant in promoting EV sales in the three cities we consider: Oslo, Bergen and Stavanger. This is true whether you estimate users/drivers saving/cost from EV or non-EV perspectives. Furthermore, we find that charging stations, unemployment, income and vehicle kilometers are significant predictors of the sales of EV, a result which is confirmed by previous studies. But, in contrary to our suspicion, we did not find any significant rebound effect (that may result road congestion) due to the change in consumer driving behavior. Nonetheless, this result is also in agreement with previous survey studies on rebound effect. Overall, our research contributes to the existing literature since it analyzes EV toll exemption at a very detailed level, which was not attempted in previous research having similar goals.

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## Preface

This thesis is written as a part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics (NHH). The thesis is written during the spring semester of 2017 in relation to our independent work in our major profile Energy, Natural Resources and the Environment.

We are grateful to have had the opportunity to write our thesis on such an exciting and relevant topic as adoption of electric vehicles. Throughout our work it has been interesting to gain knowledge and learn about the success story of EVs in Norway and how it can be a step towards a more environmentally friendly future. We firmly believe that the world must look towards solutions like EVs in order for us to have a sustainable future. It has been a challenging process in attempting to quantify the toll road exemption's impact on EV adoption in Norway, but ultimately it has first and foremost been a rewarding one.

We would like to express our sincere thanks to our supervisor Po Yin Wong for her support and guidance throughout the process. We are grateful that her door was always open for insightful discussions. Her advice and constructive criticism improved the quality of our work and have been of great help. We also want to thank everyone who helped providing us with all the data necessary for our work. We especially want to thank Kari Evensen Paulsrud at Norwegian Public Roads Administration for contributing with detailed sales data on electric vehicles in Norway. Special thanks also go to Hilde Foss Christensen at Fjellinjen, Dan Isak Olsen at Vegfinans and Grethe Kleppe at BT Signaal for granting us very detailed data on toll stations.

Bergen, 20th June 2017



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Abiy Getachew Sime



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## Glossary

### **Hybrid electric vehicles (HEV)**

HEV combine battery, electric motors and gasoline engine. These elements can be configured in different ways to meet different objectives: fuel economy, increased power and auxiliary power. Note here that HEV run only on fuel. This means the battery is not charged by connecting to external electrical outlets. It uses a mechanism called regenerative braking, where the normally wasted power during braking is turned into electricity and stored in the battery until needed.

### **Plugin in hybrid electric vehicles (PIHEV)**

PIHEV have both internal combustion engine (ICE) and electric motor with battery. PIHEV are powered by both conventional/alternative fuel and battery. There are basically two different configurations of PIHEV: series (extended range) and parallel (blended). In series PIHEV, the wheels are driven only by electric motor. The engine here generates electricity. On the other hand, in parallel PIHEV both the electric motors and combustion engine drive the wheel.

### **Internal combustion engine (ICE)**

ICE use conventional/alternate fuel to power the wheel

### **(Battery) electric vehicle EV (BEV)**

EV are propelled by electric motors and have no ICE. Hence the battery packs are charged by connecting to external outlets. EV uses no fuel other than electricity generated from various fuel sources. If electricity is generated from sources which has little emission, BEV are the most environmentally friendly among all discussed here.

### **Internal combustion electric vehicle (ICEV)**

Includes both HEV and PIHEV

## List of abbreviations

Adj. R2	Adjusted R2
BEV	Battery Electric Vehicle
EV	Electric Vehicle
FE	Fixed Effect
GHG	Greenhouse Gases
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
ICEV	Internal Combustion Electric Vehicle
IEA	International Energy Agency
MB	Marginal Benefit
MC	Marginal Cost
NOK	Norwegian Kroner
NTP	National Transport Plan
OFV	Norwegian Public Roads Administration
PIHEV	Plugin Hybrid Electric Vehicle
PRI	Priority to Infrastructure
RE	Random Effect
REEV	Range Extended Electric Vehicle
RFC	Reduction of Fixed Cost
RUC	Reduction of Use Cost
SUV	Sport Utility Vehicle
VAT	Value Added Tax
VKT	Average Vehicle Kilometers Travelled



# 1 Introduction

## 1.1 Concerns for greenhouse gas emission and global warming

Rising greenhouse gases (GHG) are posing a series of threat to physical and economical livelihood of individuals living around the globe. GHG, which includes CO<sub>2</sub> and N<sub>2</sub>O, are primarily produced during the burning of fossil fuel in industrial activities and electricity production. Approximately 40% of electricity production comes from coal and 20% of it comes from natural gas. Hence, GHG released during electricity production is of immense amount and has recently gained much attention from policy makers around the world. As stated by the International Energy Agency (IEA), only in 2010, the transport sector released about 6.7 Gt CO<sub>2</sub> which is equivalent to about 22% of the world total: an emission amount which strengthen the basic notion that, concerns for climate change, dwindling of primary energy sources and energy security makes the diffusion of energy-sustainable transport innovation very crucial. One of these innovations, which has potential to address the many challenges we mention above, is electric vehicles (EV). However, despite its potential to address the global warming concern, EV adoption has been very limited without stimulation from external factors, such as strict emission regulation, financial incentives and rising fuel prices. In fact, these factors are seen to be responsible for boosting the sales of EVs in different degree. For instance, financial incentives in the form of consumer subsidies are believed to have a key role for EVs to reach the required market share (Sierzchula, 2014) (Haan, 2006) (Ozaki, 2011).

Reshaping of the current energy consumption patterns highly affect the transport sector, as this sector is among the top three in terms of primary energy consumption and related GHG emission. For instance, in 2007 the transport sector contributed to about 14% (in aggregate) of the world GHG emission (which increases to 22% in 2010 as we mention above). The IEA forecast this amount to rise to 50% in 2030. If we turn our focus to EU, between 1990 and 2000, transport GHG emission (excluding aviation and marine transport) has increased by 19% contributing to 1/5 of the total GHG emission in 2000. Splitting transport in its component part in turn shows that road transport is by far the highest emitter of all transport modes (92% in 2000). An assertion which also goes in agreement with the fact that much of the world oil is used in the transport sector. For instance, transport in the industrialized

countries alone consumes 60.3% of the global oil consumption. The dependence of the transport sector on oil can also be seen in a much clearer sense from individual country perspective. For example, in the United Kingdom transport consumes 38% of the country's overall energy use. The IEA exploit this fact when proposing the alternative policy scenario which claim that by promoting a sustainable energy transport policy (in the form of higher vehicle fuel efficiency standards and mandatory use of alternative fuels), it is possible to reduce the oil consumption in road transport by 11.2% (Ozaki, 2011).

## 1.2 Research question

In this thesis, we want to answer the following research question:

- What is the effect of the Norwegian toll road exemption for electric cars on the sales of electric cars?

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## 2 EV history

In this section of our thesis we briefly describe electric vehicles history in Norway in relation to the various incentives in place.

### 2.1 EV history of Norway

The market development of EV in Norway has been said to gone through five distinct phases. These are concept development, test phase, early market, market introduction and market expansion (the current) phase (Figenbaum & Kolbenstvedt, 2013). In the following text, we will briefly discuss each phase one at a time.

**Concept development (1970–1990):** During this phase, some prototypes of electric vehicles started being developed in Norway. The EV market was seen as a niche for a selected few interested in electromobility, and environmental concerns were not prioritized by individuals buying the first electric vehicles. Incentives and measures by the government and other institutions were limited to research funding.

**Test phase (1990–1999):** The focus now was on testing the technology and lowering the barriers to purchasing an electric vehicle. It was during this period that the first electric vehicle was registered and is considered a great achievement in Norwegian EV history. Throughout this phase some incentives for EV adoption were introduced by the government: exemption from registration tax (1991), free parking (1993, -1998), reduced annual license fee (1996), road toll exemptions (1997) and reduced imposed taxable benefit on company cars (1998).

**Early market (1999-2009):** Large firms became active in the Norwegian market. The Norwegian manufacturer Think was bought by Ford and Norwegian investors started to take interest in promoting the growing EV trend. The phase was uniquely characterized 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, while bus-lane access was

introduced in 2005. The period ended with the financial crisis which started in 2008, which left the development of the EV market in trouble.

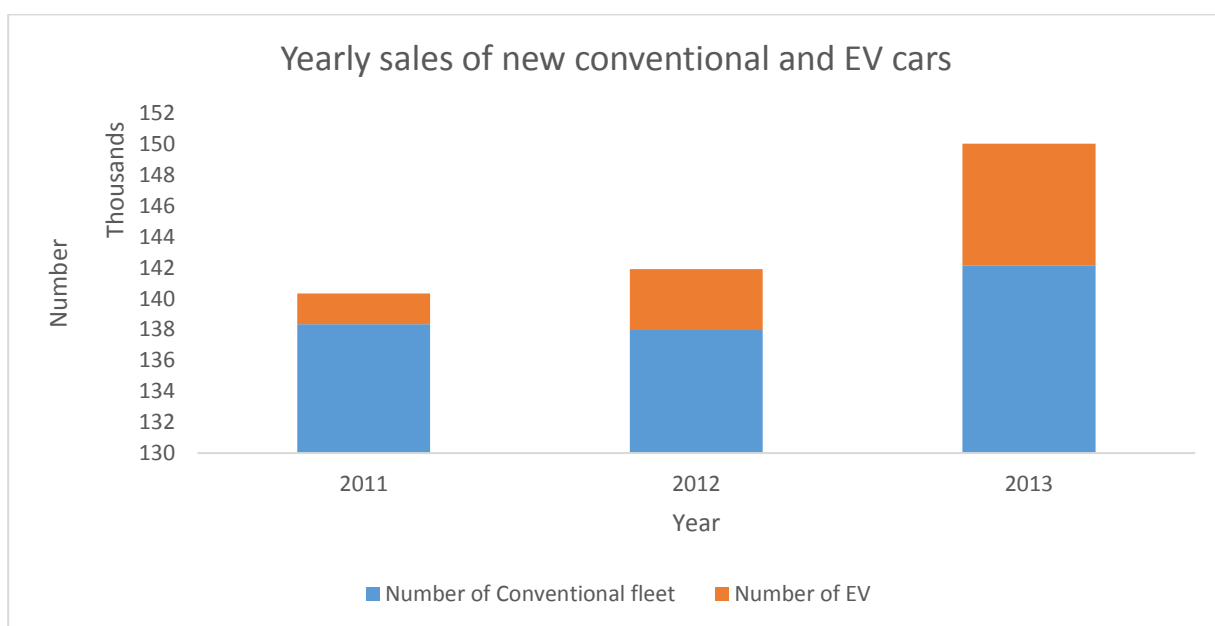
**Market introduction (2009-2012):** In this phase established automotive manufactures started having a more active role in the EV market. Norwegian manufacturers such as Think and Pure Mobility were pushed out of the market by the bigger companies as they went bankrupt in 2011. The Norwegian market was developing strongly with more competition, larger volumes and decreasing prices. Models like the Nissan Leaf and the Mitsubishi I-Miev were introduced to the Norwegian market. These models had a big influence as their technology were much more similar to ICE vehicles and were priced at a level that attracted consumers who were not only motivated by the climate aspect. The first publicly available fast chargers went on-line in 2011 and the charging infrastructure in Norway was moving rapidly. The combination of a fast-developing charging infrastructure, steady supply of vehicles from major manufacturers, and that most of the currently existing incentives were active, made that the barriers to purchasing EVs was at an historical low.

**Market expansion (current phase) (2012– present):** The market expansion phase began end of 2012 and is currently underway. This phase is characterized by a strong demand among consumers and continuous market entrance (by manufacturers) which is lowering the prices and increasing the supply 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. In this phase, it is expected that the many incentives implemented for EV adoption are to be phased out.

## 2.2 Norway as a case study

Norway is one of the leading countries when it comes to adoption of EVs. With the Norwegian government's generous incentive schemes for adopting EVs and focus on clean energy, Norway has managed to become the country with the highest EV market penetration per capita in the world (Cobb, 2017). With a total of 45 492 vehicles sold in 2016 it ranks as number three in the world in terms of total number of EVs sold. In March 2014, Norway became the first country where 1 percent of cars on the roads is an EV (Klippenstein, 2014). Only from

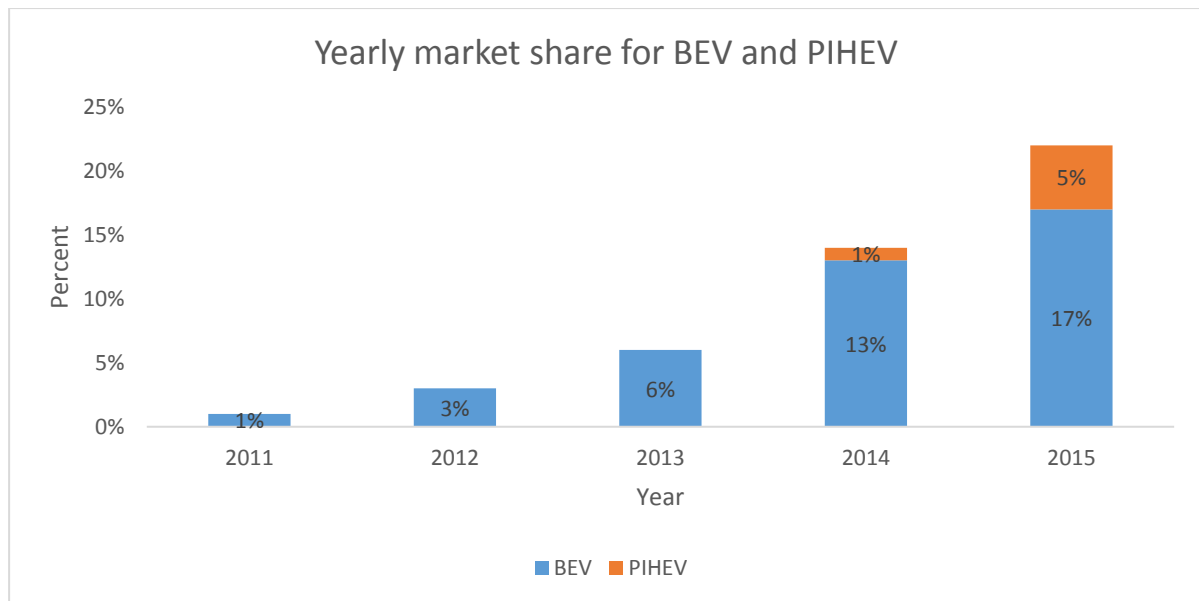
2011 to 2013, the share of new EVs to conventional cars sold increased dramatically from 1.4% to 5.5% as shown in figure 1 below, where in 2015 this same share of EV hit a record of 22.39%. However, as figure 2 below shows, the Norwegian EV market development is not equally distributed between battery electric vehicle (BEV) and plug in hybrid electric vehicle (PIHEV)<sup>1</sup>. With Norway managing to achieve such accomplishments in regards to clean energy transport, we felt strongly compelled to further study the effectiveness of one of the Norwegian government incentives: EV toll road exemption.



*Figure 1: Yearly sales new conventional and EV cars*

Source: Adapted from Holtmark (2014)

<sup>1</sup> The exact definition of BEV and PIHEV is given in the literature review section as well as in the glossary



Source: Haugneland (2016)

*Figure 2: Yearly market share for BEV and PIHEV*

## 2.3 Problem background

The Norwegian government incentives designed for promoting the commercialization of electric vehicles played a crucial role in developing the market for EVs. However, currently many would consider the market to be close to maturity and therefore expect government incentives to be phased out. The hope is that a mature market for EVs will be able to survive on its own as government incentives are quite costly and cannot last forever. In a report by Fearnley (2014) the cost of free parking alone in Oslo, Bergen, Stavanger, Trondheim and Kristiansand is estimated to be between 86-123 million NOK per year. There is a growing agreement among the political parties that the Norwegian government has managed to facilitate a market for EVs through the generous incentive packages, and now the market should sustain itself without major interventions. There is evidence that some of the first incentives that are likely to be removed are free parking, access to bus lanes, free ferries and exemption from toll roads (Thoner, 2015). In fact, some of these incentives are already removed in some places. For instance, in Trondheim, since the start of 2017 EVs no longer have access to free parking (Trondheim Parkering, n.d.). Moreover, the Norwegian Public Roads Administration also make it clear in its “National Transport Plan from 2018–2029 (NTP)” that EVs will move from free toll to low toll fare (Blaker, 2017). Hence, if these

incentives indeed are to be removed within a short time, it is crucial to gain a proper understanding of what impact they have had on EV adoption.

With EVs in Norway headed towards a future where public incentives from the government no longer plays a role, the continued success of EVs depend on how impactful these interventions have been in the development of the market. The purpose of increasing EV adoption was a step towards a greener future with cleaner environment and less emissions. This is a costly process and as the market matures the efficiency of these investments declines. In other words, the public subsidy is by far greater than the reduction in carbon footprint attained by EVs. Hence, it comes a point where the money spent by the government to achieve the goal of a greener future might be better spent outside of EV incentives. Many politicians believe we are rapidly approaching this moment and investments are better applied to other projects that can have a greater impact on cleaner environment. It is therefore of great interest that these incentives are analyzed for policy makers to understand their importance and impact on EV adoption in Norway. Through such analysis a proper understanding of the incentives can be gained and used to evaluate their cost/effect relationship. Thus, policy makers can be able to determine which policies should be maintained and which should be removed.

In this regard, the aim of our study is to evaluate the significance of toll road exemptions on sales of EVs at a very detailed level. In our study, we employed monthly data on toll traffic and sales of EVs. Earlier studies on the effectiveness of the Norwegian EV incentives have already estimated the impact of toll exemption on the sales of EVs, but to our understanding, none have estimated toll road exemptions to such a detailed degree as we do. One example is the work by Mersky et al (2016), where they included toll road exemptions as a binary variable. One reason to model toll road as binary is its difficulty to estimate the exact value over a period. In this regard, we try to estimate its average value and asses its impact on the sales of EVs. We believe our way of analysis reflect a clear insight to the evaluation of the effectiveness of the policy. Accordingly, we hope that our study can contribute to a deeper and more detailed understanding of exactly how impactful this policy is towards EV sales in Norway. Nevertheless, our way of approach can never be considered as exhaustive. In fact, there might be several approaches and with this regard we stress that future studies should be done to have a conclusive view of the policy.

### 3 Literature review

In this section of the thesis, we thoroughly discuss electric vehicle (EV): definitions, factors & determinants of EV adoption and financial incentives given to buyers of EV.

#### 3.1 What are electric vehicle (EV) and hybrid electric vehicle (HEV)?

Electric vehicles (EVs) are vehicles which are powered partly or fully by an electric motor. These include battery electric vehicles (BEV), (plug in) hybrid vehicle (PIHEV or just HEV) and range extended electric vehicle (REEV). In general terms, EVs emit less carbon dioxide (CO<sub>2</sub>), have higher energy efficiency, lower user cost (per km), lower noise level and have a lower contribution to local air pollution. But, their sulfur dioxide (SO<sub>2</sub>) emission level is highly dependent on the power grid used for charging (Bjerkan, 2016). Even though EVs include BEV, PIHEV, HEV and REEV the focus of our thesis are BEVs as they are the main group captured by the governmental incentives. We will therefore throughout our thesis mainly refer BEVs as EVs.

Hybrid electric vehicles (HEVs) combine petrol engine with electric motor and a storage battery. The battery itself is also charged by regenerative breaking. Despite the extra weight of electric motor and battery, in overall driving performance, HEVs are more fuel efficient than internal combustion engine (ICE) car of equivalent size and performance. HEVs are also more powerful than an equivalent engine of non-hybrid vehicles. In the past few years, several researches have been conducted which compares the two groups (HEV vs ICE) using different parameters. For example, Ogden (2004) compares the theoretical fuel economy with the total life cycle costs for a conventional vehicle powered by alternative fuels verses HEV whose ICE is powered by diesel, gasoline, hydrogen and natural gas. He finds that HEV can achieve a lower cost (higher efficiency) by using a variety of alternative fuel sources. Hence, HEVs have a lower societal life cycle cost (including environmental externality) than internal combustion engine, but the market currently does not factor that (as HEV are usually sold at a price premium). On the other hand, Canes (2003) compare the total life cycle costs of equivalent hybrid and gasoline vehicle. He argues that HEVs have a higher total life cycle cost (total



ownership cost<sup>2</sup>) even when we take pollution cost into account. Here it should be noted that, these sort of calculations (which also consider vehicle price, fuel and maintenance expense) is extremely sensitive to many assumptions about ownership period, discount rate, conventional gasoline model etc. (Canes, 2003) (Ogden, 2004).

## 3.2 Factors influencing EV adoption

EVs as opposed to HEVs, are recent innovation technology introduced to the consumer market at larger scale only in 2010. Because of this, there is little research which analyzes factors affecting EV adoption rate. The lack of research is even pronounced when it comes to studies that use empirical data. Hence, previous literature mostly uses stated consumer preference to analyze EV adoption factors. However, because of the so-called attitude-action gap, there may be little relation between survey information and actual consumer purchase of these low emission vehicles. Consequently, research that rely on revealed consumer preference (empirical research) may be preferred when it comes to revealing factors affecting consumer EV purchase behavior (Sierzchula, 2014). In this line, since our research is empirical, our conclusion will not suffer attitude-action gap.

HEVs, though represent a less radical innovation, can serve as a comparison basis to EVs. This is because HEVs share several same key elements as EVs including battery, electric motor and low environmental impact. As HEVs has been in market for quite long time (since late 1990) there are several literatures that use revealed preference to analyze factors affecting HEV adoption rate. In the absence of such research for EVs, we can incorporate some of the variables which are found to be important determinants of consumers HEV uptake to EV model. These variables include education level, gas price and environmentalism. Consequently, by using HEV revealed preference research, EV consumer survey and theory, Sierzchula et al (2014) collect and categorize factors that affect consumer EV purchase decision into three: those factors related to the technology itself, those related to individual consumer and those related to factors external to both the vehicle and consumers (referred as context). The technology factor comprises of the specific aspects of EVs, such as battery cost,

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<sup>2</sup> Life time ownership cost includes the aggregate of price of vehicle, one-time tax (e.g. registration tax...), annual circulation tax, pretax fuel price and fuel tax (with the consideration of vehicle fuel economy and distance travelled) and maintenance cost with the appropriate choice of discount rate for future cost (Yan, 2016).

driving range and charging time. The latter two aspects distinguish driving performance while battery cost are mostly reflected in the high purchasing price of EVs as compared to ICEVs. As identified in the literature, the price premium (mainly due to battery cost) is the single biggest obstacle to EV adoption. IEA (2011, as quoted in (Sierzechula, 2014)) stated that an EV with battery energy of 30 kwh (approx. enough to drive 85 miles<sup>3</sup> with 0.17 kwh/mile) has a price premium of \$ 10,000 as compared to comparable ICEV. Battery cost is also related to the driving range of EVs. As we increase the capacity of the battery (in terms of kwh), consumers will get longer driving range, which is possible only at increasing cost. This implies that for a limited driving range, consumers may be willing to incur the extra cost to drive longer. But, consumers become less sensitive as the driving range increases. Another technological factor affecting consumer EV adoption is vehicle charging time. Depending on a battery size (capacity), EVs usually take long time to be refueled as compared to ICEVs. For instance, while ICEVs take roughly four hours, EVs take  $\approx 30$  min (at fast charging station) or  $> 10$  hours (in 110-220 v outlet) depending on battery kwh. Overall, price premium, limited driving range and long charging time all contribute negatively to EV adoption rate (Sierzechula, 2014). Of these factors, our thesis considers only driving range (by including vehicle kilometer variable in the regression equation) and cumulative number of charging stations.

In addition to factors related to the EV technology itself, consumer characteristics are also important in determining the level of uptake of EVs. Previous literature has identified education level, income and environmentalism to have a positive significant impact on the sales of EVs. Nevertheless, for consumers, these factors are found to be less important than cost and performance characteristics of vehicles which are identified above (Sierzechula, 2014).

Many studies have identified fuel (gasoline or diesel) price as having the most predictive power of HEV/PIHEV adoption. Sierzechula et al (2014) refer fuel price as one of the context factor that influence adoption rate. In addition, though less commonly incorporated in many studies, electricity price is another context factor for HEV/PIHEV adoption. Together, fuel price and electricity price, determine the operating expense of HEV/PIHEV, which in turn determine their adoption rate. In addition to fuel and electricity price, many studies also identified the availability of charging stations as an important determinant factor for consumer adoption of alternative fuel vehicles. Contextual factor can also be something related to the

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<sup>3</sup> 136 km

nature of city, for instance urban density. Denser cities are believed to be more conducive for EV adoption than less denser ones, as shorter average travel distance will be ideal (which also means wider use of EV). In Norwegian context, fuel price can on average be regarded as the same across cities. Moreover, urban density can reasonably be assumed constant for our period of analysis. Hence, both these factors are again captured by the city and year fixed effect keeping our result robust.

There are still other context factors which are specific to EV. One of this is vehicle density. Vehicle density refer to the number of models available for the consumers to buy from. Another factor is local involvement. Local presence of manufacturing element may be a significant factor for EV adoption. As a radical emerging technology, EV adoption is also affected by public visibility. Public visibility explain the length of time EV has been commercially available (Sierzchula, 2014). Vehicle density and presence of local manufacturing plant are not included in our model. However, we expect to be significant factors in boosting EV sales.

### 3.3 Empirical research on determinants of EV adoption

Governments (federal, state or local) traditionally employee many policy options to intervene into a market of new technology. These include, tax or subsidy to account for externalities, regulation to induce adoption of new beneficial technology and resource input tax to promote innovation and efficient use of resources. In the case of electric vehicles, many governments prefer the first option: a tax deduction or credit, purchase price fee reduction, free parking, free toll road or privilege to high occupancy vehicle lane etc. As electric vehicle sales increases (both in absolute value and as the share of total vehicle) it is important for policy makers to gage how effective and efficient these incentives are in promoting demand (Diamond 1, 2006).

Gallagher and Muehlegger (2008) investigate the specific relative effect of each determinant for HEV sales in the US. These determinates include tax incentives, gasoline price, social preferences and other non-monetary incentives (free parking and preferential access to high occupancy lanes). Their findings suggest that social preferences have the highest significant explaining power of HEV sales increase (33%) followed by gasoline price (28%) and tax incentives (12%). Nevertheless, they argue that though a rise in gasoline price is associated with an increase in HEV sales, because of the cross-price elasticity demand of gasoline, the

demand for high fuel efficient cars will drop as HEV themselves use fuel. For instance, a 1% increase in gasoline price is associated with 0.86% drop in demand for HEV as compared to non-hybrid vehicles. In their famous paper, they succinctly denote this as “*giving green to get green*”. Here it should be noted that, when analyzing government incentives, it is not only the generosity of the incentive, but the form of which it is given to consumers must be considered. For example, a sales tax waiver of \$1037 have about three times more impact in inducing HEV sales than income tax credit of value \$2011. By employing a point estimate for the income tax credit, Gallagher and Muehlegger (2008) clearly show that this effect is not due to consumer discounting of future benefit. Hence, sales tax waiver is by far more effective than income tax credits in accelerating the diffusion of HEVs. In a market where there is both BEVs and HEVs (for instance Norway) due to dissimilar cost distribution between BEVs and HEVs, upfront incentive is more beneficial to BEV owners than HEV owners (Gallagher, 2008) (Chandra, 2010) (Bjerkkan, 2016).

Chandra et al (2010) analyzes the impact of provincial sales tax rebate (for the provinces of Canada) on sales of HEVs. The Canadian provincial data allows them to easily isolate the impact of tax rebate because of two features. First, unlike the US case where most federal and some state rebate programs depends on income, the Canadian program is income neutral. Hence, no additional data on income distribution is needed. Second, again unlike the US case where concurrent monetary and non-monetary incentive programs exist, Canada had only one HEV incentive program during the time of their study (1989–2006). The result indicates that an increase in sales tax rebate of \$1000 will accompany an increase in market share of HEVs by 31%–38%. In addition, the analysis shows that consumers substitute intermediate passenger cars by hybrid passenger cars. This can be explained by the fact that the two vehicle segments are in fact similar in terms of cost and vehicle features. For instance, the two most selling hybrid passenger cars, Toyota Prius and Toyota Camry, belong to the intermediate segment and are priced and have features in the range of the intermediate category. The same explanation can be made for the other vehicle segments which has seen substitution in the analysis: the crowding out of high performance compact passenger cars by smaller hybrid models and substitution of intermediate sport utility vehicle (SUV) by hybrid SUV. Other vehicle categories did not experience a statistically significant decline as the result of the introduction of the incentive program. This implies that the HEV incentive program is not efficient in a sense that it did not encourage people to substitute the most fuel inefficient cars

which includes large SUV, sport and luxury passenger cars. Nevertheless, it should be noted that this trend might change in the long run as more and more HEVs are introduced in other classes. But, in the short run, aggressive fuel tax is suggested as one alternative policy option to encourage people to shift away from fuel inefficient cars. Hence, a larger relative price difference (more than those seen by sales tax incentives) is needed to influence consumer's purchasing behavior (Chandra, 2010).

Mersky et al (2016) conducted a more detailed analysis of the sales of battery electric vehicle (BEV) in 20 counties and 430 municipalities of Norway. Their main goal is to identify which factor(s) (among local incentives, local demographic factors and vehicle km traveled) contribute more for higher BEV adoption. The result of the cross-section regression (which is done at regional and municipal level) confirmed that access to charging infrastructure and regional income have the highest predictive power. Moreover, short range BEVs (such as Renault, Citroën etc.) are more sensitive to income and unemployment than long range vehicle (such as Toyota, Ford, Fiat etc.). This can be explained by the fact since short range BEVs are mostly used for shuttling employees or used as perks for employee, its demand is more elastic with income of employee (also an indicator of employee bargaining power). Therefore, if an employee is at a lower position in the company structure, he/she will have less bargaining power to demand a long-range BEV vehicle while a company give short range BEV perks to his employee. They also find that toll exemption and the privilege to use bus lane (both of which are considered as binary variable in regression) do not have a statistically significant role in explaining BEV adoption. But, this may be due to the presence of major city binary in the regression. Since there is a high correlation between major city and toll road some or all of toll road impact may be captured by major city binary. In their research, they acknowledge the limitations of their result regarding the major determinates and the role of access to charging stations. Although one can argue that charging stations are built in response to demand for BEVs, it may also be argued the other way around. That is, if the government focuses resources in connection to building charging stations, then it makes more sense to build it where there is already (expected to have) more BEVs (reverse causality) (Mersky, 2016). Although, our approach of determining the magnitude and significance of toll savings for BEV sales (panel data analysis) is different from them (pure cross-section), at this point we are expecting to get toll exemption to be a significant predictor of BEV sales.

Norway has become one of the forerunner in terms of BEV market share. One likely explanation for this is the existence of strong comprehensive incentive package for EV

owners'. With this regard Bjerkan et al (2016) conducted a survey among 3400 BEV owners to: 1. Describe the role played by each incentive 2. Determine incentives that are critical for BEVs purchase decision 3. Identify what groups of users responded to the different incentive types. Their conclusion is that, first: exemption from purchase tax and VAT are critical for BEV purchase decision for more than 80% of the respondents. And toll road exemptions and reduction in vehicle license fee are each critical BEV purchase factor for about half of the sample. Second: after classifying incentives into three groups, as reduction of fixed cost (RFC), reduction of use cost (RUC) and priority to infrastructure (PRI), the result of the logistic regression implies that: male, above 45 years of age, Tesla owners and those who bought BEVs within last years are the prominent target groups for RFC. Whereas, those with college or university degree, belonging to the lower income group and living near to the city of Trondheim respond to RUC incentives. The last group, those with elementary education and living near to Oslo respond to PRI. Surprisingly income is not a prominent indicator of BEV sales in the survey (Bjerkan, 2016).

## 4 Theoretical background

In the first part of this section, we explain why the market fails to efficiently allocate and ration environmental commodities (e.g. pollution). In the second section, we argue that even in the case where government interventions seem reasonable, some of the measures taken by the government have itself negative effect (rebound effect).

### 4.1 Market failure

A market is an institution where sellers and buyers meet and exchange goods and services at a price determined by it. This means, prices may be purely determined by the forces of demand and supply or may be skewed by government interventions. Price setting is one mechanism of allocating and rationing scarce economic resources, which in theory should be fair and efficient. In this line, government also provides foundations for the market economics to work. For instance, by providing property right and contract enforcement, government creates an environment where people have an incentive to go to contract and invest where and when they feel. Before going in depth to market efficiency and government interventions, let's briefly discuss some important definitions. A free market is a market where the forces of demand and supply purely determine the equilibrium prices at which the market clears. An efficient allocation of resources is one in which no further improvement to one (more) member of the society can be made by changing the allocation without hurting the other(s). A perfect market is where we have an efficient allocation of resources and if any other price than the equilibrium price is charged, welfare fails. In other words, if government intervene in a perfect market, efficiency will be lost and hence dead weight loss results (Ajefu, 2015).

For a market to be perfect, the following conditions must be fulfilled (these are based on the requirements of the first theorem of welfare economics): many sellers and buyers (this means individually each seller and buyer cannot influence or control market price), free industry entry and exit (which means in the long run firms make normal profit), homogeneous producers (no market power, producers are price taker), no transaction cost and complete information (sellers and buyers have complete information about prices). When any of these assumptions fails, the market is imperfect and will not efficiently allocate resources. This give a rationale for government interventions. Government may also intervene in a perfect market where externalities associated with goods produced or services consumed is not captured by the

market prices. Or, when necessities become unaffordable because of inequalities. On the other hand, a government intervention may not be needed even in the case where the market is not perfect. One such case is a free market with perfect knowledge and complete market<sup>4</sup> for all goods and services. The reason is self-interest behavior: because consumers are rational, they did not pay more than the marginal benefit they get from consuming goods/services. And, because sellers want to maximize profit, they did not sell goods/services lower than the marginal cost price. Consequently, in a free market, the forces of demand and supply equate marginal cost with marginal benefit ( $MB=MC$ ), a condition necessary for efficient allocation of resources (Ajefu, 2015).

When the assumptions for the perfect market condition are not met, the market fails and hence it is impossible to enhance total welfare without hurting one or the other parts of the society. When the demand and supply curve reflect the true value and cost to consumers and producers respectively, total welfare can be defined as the sum of producer and consumer surplus. A consumer buying goods/services at the ruling price will get a benefit (satisfaction, welfare) greater than the cost he/she is paying, which is called a consumer surplus. Similarly, a producer will supply goods/services when the price is greater than or equal to the production cost, hence the producer will get a bonus (satisfaction, welfare) called producer surplus. When a private producer chooses to maximize its own profit without considering the negative production externalities it imposes on the society, the market becomes distorted (producer and consumer surplus will deviate from the socially optimal level depending on the elasticity of demand and supply). Externalities is not always negative, sometimes we do have positive externalities. In the case of negative externalities, individuals will produce too much of the goods/service because he/she does not bear the full cost of producing it. In positive externalities on the other hand, individual will produce too little of the goods/service because he/she does not reap the full benefit from it. In both cases, the market allocates private marginal cost to private marginal benefit, where otherwise the social marginal benefit and cost should be equated. This mean, private and social optimum level of production/consumption is different and the market mechanism will not produce a pareto efficient<sup>5</sup> allocation of resources. In this situation, a government can enhance the performance of the market by influencing the behavior of buyers

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<sup>4</sup> A complete market provides all goods and services where their cost of production is less than the consumers' willingness to pay for it

<sup>5</sup> A pareto efficient allocation is an allocation resources where no further improvement is possible which makes everyone better-off



and sellers, since market performance is a function of economic agents' intuition (Ajefu, 2015).

In addition to externalities, public goods are another case where the market fails to provide efficient allocation of resources. Public goods are non-excludable (practically not feasible to limit access) and non-rival (one's act of consumption will not diminish others to consume). Examples include national defense, global climate, urban air quality and greenhouse gases. Public goods are either not supplied by the market at all, or supplied at a quantity which is not socially desirable (see figure A.1 in appendix). Hence, government should intervene to solve this free riding problem. Government can do so by demanding each member of the society to contribute to the provision of the public goods (for instances using taxes) or by supporting individuals to supply a public goods at a quantity which is desirable for the society (for instances using subsidies<sup>6</sup>). Government interventions is commendable because a market don't control individual's act of imposing a cost on a society. Hence, the government acts like a parent who knows what is best for his children better than the children themselves (this view is known as paternalism). Here, readers should note that efficient allocation of resources does not necessarily mean fair or equitable distribution. In fact, a market doesn't concern at all how benefits are distributed between members of a society. If a market equilibrium is efficient, then it means both that there are no leftover resources and no way of reallocating goods without hurting someone. Whereas, equity is related to fairness and justice. Consequently, there is a tradeoff between efficiency and equity, however, early economist like Adam Smith stressed that a society should not loose equity in a search to maximize efficiency (Ajefu, 2015) (Kolstad, 2011).

## 4.2 Rebound effect

Even though electric vehicles are energy efficient technology, which saves energy use per vehicle kilometer, the introduction and subsequent adoption of even more efficient technology is often accompanied by a rebound effect. This may counteract the positive benefit gained from higher efficiency. Rebound effect is an area of ongoing research and much variation is

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<sup>6</sup> Taxes and subsidies will give the same result in the short run when the industry is composed of homogeneous firms. In the long run or in the short run with heterogeneous firms, a tax is more efficient than subsidy (Kolstad, 2011).

seen in its identification, definition and quantification. However, the common denominator is that when a product or service becomes more efficient (in its energy or other resource use), it become cheap and its demand will rise. We can have two levels of rebound effect depending on whether the demand for the same product/service or other related product/service is increased. If the demand for the same product/service rise, because now it becomes cheap, we say this a direct rebound effect. For example, if car becomes fuel efficient, it uses less fuel per kilometer drive, and hence lower cost of transportation. This means that people will prefer car to public transport, drive longer than they would otherwise or leave the engine on when they wait to cross rail roads etc. When it occurs, direct rebound effect is always negative. If the demand for a related product/service rise, now because more budget is available, we call this indirect (secondary) effect. In this case, a reduction in fuel cost raises the consumer's purchasing power. This means, the consumer now spends more on other commodities, which also require energy use during construction or operation. By assuming a linear relationship between energy intensity and money (time), we can analyze whether secondary rebound effect is positive or negative.

Apart from economic (price based) rebound effects which is discussed in the above paragraph, there are other effects, which some authors argue that even without economic effect, may have positive or negative sign. One of which is the socio-psychological rebound effect. This arises when the social and/or psychological cost attributed to consuming a given service becomes reduced. Using the same analogy as to economic rebound effect, socio-psychological rebound effect can be split into direct and indirect effect. The direct effect includes people drive frequently and longer and buy additional fuel efficient cars (where otherwise they would not do). On the other hand, the indirect effect includes people to abuse the "social credit" they earned (when they purchase fuel efficient cars) in other socially unacceptable behaviors. In fact, as a new phenomenon to be explored, the indirect socio-psychological rebound effect is expected to be the research area for future studies (Haan, 2006).

But what is the purpose of distinguishing between economic and socio-psychologic rebound effect? If a person buys a fuel-efficient car and drive more, how can we tell that this effect comes from economic incentives or socio-psychologic sanction? In the case of electric passenger cars, making this distinction makes sense. This is because, electric cars at present are sold at a price premium and continues to be sold at higher price in the future, because of the additional technology needed for electric powertrains. So, in the first five years of vehicle ownership, there is a surplus sale price as compared to saving on fuel cost. Hence, there is no

way to justify this person's behavior from economic reasoning point of view, as the cost per vehicle kilometer remains the same. The cost is only transferred from operation to investment. Therefore, Haan et al (2006) claimed that if there is a rebound effect (in this case), then it should be attributed to the socio-psychological effect.

## 5 Background of model for electric vehicle

### Electric vehicle demand model

In this section of the thesis, we first briefly describe the EV model developed by Diamond (2006) and Berry (1995) and then we suggest our modification of this model to fit our analysis and context. Established demand models for conventional automobile (pure diesel or gasoline) though they are important and useful, is of limited use when applied to new electric cars. This is mainly because (unlike conventional cars) EVs are restricted to limited selection of models and they exist only for short time in the market. This in turn means we will have a reduced number of model-year data points for EVs. In addition to this since EVs are new technology it is not in an equilibrium market and our model should account for technological diffusion from time to time.

Local subsidies or incentives to electric cars basically change the quality adjusted relative price of electric cars. By doing so it affects the demand for electric cars. Hence, if we use aggregate car sales data at national level we can't capture these variations which leads the result from our model to be biased. In a situation where there is no data that fit individual consumer characteristics to the products those individual purchases, deriving a demand system may be extremely difficult. Nevertheless, as most literatures do, it is possible to utilize only product level characteristics (such as prices, quantities and other measurable characteristics) to estimate all the parameters of the demand. Therefore, the utility that consumer  $i$  derives from consuming product  $j$  is a function of both individual characteristics (vector  $\zeta$ ) and product characteristics (vectors  $x$ ,  $\varepsilon$ ,  $p$ ). Here,  $x$ ,  $\varepsilon$ ,  $p$  represents the observed, unobserved characteristics and price of product  $j$  in this order. For differentiated products, like cars for instance, we can represent this utility in equation form as:

$$u_{ij} = f(\zeta_i, x_j, \varepsilon_j, p_j; \theta)$$

Where:

$u_{ij}$  is the utility of consumer  $i$  from purchasing car  $j$

$\zeta_i$  is consumer  $i$  preferences for car  $j$  and its socio-economic conditions

$x_j$  is the observed characteristic of car  $j$  (size, engine power, emission intensities, unique features...)

$\varepsilon_j$  is unobserved characteristics of car j (style, brand reputation, quality...)

$p_j$  is the price of car j

$\theta$  is an estimate for a vector of parameters. It usually includes any parameter that determine the distribution of consumer characteristics.

In agreement with what is discussed above,  $\zeta$  is usually assumed to have a known distribution. That distribution may be an empirical distribution of characteristics or the usual standardized distribution with mean and covariance. Consumer i will purchase car j, if and only if,  $u_{ij}(\zeta_i, x_j, \varepsilon_j, p_j; \theta) \geq u_{ir}(\zeta_i, x_r, \varepsilon_r, p_r; \theta)$ ,  $r = 0, 1, \dots, J$  and  $r \neq j$ . Here,  $r=0, 1, \dots, J$  represent purchase of a competing differentiated car. Alternative  $r = 0$  represent the consumer not buying any car and instead allocate the budget to other commodities. Then the aggregate demand for car j,  $A_j$ , is modeled as a set of values for  $\zeta$ , (population parameter) which induces the choice of car j among all population. In equation form this can be represented as:

$$A_j = \{ \zeta : u_{ij}(\zeta_i, x_j, \varepsilon_j, p_j; \theta) \geq u_{ir}(\zeta_i, x_r, \varepsilon_r, p_r; \theta), r = 0, 1, \dots, J \text{ and } r \neq j \}$$

Hence, from the demand model we can extract the functional form of car j's market share,  $S_j$  as:

$S_j = f(x_j, \varepsilon_j, p_j, \zeta; \theta) \dots (1)$ . This means that the market share of car j is a function of its price, observed and unobserved characteristics of which are a characteristic of a population. A special case of the above equation is  $u_{ij}(\zeta_i, x_j, \varepsilon_j, p_j; \theta) \equiv \beta x_j - \alpha p_j + \varepsilon_j + e_{ij} \equiv \delta_j + e_{ij}$

Where  $\delta_j = \beta x_j - \alpha p_j + \varepsilon_j$ . Here, we assume that the vector of consumer preference,  $\zeta$ , has only one element,  $e_{ij}$ . In the population of consumers,  $e_{ij}$  has a mean of zero. This implies that,  $\varepsilon_j$  is the mean of unobserved utility across a population of consumers. Therefore, an average consumer preference and representative car characteristics can be assumed in market share data.

However, since Norway is a small market without its own auto manufacturer (not considering the headquarters of big car manufactures in Norway) it has insignificant influence in the supply of car, if it has at all. Auto manufacturer sell a model (model generation) of a car with almost similar specification across different counties and cities of the country. Therefore, both observed and unobserved car characteristics ( $x_j, \varepsilon_j$ ) are assumed to be constant across the

different cities. Equation 1 then reduced to:  $S_{cj} = f(p_{cj}, \zeta_c; \theta) \dots (2)$ . Where  $S_{cj}$  is the market share for car  $j$  in a city,  $c$ . Since our aim is to estimate the effect of toll road exemption on the sales of electric cars, and since all electric cars are equally benefited from this incentive, without being differentiated on its characteristics, it is logically to group all electric cars as homogenous single model. Hence, equation 2 can be further reduced to:  $S_{ce} = f(p_{ce}, \zeta_c; \theta) \dots (3)$ . Where  $S_{ce}$  is the market share of electric cars in city  $c$ .

Consumers' preferences  $\zeta_c$ , vary from city to city due to several factors. One important factor is income variation across cities. Another related factor is unemployment rate variation between cities. In standard economics, the aggregate demand for any good (normal good) is a function of individuals' income. Individual consumer (say  $i$ ) demand for a product (say  $j$ ) on the other hand, is proportional to  $(v_i - p_j)$ , where  $v_i$  is individual utility and  $p_j$  is the price of good  $j$ . Individual utility in turn is expected to be influenced by the benefits and status which the observed and unobserved characteristics of the good deliver to individual. In Norway, among the many nationwide benefits (incentives) given to electric cars owners, toll road exemption is one. But, since toll road prices vary by time and cities we need to account for this when we want to measure the value of the benefit for an electric car owner (referred here as  $B$ ) at a city.

The price element of the consumer demand is composed of two elements, upfront price and expected life time fuel cost (discounted to the present). This can be designated as:  $p_e = p_{upfront} + \gamma p_{fuel}$ <sup>7</sup>. The upfront price for electric vehicle is the list price minus any incentives available (for instance sales tax rebate). In Norway, due to uniform nationwide campaign for electric cars this part is unlikely to vary by city. The life time fuel cost on the other hand depends on the expected electricity price ( $p_{elec}$ ) and average kilometers traveled of each city ( $VKT_c$ ). Note that we only use expected fuel cost even though the total ownership cost of an electric car also includes maintenance cost, battery replacement cost and other cost. This is because in our analysis we assume these costs to be constant among cities and hence captured by the city fixed effect. One explanation for this is the difficulty of getting specific data on each of them. In Norway, the expected fuel cost is also on average unlikely to vary by city, and hence the life time fuel cost varies on city level due to the variation of  $VKT_c$ . Therefore, equation 3 is reduced to:  $S_{ce} = f(v_c, VKT_c, B; \theta) \dots (4)$ . An alternative functional form is the

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<sup>7</sup> In the literature, there is a debate about how individual's factor fuel cost during a car purchases. This is due to the choice of the discount rate to be used and the expectation of future fuel prices (Diamond 2, 2009)

logarithmic odd<sup>8</sup> form of market share,  $l_{sce} = \log\left(\frac{s_{ce}}{1-s_{ce}}\right) = f(v_c, VKT_c, B; \theta)$ . ....(5). This form is useful since it avoids market share forecast outside (0,1) range. However, since our data do not have negative EV sales, we employ log form only to estimate the percentage change of EV sales due to a unit change of the independent variable, keeping all other factor constants.

In the beginning of this section, we said that EV is a new technology and any model for it must address the effect of time on the diffusion of the technology. Had EV been a mature technology (where consumers have established preferences) its market share will vary over time if the price changes or if the characteristics of the vehicle change or if the options the consumers have changed. However, as a new technology, EV market share evolves over time in a typical classic diffusion pattern towards an equilibrium market share. This means consumers take time to respond to price and technological characteristic change as they adapt their consumption habit and their demand for the new technology. The classic adoption pattern is called “sigmoid” or “s-shaped”. At the beginning of the technology introduction (onset) diffusion is slow and then it increases exponentially and comes to a stable state. In a stable state, it is believed that EV completely replace the old technology and in effect has a stable market share (Diamond 1, 2006).

Previous literature uses the probit or rank to model the adoption process of EVs. The odds of adoption of EV is a function of various factors which vary across space and time. For instance, change in price and information about EVs will increase individual utility. Hence, the market share for EVs will increase over time (s-shaped). In line with this, government interventions in the form of incentives (tax incentives, toll road exemptions etc.) or public campaigns will lower individual adoption threshold by either changing the effective price or raising public awareness of the technology. Consequently, the diffusion of EVs will speed up and/or its market share will increase. In other words, given any time “t” at the diffusion process, the market share with incentives is higher than the one without incentives. Note here that having a fluctuating market share for EVs or a market share which does not follow the “s” curve at all will not deter us from our goal. This means, it is still reasonable to assume that people will buy more EVs with incentives than without. However, there is one condition that must be satisfied. Incentives should be given to all EV purchasers regardless of their behavior to

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<sup>8</sup> Logit is the inverse of the “sigmoidal” function given by  $\text{Logit}(p) = \log(p/1-p) = \log p - \log(1-p) = -\log(1/p - 1)$ . If the parameter of the function represent probability, then logit give log-odd function (Wikipedia).

purchase EVs without incentives. It is clear from this condition that there will be some “wastage” payment in a sense that some portion of the incentives will not induce consumers purchasing choice behavior. This “wastage” payment will be large if the price elasticity of demand is low (inelastic demand schedule) (Diamond 1, 2006).

From the above discussion, it is easy to observe that time is one important factor to account for the diffusion of technology. But, time is also important to account for change in prices, model characteristics and consumer preferences over time. This implies that equation 5 include time as independent variable:  $l_{sce} = \log \left( \frac{s_{ce}}{1-s_{ce}} \right) = f(v_c, VKT_c, B, t; \theta) \dots (6)$ . However, for our analysis, change in model characteristics is less important as we categorize all electric cars as one group and our analysis is done at city level, not at individual households. On over all, by assuming equilibrium market supply where auto suppliers can meet the demand and consumers have no constraint to access the vehicle sales, we argue that equation 6 will designate the final form of the model.



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## 6 Description of the data

In this part of the thesis, we describe the dataset used in our analysis, including their evolution over time and summary statistics.

The scope of our analysis is the three major Norwegian cities Oslo, Bergen, Stavanger and their surrounding areas. For Oslo we have also included Akershus county as these two are highly connected.

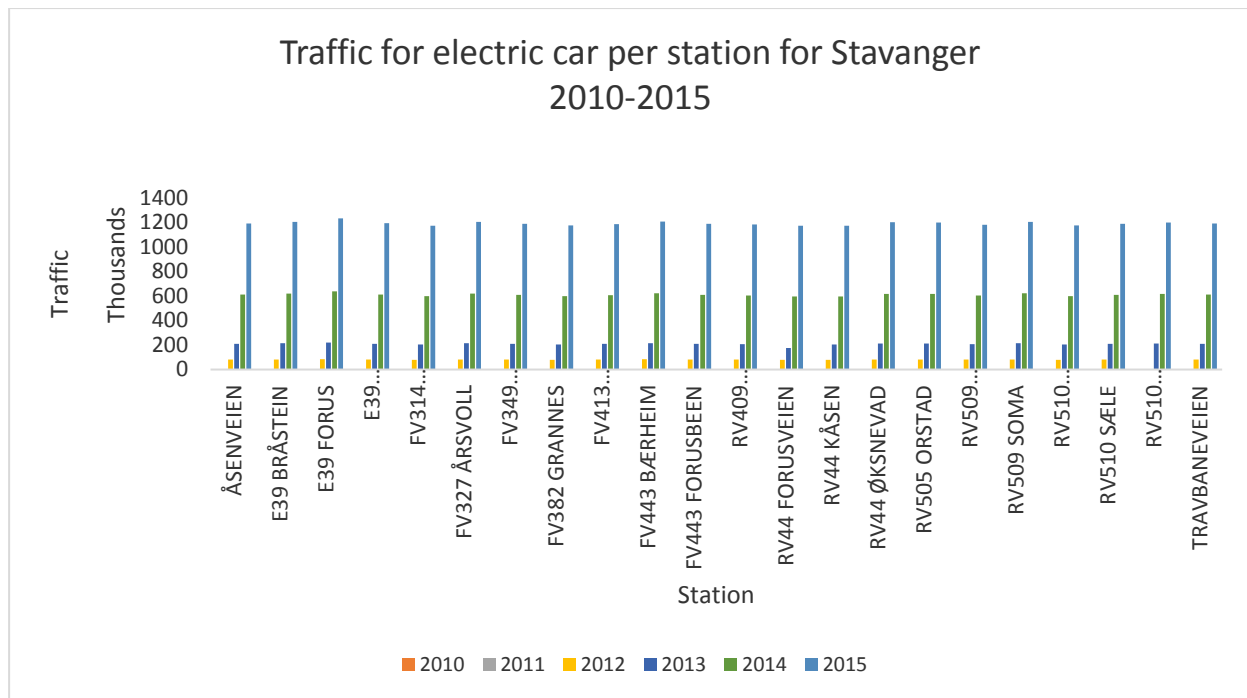
The data used in this thesis are: EV sales data from OFV<sup>9</sup> (Opplysningsrådet for Veitrafikken), toll road data from toll road companies from Bergen, Oslo and Stavanger, charging station data from NOBIL database and average income, vehicle kilometer and unemployment data from statistics Norway. All the data is from the period 2010-2015, except for Oslo and its surroundings which is from 2011-2015. In the following text, we will describe these data in detail.

### 6.1 Toll road data

EV traffic per station is plotted in a bar graph for each city as shown below in figure 3, 4 and 5. For Stavanger, as figure 3 below shows, EV traffic is very similar per station per year, but continuously increasing from 2012 –2015.

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<sup>9</sup> OFV=Norwegian Public Roads Administration



*Figure 3: EV traffic per toll station for Stavanger*

Unlike Stavanger, Bergen has a very dissimilar EV traffic per station per year. Especially in 2014 and 2015 the variation becomes significant. As figure 4 below shows stations Fjøsangerveien, Gravdal, Nyebroen and Sandviken experience high amount of EV traffic in 2014 and 2015.

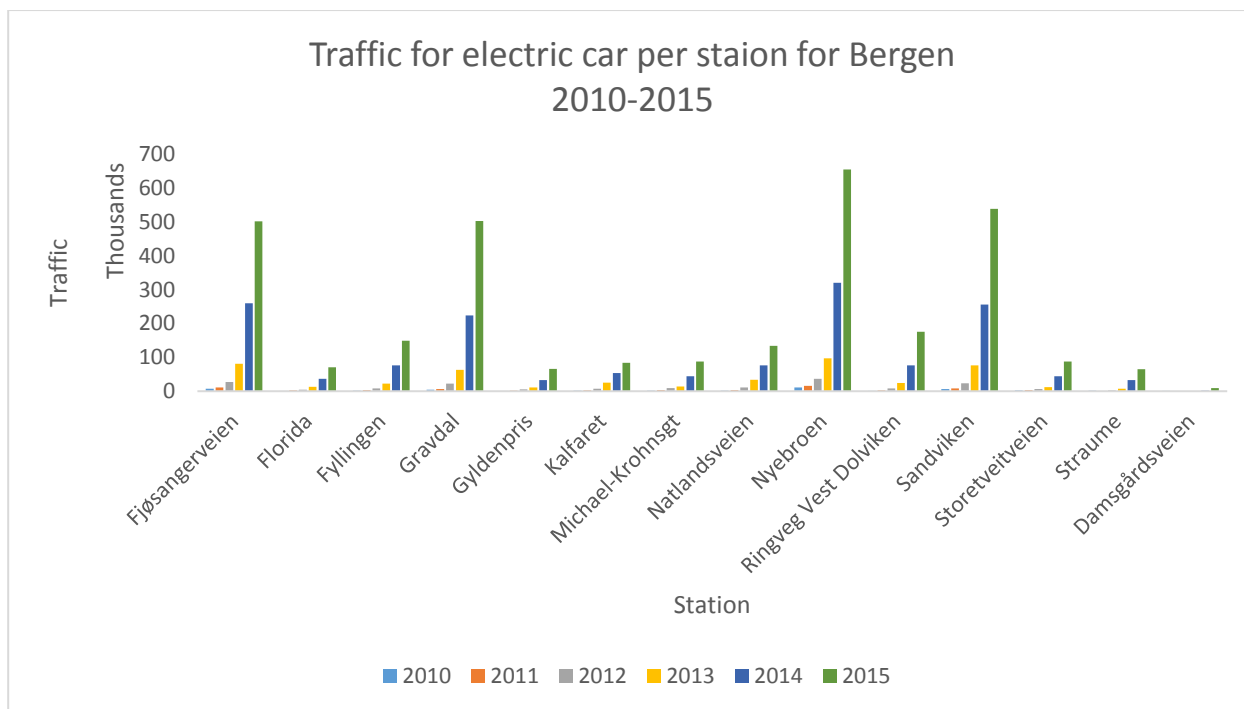


Figure 4: EV traffic per toll station for Bergen

For Oslo and surroundings, EV traffic highly varies per station and continuously increases from 2012-2015. As figure 5 below shows stations E 18 hovedløp, E18 Maritim, E6 Europaveien and Store Ringvei have the highest EV traffic, especially in 2014 and 2015.

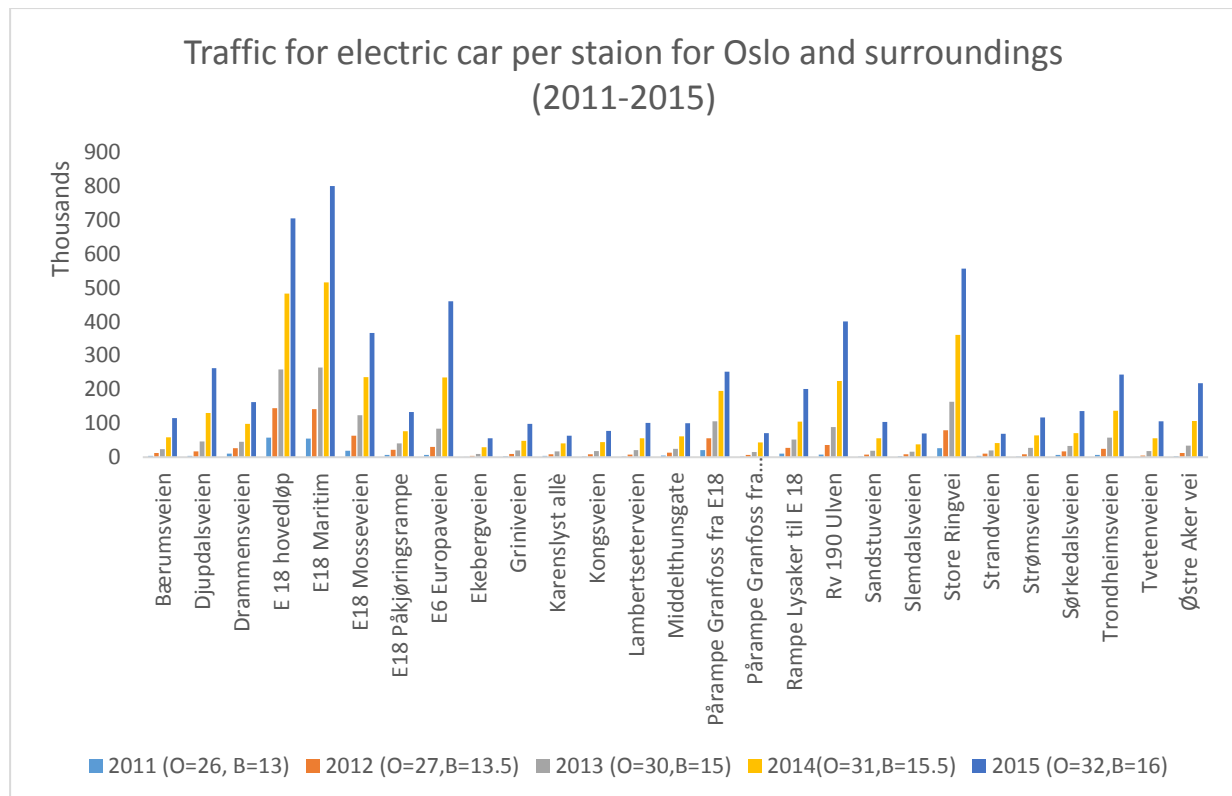


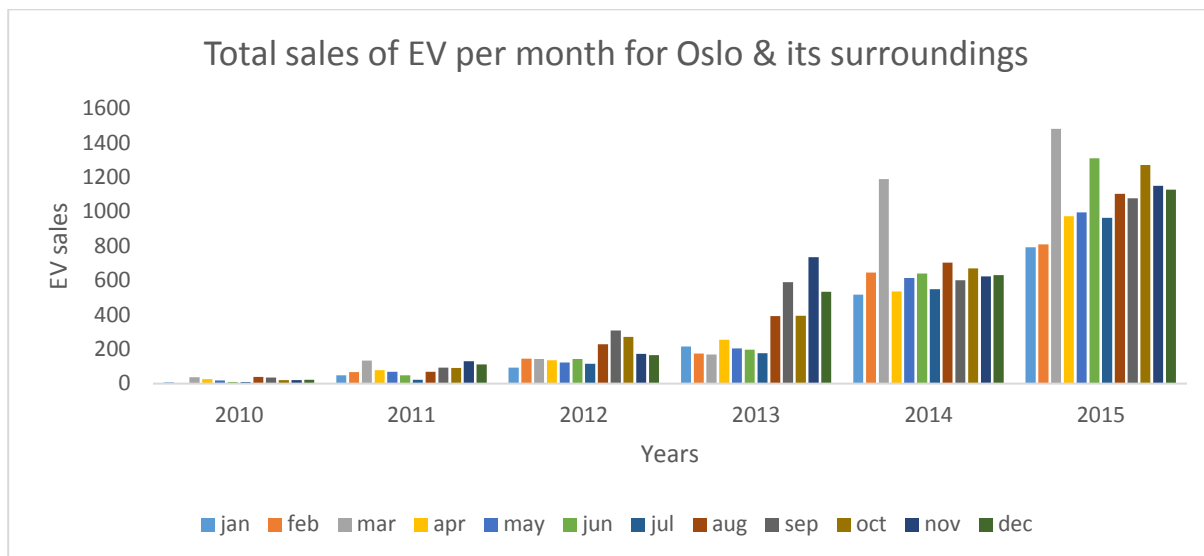
Figure 5: EV traffic per toll station for Oslo

## 6.2 Sales data (Evsales)

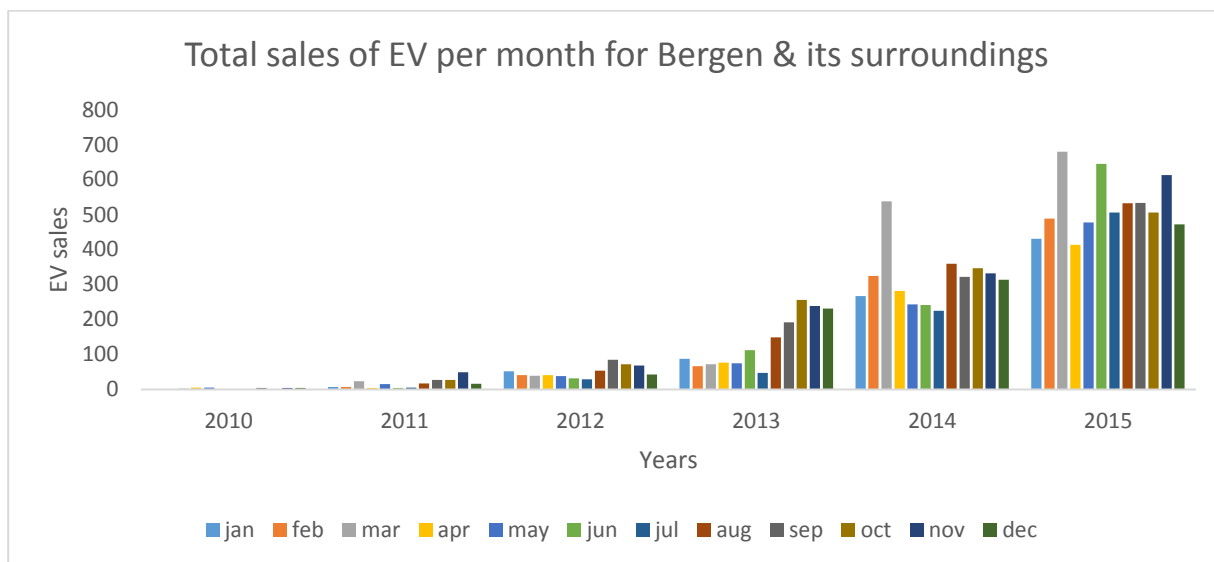
Detailed data on sales of cars is obtained from OFV (Opplysningsrådet for Veitrafikken). These data comprise of the sales of electric cars as well as sales of diesel and gasoline cars, the municipality of the sale and the model and manufacturer of each vehicle. We will only present data related to electric vehicles as these are the focus of our thesis.

As figure 6, 7 and 8 shows, the sales of electric cars in the three major cities in Norway (Oslo, Bergen, Stavanger) is steeply increasing from 2010–2015. The average yearly EV sales for Bergen ranges from 2 (for 2010) to 525 (for 2015) (figure 7). On the other hand, the yearly average EV sales varies from 1(2010) to 316(2015) for Stavanger (figure 8). On contrary to the two cities, Oslo & its surroundings has a lot more sales of EV in each year. On average terms, Oslo has at least 21 (2010) and at most 1088 (2015) EV sales per year (figure 6). Except for Stavanger in 2015, for all cities during 2014 and 2015, the maximum sales occur in march and this is probability related to the fact that many people have some additional income (in the

form of bonuses) for the new year and ideally wait for one month to make a big purchase decision (big in terms of their disposable income).



*Figure 6: Total sales of EV per month for Oslo*



*Figure 7: Total sales of EV per month for Bergen*

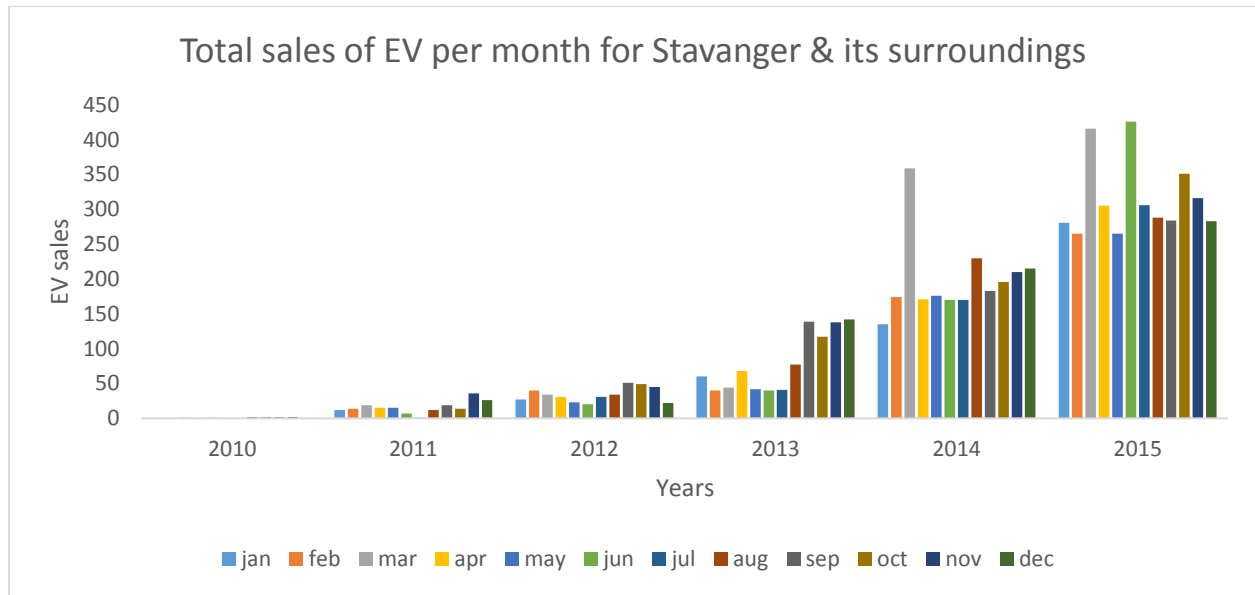


Figure 8: Total sales of EV for Stavanger

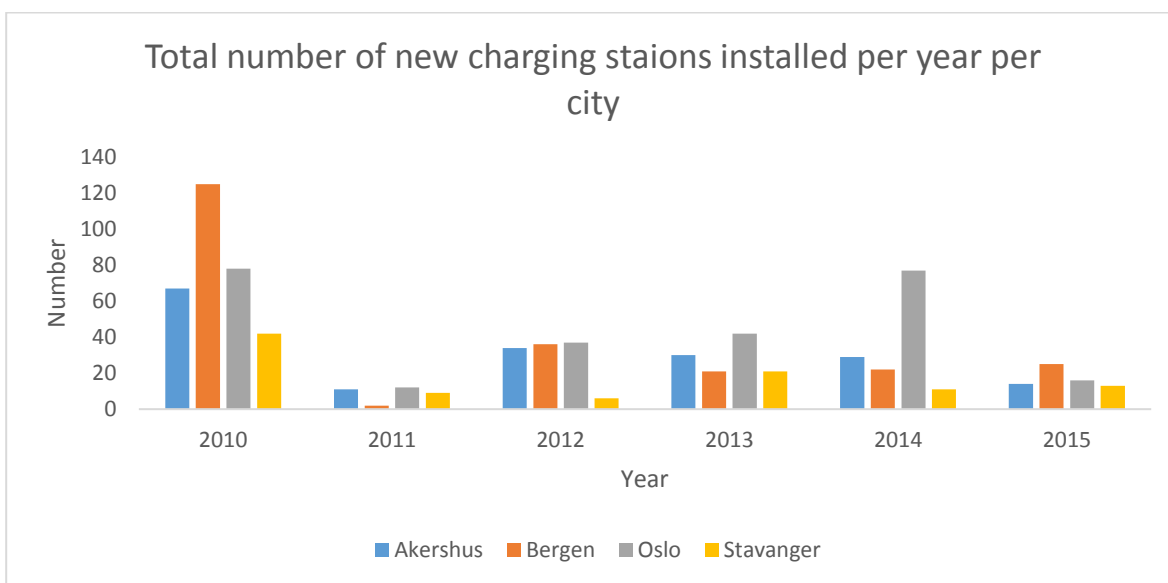
### 6.3 Charging station data (charst)

Charging station data is collected from NOBIL database which is developed as a cooperation of Enova and Norwegian Electric Vehicle Association. The data is detailed to the extent that it distinguishes the type of charging devices, the points available for charging, the date of initial operation, the final date of update in the database, public availability, the municipality and exact geographic coordinate location, and the time it takes for fully charging. However, for our analysis it presents one limitations. The database only presents the first date of installation and final date of update with total charging points available. It is difficult to know the historical evolution of a charging station through the period of our analysis. For instance, if a charging station is first built in 2012 but have never been updated in the data base till 2015, then we are not sure of whether it is still working or shifted or abolished at all. For this reason, in our analysis we only use the number of charging stations available under the first date of operation. This means we assume all charging stations which start operation in a year earlier than 2015 continue to operate until end of 2015. Moreover, we did not distinguish charging stations with one charging point with charging stations with many charging points. For our analysis, this might create a downward bias as compared to considering charging points. However, since our objective is measuring the effect of toll exemption towards EV sales, we believe this bias is insignificant in relation to our objectives. When we observe the spatial distribution of charging stations over time, many new charging stations are built in 2010 than

other successive years in all cities as seen in figure 9 below. In addition, as figure 9 and table 1 shows, Oslo, Akershus and Bergen are the three regions with large number of new charging stations per year.

*Table 1: Total number of charging stations*

Total number of charging stations						
City/Year	2010	2011	2012	2013	2014	2015
Akershus	67	78	112	142	171	185
Bergen	125	127	163	184	206	231
Oslo	78	90	127	169	246	262
Stavanger	42	51	57	78	89	102



*Figure 9: Total number of new charging stations per year per city*

## 6.4 Average vehicle km travelled (vkm)

Average vehicle kilometer data is collected from statistics Norway. The trend for the three cities of our consideration can easily be observed in figure 10 below. In almost all years (2010-2015), people drive longer distance in Akershus and Oslo. Moreover, in all cities people drive slightly less km in 2015 than in 2010.

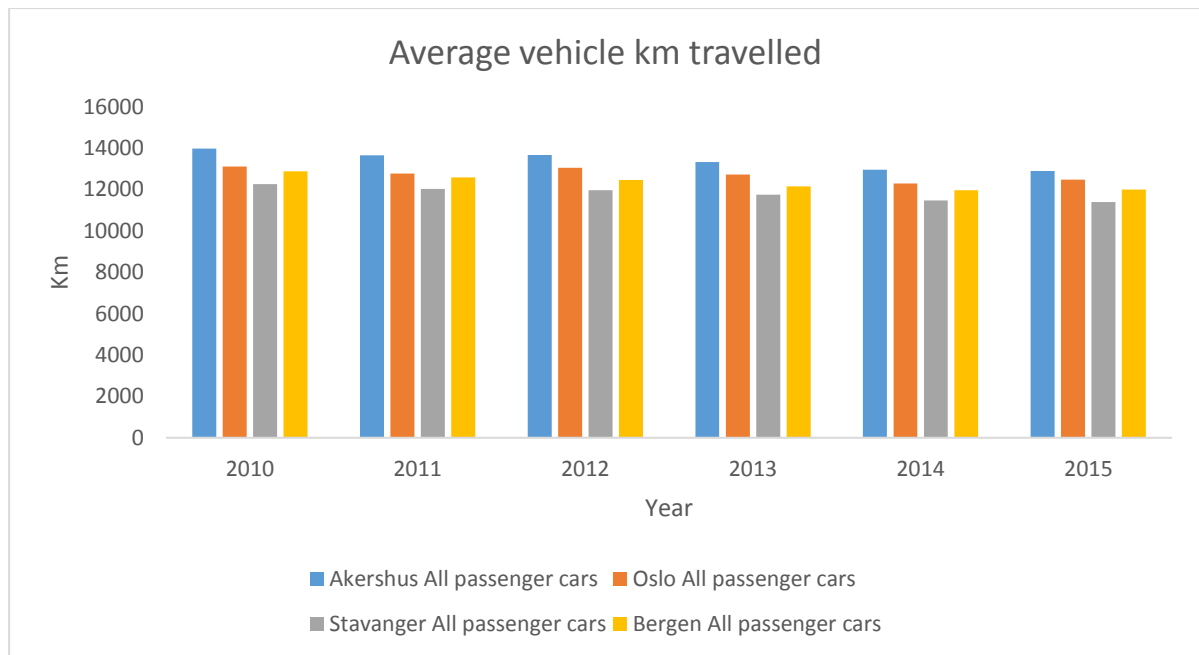


Figure 10: Average vehicle kilometer per city per year

**Bus lane** (buslane): this is a binary variable which signifies whether the city has a bus lane privilege access for electric cars.

## 6.5 Demographic data

Median individual income before tax (income) for each city is obtained from statistics Norway (see table A.1 and figure A.3 in appendix). In reporting income and other monetary values, the currency is left in NOK just to avoid the distortion in value due to the fluctuation of currency exchange rate. The other demographic variable, unemployment rate (unemp) is chosen among other unemployment measures because it is the most general form given at the city level. The correlation between income and unemployment is drawn in scatter plot and the correlation coefficient is noted (see figure A.2 in appendix). This is done to check for the multicollinearity problem of including both variables in the regression.



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## 6.6 Summary statistics

In our analysis we use two models for estimating the effect of toll road exemption: A main model and an alternative one. The details of the two models will be discussed in the strategy section, but for now, we first present the summary statistics for the data used in the main model and this is followed by the summary statistics for the data used in the alternative model. The main model is where all traffic (EV + Non-EV) is taken as the main independent variable of our interest. The alternative model on the other hand is where we split the traffic into EV traffic and Non-EV traffic and try to assess whether this categorization has any impact on the decision behavior of customer. This means, a customer may estimate the road use cost of a typical Non-EV driver and decide either that cost is not significant at all and hence buy Non-EV car anyway. Or, the cost is so important that he/she prefer to avoid it by choosing to buy EV car, keeping all other factor constant. The same kind of mental experiment can be done by evaluating the road use (toll) savings from the perspective of EV. Note that the variables `avgtraffic` and `avtoll` for the whole (EV and Non-EV) and for EV and Non-EV separate and price are defined in the next section.

### Summary statistics for the main model

*Table 2: Summary statistics for the main model*

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
avgtraffic	202	248,328	81,514	25,199	356,863
price	202	17.65	4.172	12	24
avtoll	204	4.450e+06	2.195e+06	0	8.495e+06
lagtraffic	166	247,038	82,411	25,199	356,863
Evsales	204	236.6	296.6	0	1,481
charst	204	178.6	117.4	42	447
unemp	204	2.697	0.187	2.400	2.900
income	204	443,015	38,894	367,700	513,550
buslane	204	1	0	1	1
vkm	204	12,975	270.3	12,634	13,363
Number of city	3	3	3	3	3

### Summary statistics for alternative model

*Table 3: Summary statistics for the alternate model*

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
avgnonEVtraffic	200	244,777	78,589	25,109	354,038
avgEVtraffic	200	4,766	6,262	26.86	24,662
price	200	17.67	4.190	12	24
avnonEVtoll	200	4.415e+06	2.056e+06	489,623	7.964e+06
avEVtoll	200	102,933	147,746	432.5	568,432
lagtraffic	164	248,503	81,825	25,199	356,863
Evsales	204	236.6	296.6	0	1,481
charst	204	178.6	117.4	42	447
unemp	204	2.697	0.187	2.400	2.900
income	204	443,015	38,894	367,700	513,550
buslane	204	1	0	1	1
vkm	204	12,975	270.3	12,634	13,363
Number of city	3	3	3	3	3

## 7 Strategy

In this part of our thesis, we discuss how the main independent variables of our interest are defined, estimated and present the method used for our analysis.

### 7.1 Toll road savings

Among the Norwegian government incentives for private adoption of electric vehicle, this thesis focuses on toll road exemptions for electric cars. Previous quantitative studies which analyzes the effectiveness of the Norwegian government incentive package modeled toll road as binary (if toll road present in a certain locality, it will have a value 1 and if not it will have a value of 0). In this thesis, we model toll road not as binary but as a discrete variable where its value depends on toll price and average monthly toll passage of a representative car. These values vary from city to city because of variation in both toll price and average monthly toll passage of a representative car. In our models, cars are grouped into two categories: electric and non-electric. Therefore, within group variation is ignored. From the perspective of the goal of the thesis, we believe that not accounting for within group variation causes very little biases, since toll exemption is based on either being electric or non-electric. Of course, there exist a major bias that arises from the fact that some non-priced traffics are counted as if it were priced. This means, if a representative car pass through more than one toll road stations in an hour time (which is more likely) it will pay toll charge only once. However, our model counts as many as the number of toll station it cross, ignoring the time gap between each passing's, thereby give us an upper bound for the toll charge (an upper bound as compared to considering only the priced traffic).

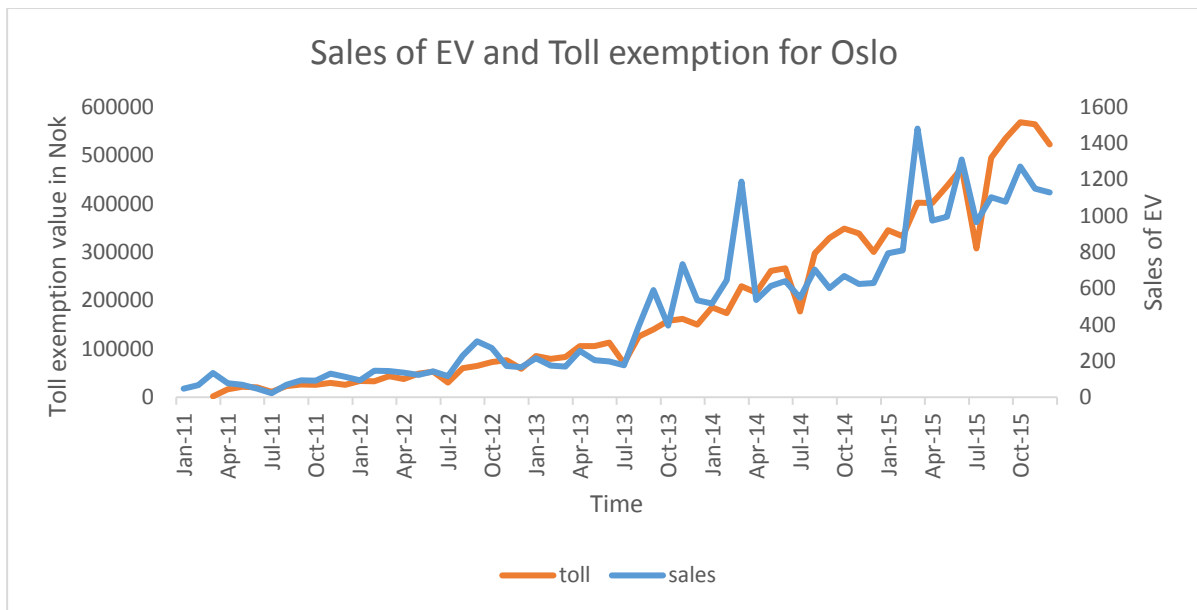
We use data on the monthly toll road traffic (distinguished as electric and small non-electric) and toll price from the respective companies operating the toll road in each city (Bergen, Stavanger and Oslo). Therefore, monthly data on total number of cars pass and electric cars pass from each toll station in each city at each price is registered from year 2010–2015. The only exception to this is Oslo and surrounding, where the data is from March 2011 to 2015.

The value of toll road saving is found by taking two level of aggregation. First, aggregation per city per month. This means a representative station traffic (average EV traffic) per city is formed by summing monthly EV traffic from all station in a city and averaging it to the total

number of toll stations in a city. The second level of aggregation is done at price level. Since toll charges for rush hour and out of rush hour is different and since the data does not distinguish the traffic in terms of time (at least for Oslo), we use an average price per month. This is easy to get as the range of toll prices (rush hour and out of rush hour) are the same for all station per city per month (except very little variation for Stavanger<sup>10</sup>). Of course, it varies from city to city and for a city it generally increases over time. Therefore, by multiplying the average monthly traffic on a representative toll station by the average monthly price, we find the average toll saving per month per city for a representative toll station. In other words, we can estimate the average value of toll road exemption for electric car per city per month. We correlate this value with sales of electric cars in the same city under consideration for each month of the year 2010-2015. As figure 11, 12 and 13 below shows, EV toll road exemption and sales of electric cars are highly correlated (correlation coefficient  $\approx 0.9$ ) even on month to month basis. Later in the data analysis section, we use econometric techniques to estimate the magnitude and significance of this correlation. But for now, it seems clear that higher toll road savings result in higher sales for electric cars or vice versa. In fact, the rising trend in EV traffic from 2010 to 2015 may be due to the increasing number of available cars in each successive year, and/or it may also be the case that the driving behavior of people is changed over time (if the latter is the case, last year higher traffic may cause a negative rebound effect in sales of EV). In the data analysis section, we include lagged traffic to capture this effect. Moreover, we use a fixed effect estimation technique to control for people's preference and generation of electric car attributes over time which are both assumed to be constant over city/year and hence capture by the city/year fixed effect. This again allows us to assess the causality of toll savings on electric cars sales, if any.

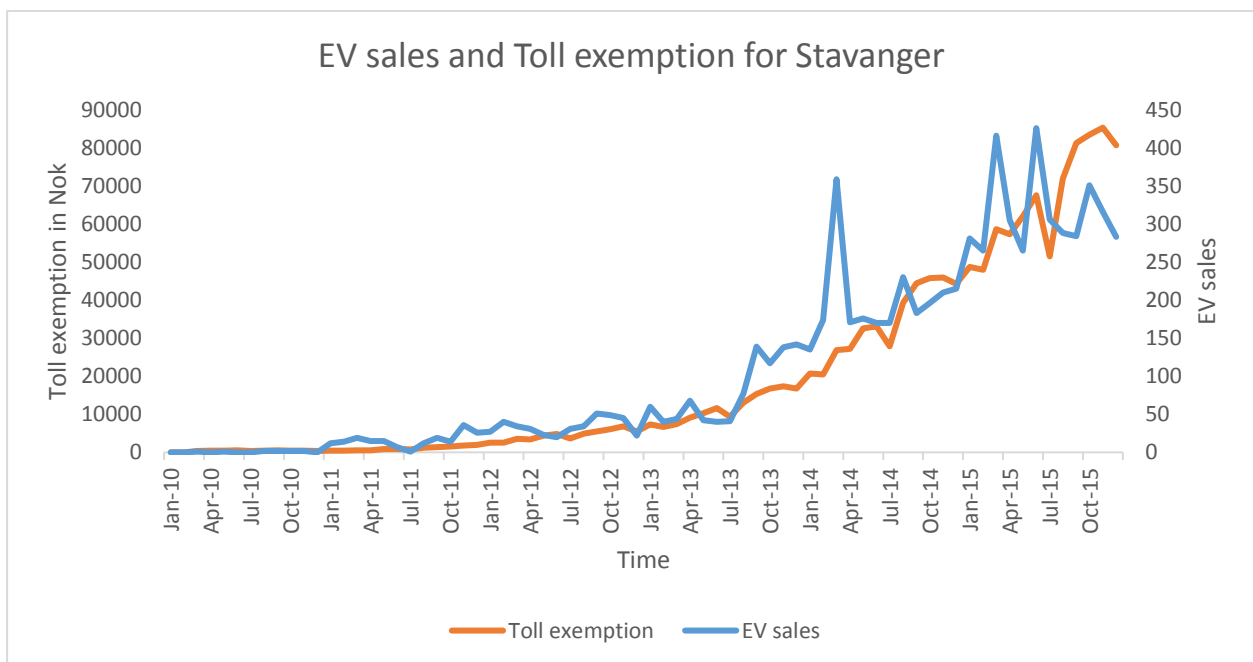
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<sup>10</sup> Since this incidence is very rare, we ignore this variation and follow the same procedure as the other cities



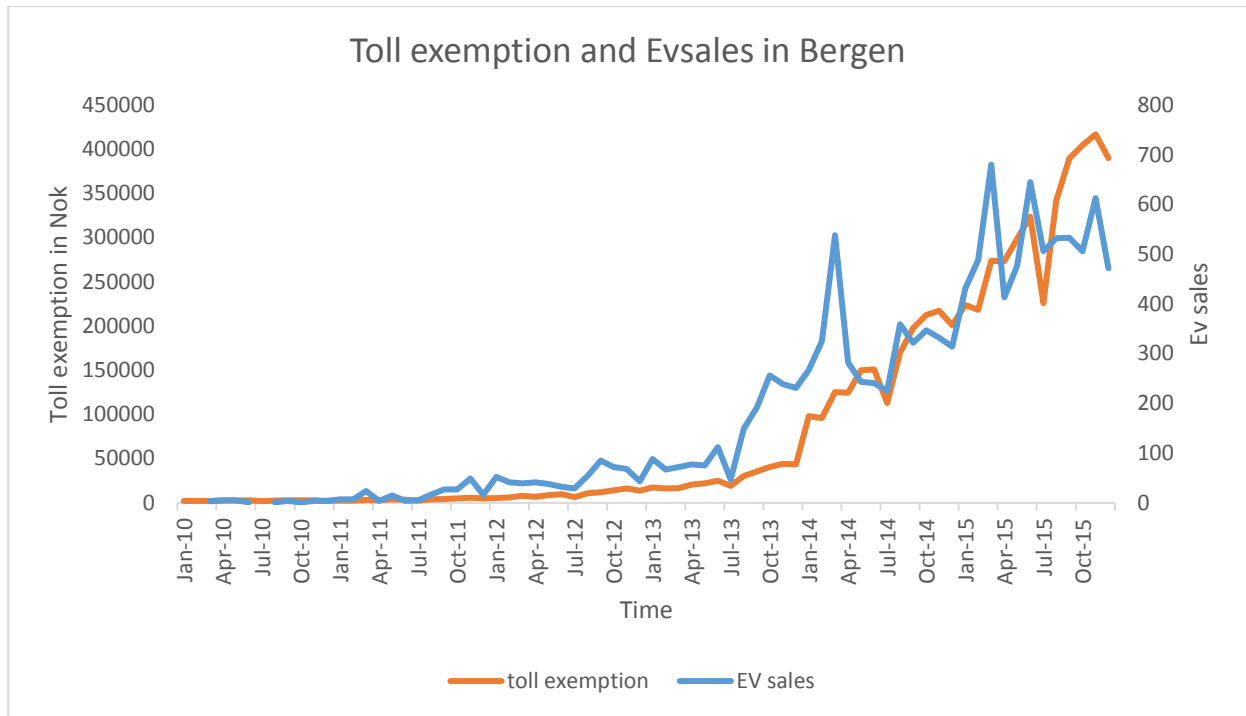
Correlation coefficient 0.929909

Figure 11: Sales of EV and toll savings for Oslo



Correlation coefficient 0.927518

Figure 12: Sales of EV and toll savings for Stavanger



Correlation coefficient 0.925116

*Figure 13: Sales of EV and toll savings for Bergen*

## 7.2 Toll variables in the main and alternate model

The distinguishing variable for the main and alternate model is whether we consider total traffic or separate traffic. This means, in the main model we consider total traffic, the sum of traffic for EV and non-EV. Hence, the average traffic and toll cost is calculated based on total traffic by following the method discussed in the previous paragraph. On the other hand, we consider EV traffic and non- EV traffic separately in the alternate model. Accordingly, we have separate average and toll values for each. The main reason for splitting toll traffic into EV and non-EV is to assess the impact of the separate group's toll savings/cost on the sales of EV. This is in line with a decision-making process of a typical customer. A customer may estimate the road (toll) cost saved by EV users and decide whether that saving is significant, in which case he/she decides to buy EV. Or, the customer may value the saving as insignificant and buy non-EV, keeping all other factor constant.

## 7.3 Data Analysis

We use panel data analysis for the period 2010–2015 where our unit of observations are the three major cities of Norway (Oslo, Bergen and Stavanger). This means, we follow these cities for six years and observe the sales of electric cars, average traffic, average toll, cumulative number of charging stations, vehicle kilometer and demographic variables (unemployment, income) per month. By using year, month and city fixed effect, all unobserved variables which is constant on either yearly, monthly or across cities (say  $a_i$ ) is captured and eliminated from the regression equation. In our model, our samples cannot be treated as a random sample from a large population. This is because our unit of observations are three large cities of Norway (Oslo, Bergen and Stavanger). Hence,  $a_i$  can reasonably be considered as a separate intercept for each cross-sectional unit (cities). In other words, we allow the unobserved effect to be correlated to one more of the explanatory variables since our samples are not random samples (Wooldridge, 2013). Accordingly, we argue that fixed effect (FE) is more convincing than random effect (RE) in our case.

In this thesis we categorize vehicles into two groups: electric and non-electric. On the non-electric group (gas or diesel vehicles) trucks and motor cycles are excluded. Cars in each category (electric and non-electric) are assumed the same. This means we will exploit only between groups variation. The within group variation is taken as minimal. In fact, considering the goal of the thesis, utilizing only the variation between the groups is sufficient to answer the question raised at the outset.

## 7.4 Regression methods

Our analysis is done by using six periods (where our panel variable is city and time variable is month which range from  $t=1$  to  $t=72$  with  $\Delta=1$  unit) panel data method (2010–2015). Our dependent variable is monthly EV sales per city. The independent variables in the regression are: average monthly traffic per city, average monthly lag traffic per city, average monthly toll per city, average monthly toll price per city, yearly cumulative number of charging stations per city, average yearly before tax income per city, average yearly unemployment rate (in percent) per city, average yearly vehicle kilometer per city, bus lane (as binary) per city, dummy variables for controlling city, month and year variations. Lagged



traffic is included in the regression to control for the rebound effect of free toll road. This means, consumers/drivers may change their driving behavior because of the EV toll exemption, which for instance result in road congestion: a dual nature of toll exemption. On one hand, it may incentivize people to buy EV. On the other hand, it may also discourage consumers who think to purchase EV, as 16% of Norwegian buy EV for the reason of convenience and time savings (Aasness, 2015).

Gas price, which most literature suggest having strong positive effect for driving EV sales is not included in the regression as it shows little variation on average between cities (in Norway the consumer gas price is determined largely by tax (60%) and world oil market price (30%)) (Mersky, 2016). This means, it is captured by the city fixed effect and dropped from the regression equation. Similarly, consumer environmentalism which again is a strong incentive for people to buy EV can reasonably be assumed constant over the short period of our analysis. Thus, it is captured by the year fixed effect and removed from the regression equation. On the same note, urban density which is among the strong incentives for adopting EV is constant over our short period of analysis. Consequently, it is captured by the year fixed effect and disappear from the regression equation.

## 7.5 Main model specification

These variables are then used in standard linear regression equation of form:

$$EVsales_{cmy} = constant + \beta_1 av.price_{cy} + \beta_2 av.traffic_{cmy} + \beta_3 (av.price_{cy} * av.traffic_{cmy}) + \beta_4 lagtraffic_{cmy-1} + \beta_5 vehiclekilometer_{cy} + \beta_6 chargingstations_{cy} + \beta_7 unemployment_{cy} + \beta_8 income_{cy} + \delta_1 buslane_{cy} + d_1 year_y + d_2 month_m + d_3 city_c + u_{cmy}$$

where c, m and y stands for city, month and years respectively,  $year_y$ ,  $month_m$  and  $city_c$  represent year, month and city dummies respectively.  $u_{cmy}$  is the usual time dependent error term. The interaction term of av.price and av.traffic is a parameter for estimating the average monthly toll savings/cost for EV and non-EV respectively. When doing the fixed effect regression in STATA, we use only year and month dummies as city fixed effect is already controlled by the, fe command.

## 7.6 Alternate model specification

The alternate model specification is designed to easily assess the two groups (EV and non-EV) impact on EV sales separately. In the linear regression equation form:

$$\begin{aligned} EVsales_{cmy} = & constant + \beta_1 av.price_{cy} + \beta_2 av.EVtraffic_{cmy} + \beta_3 (av.price_{cy} * \\ & av.EV traffic_{cmy}) + \beta_4 av.nonEVtraffic_{cmy} + \beta_5 (av.price_{cy} * av.nonEV traffic_{cmy} \\ & + \beta_6 lagtraffic_{cmy-1} + \beta_7 vehiclekilometer_{cy} + \beta_8 chargingstations_{cy} + \\ & \beta_9 unemployment_{cy} + \beta_{10} income_{cy} + \delta_1 buslane_{cy} + d_1 year_y + d_2 month_m + d_3 city_c \\ & + u_{cmy} \end{aligned}$$

Where av.EVtraffic is the average traffic for EV and av.nonEVtraffic is the average traffic for non-EV cars. The other variables, including interaction terms, dummy variables and error terms are defined in the same way as the main model (see main model specification in 7.5 above).

## 8 Results

In this section of our thesis, we present and discuss the results from both the main and alternate models and choose the best model for further policy analysis. The result of the main model is shown below in table 4.

### 8.1 Result of the main and alternative model

#### **Results from the main model**

In table 4 below we have four different models for explaining the variation in EV sales. The models vary either based on the inclusion or omission of the three independent variables of our interest (price, traffic and toll) or whether EV sales should be in logarithmic or level form. Let's briefly discuss and compare these models.

Table 4: Regression output from the main model and its variations

	(1) Evsales	(2) Evsales	(3) Evsales	(4) lnEvsales
price	9.447** (0.846)	11.21* (2.474)	-54.41 (24.31)	0.262** (0.0133)
avgtraffic		0.00181 (0.00158)	-0.00251 (0.000994)	0.0000208* (0.00000225)
avtoll			0.000227 (0.0000886)	-0.000000854** (5.50e-08)
lagtraffic	0.000271 (0.000248)	0.000203 (0.000311)	0.000206 (0.000280)	4.24e-08 (0.000000663)
charst	2.151*** (0.0296)	2.204*** (0.0333)	2.009** (0.102)	-0.00164 (0.000703)
unemp	-3461.6** (270.1)	-3962.4* (520.3)	-3340.4** (228.4)	-15.52* (2.814)
income	0.00373* (0.000437)	0.00208 (0.000804)	0.00364* (0.000669)	-0.0000426*** (0.000000856)
buslane	0 (.)	0 (.)	0 (.)	0 (.)
vkm	-1.837** (0.147)	-2.335* (0.355)	-1.806** (0.176)	-0.0214** (0.00134)
_cons	30902.6** (2677.6)	38939.3* (5859.2)	30998.1** (2928.4)	336.5** (24.26)
City Fe	yes	yes	yes	yes
Year Fe	yes	yes	yes	yes
Month Fe	yes	yes	yes	yes
N	166	166	166	166
adj. R <sup>2</sup>	0.869	0.873	0.880	0.908

**Model 1:** in model 1 we have included only price omitting avgtraffic (average traffic) and avtoll (average toll). In comparison to model 3 (a model with all the 3 variables), price is significant in this model. However, since price don't remain equally significant in all other models, we can't trust this result. It might be the case that since we omit other important variables, their cumulative effect is picked up by price, making it significant. The other variables in this model Charst (Charging station), unemp (unemployment rate), income and

vkm (vehicle kilometer) are all significant and of the correct sign. Their magnitude is equivalent to the magnitude of the corresponding variables in model 3.

**Model 2:** in this model, we have included avgtraffic in addition to price. Like model 1, Price is significant in this model as well, but income, which is significant in all other models is not significant here. We have discussed in the literature review section that income is one of the determinant factor for sales of EV. Hence, this model is inferior in a sense that it overlooks an important factor that is responsible for the sales of EV, while the three other models correctly explain it. The other variables, charst, unemp and vkm are all significant and of correct sign. Their magnitude is also equivalent (a bit higher in model 2) to their model 3 counterparts.

**Model 3:** this model includes all the 3 variables of our interest and moreover the dependent variable is in level form (because of this we treat it as a base model for our comparison). Here price, avgtraffic and avtoll are all insignificant. The rest of the variables (charst, unemp, income and vkm) are all independently significant and of correct sign.

**Model 4:** this model is included to test whether the level or the log form of Evsales should be used. Here, price becomes significant but with small magnitude. As we argue above, this result is incorrect. Avtoll is also significant but its magnitude is almost zero (it has no economic significance). Unemp is significant but the magnitude is far smaller than all others models. The strange result in this model is income. Income is significant with very small magnitude as compared to model 3 and others. But, the sign is incorrect. This is a very strong reason not to proceed with the log form. The last variable, vkm is significant but its magnitude is small as compared to model 3 and others.

**Adjusted R2:** there is no big difference in the adjusted R2 among the four models we consider above. Thus, adjuster R2 will not help us a lot in choosing the best model. Nevertheless, from the above discussion it should be clear that model 3 (with the three variables of our interest included) is superior in explaining the sales of EV. Therefore, in future sections, we will rely on it and further explore its implications.

### **Result from alternate model**

The result of the alternate model is shown in table 5 below. As we have already mentioned, the motivation to develop the alternate model is to test whether the separate traffic and the corresponding toll of EV and Non-EV has any significant impact on EV sales individually. As

we do for the main model, let's explore the different variation of the alternative model based on the inclusion or omission of the three independent variables of our interest (price, avgtraffic for both EV and non-EV and avg toll for both EV and non-EV).

*Table 5: Regression output from the alternate model and its variations*

	(1) Evsales	(2) Evsales	(3) Evsales
avgnonEVtraffic	-0.00233 (-2.56)		0.00158 (1.16)
avgEVtraffic	0.0634 (1.06)		0.00933 (2.71)
price	-47.36 (-1.74)	9.399** (11.59)	4.530* (6.90)
avnonEVtoll	0.000231 (3.47)		
avEVtoll	-0.00256 (-0.94)		
lagtraffic	0.000251 (0.96)	0.000277 (1.12)	0.000239 (0.83)
charst	2.347 (4.27)	2.145*** (159.12)	1.798*** (85.98)
unemp	-2734.2 (-4.03)	-3192.8* (-9.10)	-4315.4** (-17.25)
income	0.00866 (1.85)	0.00452* (4.94)	0.000938 (0.92)
buslane	0 (.)	0 (.)	0 (.)
vkm	-0.513 (-0.42)	-1.588* (-5.46)	-2.656** (-10.82)
_cons	10099.7 (0.50)	26596.6* (5.22)	44748.6** (11.30)
<i>City Fe</i>	yes	yes	yes
<i>Year Fe</i>	yes	yes	yes
<i>Month Fe</i>	yes	yes	yes
<i>N</i>	164	164	164
<i>adj. R<sup>2</sup></i>	0.881	0.870	0.875

**Model 1:** in this model, we have included price and both traffic and toll for EV and non-EV. The result shows that both separate traffic and toll (for EV and non-EV) are insignificant. But, *avnonEVtoll* (average non-EV toll) is significant at the 10% significance level, with very little economic significance. Similarly, *charst* and *unemp* are significant only at the 10% significance level. The rest of the variables (*price*, *income*, *vkm*, *lagtraffic*) all are insignificant.

**Model 2:** in this variation, we include only price omitting both separate traffic and toll. Price becomes significant now. However, since price is significant when we omit either separate toll or both separate toll and separate traffic, it is reasonable to suspect that price picked up the cumulative effect of the missing variables. Thus, we don't trust this result. All other variables (*charst*, *unemp*, *income* and *vkm*) are all significant with the correct sign. In fact, this model closely resemble variation 3 of the main model except price.

**Model 3:** here we include price and separate traffic omitting separate tolls. Like model 2, price is significant in model 3, but with smaller magnitude. *Charst*, *unemp* and *vkm* are all significant with the correct sign. However, *income* is insignificant in contrary to many studies on EV.

Even though there is less gain attained by splitting traffic and toll, one important conclusion can be made. That is, whether you see it from the perspectives of EV or non-EV, toll exemption for electric cars are insignificant for the sales of electric cars. Apart from this, as the above discussion makes it clear, it is worthwhile to focus on the main model for further discussion of (significant) coefficients and policy issues. Consequently, in the next section, we will see the impacts of the different fixed effects applied to model 3 of our main model.

## 8.2 City, year and month fixed effects

Table 6 below shows model 3 of the **main model** and its variation when city, year and month fixed effects are added one at a time (note that the same kind of experiment is also done for the other variations in the main model, see table A.2 in appendix). First, let's briefly describe the variations and then we proceed to interpret the coefficients of our chosen model.

## Main model with city, year and month fixed effects

Table 6: Regression output of the selected model with its variations of fixed effects

	(1) Evsales	(2) Evsales	(3) Evsales	(4) Evsales
price	-54.41 (24.31)	-70.07 (26.72)	-86.27 (65.30)	-23.46 (44.33)
avgttraffic	-0.00251 (0.000994)	-0.00338 (0.00169)	-0.00522 (0.00400)	-0.00157 (0.00204)
avtoll	0.000227 (0.0000886)	0.000272 (0.0000976)	0.000318 (0.000217)	0.0000746 (0.000127)
lagtraffic	0.000206 (0.000280)	-0.0000209 (0.000110)	-0.0000148 (0.0000587)	0.000387* (0.000190)
charst	2.009** (0.102)	2.397* (0.269)	0.875*** (0.142)	1.539*** (0.356)
unemp	-3340.4** (228.4)	-564.6* (79.60)	-6005.2*** (1026.8)	-627.9* (278.4)
income	0.00364* (0.000669)	0.00499 (0.00149)	-0.000134 (0.00133)	0.00275** (0.00103)
buslane	0 (.)	0 (.)	0 (.)	0 (.)
vkm	-1.806** (0.176)	-0.0726 (0.0719)	-4.080*** (0.613)	-0.444* (0.198)
_cons	30998.1** (2928.4)	920.1 (825.5)	70359.5*** (11658.4)	6546.8* (3307.0)
City Fe	yes	yes	no	no
Year Fe	yes	no	yes	no
Month Fe	yes	no	no	yes
N	166	166	166	166
adj. R <sup>2</sup>	0.880	0.849		

**Variation 1:** in this model, we have included all the fixed effects (city, year and month) and hence it acts as a base line model for our comparison.

**Variation 2:** in this model, we only include the city fixed effect. City fixed effect captures anything which remain fixed among the cities considered. For instance, financial incentives



for EV car buyers (rebate in VAT, annual registration tax and sales tax). Since in Norway these discounts are set nationwide, it will have the same values across cities and hence capture by the city fixed effect and dropped from the regression equation. Like variation 1, the 3 variables of our interest (price, avgtraffic and avtoll) remain insignificant in this model. Charst on the other hand is significant and of correct sign, but the magnitude is higher in this model as compared to variation 1. Because there is very little variation across cities (cross sectional variation) in terms of income and vkm, inclusion of only city fixed effect will make income and vkm insignificant in explaining the variation in Evsales across cities.

**Variation 3:** in this model, only the year fixed effect is included in the regression. The year fixed effect captures anything that remain fixed over the years. For instance, consumer environmentalism can reasonably be assumed constant over our study period. Another example includes geographic location, city density and demographic features (age, race, education) which are roughly constant over our study period. Like the above model variations, price, avgtraffic and avtoll are insignificant in this model. Charst are significant with the correct sign, but its magnitude is smaller than variation 1. This may be due to that fact that the development of charging stations shows little variation over the years than variation among cities. Thus, the year fixed effect will only consider this small variation and hence smaller magnitude for the coefficient of charst. Like charst, unemp is significant with the correct sign but with very large magnitude as compared to variation 1. This may be because on yearly basis the variation in unemp is very large as compared to unemp variation among cities. Thus, employing only the year fixed effect will magnify the magnitude of unemp. The same explanation can be made for vkm, which in this model has correct coefficient sign but higher magnitude as compared to variation 1.

**Variation 4:** in this last model, only the month fixed effect is added in the regression. The month fixed effect captures anything peculiar over the months that has a definite pattern. For example, due to new year sales or bonuses, people may buy more or purchase a new item in January or February or March of every year. In this model, lagtraffic becomes significant but with very small magnitude (very little economic significance) and of unexpected sign. One explanation for the significance of lagtraffic is pronounced monthly variation of EV traffic as compared to EV traffic variation between cities. However, the sign is not in agreement with our expectation. This again may be due to the omission of city and year fixed effect; thus, their cumulative effect may be picked up by lagtraffic.

In line with the discussion above, we argue that our baseline model is better than the other model variations. Consequently, important variable interpretation and policy implication will be made per variation 1.

**Heterogeneity:** since in our model of choice (variation 1), we only use city, year and month fixed effect, heterogeneity bias may arise due to omission of variable(s) that are constant in any of the two dimensions used. For instance, if consumer choice for EV remains fixed both over city and year, since we know from basic economics that consumer choice is dependent on income, leaving consumer choice in the error term may bias our result.

## 8.3 Discussion of results

In this section of our thesis, we first discuss the implication of the insignificant variables and we follow this with the interpretation of the significant variables.

Variation 1 of our main model predicts price, traffic, lagtraffic and avtoll to be insignificant predictors of EV sales in the three cities considered. Even though we use detailed monthly data for toll stations as opposed to Mersky et. al. (2016) who used binary, we arrived at the same conclusion as them. This makes us more confident that our findings are correct and we have managed to capture the effect of the toll exemption incentive. This means, the city municipality will have very little incentives to use toll cost as means to influence the sales of EV, if all other things are the same. It also means that, EV user/drivers do not significantly change their driving behavior because of EV toll subsidy. In fact, the latter effect is positive in a sense that it will not discourage people to buy EVs. Had people changed their driving behavior, there will be road congestion and this lowers consumers' utility to buy EVs, since (as mentioned previously) 16% of Norwegian buy EVs for convenience and time saving.

In contrast to insignificant variables, variation 1 of the main model also predict charst, unemp, income and vkm to be significant predictors of EV sales. In this situation, the city municipality will have tools (factors or variables) to influence EV sales in the desired direction. For example, increasing the cumulative number of charging stations in a city by 1, raises sales of EVs in the same city by  $\approx 2$  cars, keeping all other factors constant. This is a reasonable number because the additional charging station may have charging points ranging from 1 to 35. In the first stage of building charging stations, it may be more useful to cover more geographical areas as much as possible. However, after such a phase enables us to cover certain geographic

areas, it makes sense to develop the existing charging stations to have more charging points than to keep on expanding the spatial distribution of charging stations. This is because EVs are short range and people prefer conventional vehicles (ICE) for longer distances. Yet, it is not clear whether charging stations leads to increased EV sales or the other way (higher EV sales prompt the city municipality to focus more budget on building many charging stations in the city). From our regression result it is not possible to infer causality for charging stations.

The other tool (variable) the city municipality may use to induce EV sales is unemployment. From basic economics, we can infer that unemployment exist because of mismatch between labor supply and demand and/or mismatch between skills acquired by workers and those demanded by firms. If the city municipality can somehow be able to reduce the unemployment rate in a city, then it can achieve a lot more success in promoting EV sales than using other factors. This is because, as our regression result predicts, unemployment rate has a huge economic significance per unit of change as compared to other factors. On the other hand, if the city unemployment rate is high during recession and it remains high for considerable period, then unemployment will be less promising as a factor to affect EV sales. If we stick to the case where the city municipality will be able to influence unemployment rate from the regression result we can conclude a reduction of a city unemployment rate by 0.1 % will boost EV sales by additional  $\approx 334$  cars, keeping all other factors constant. To give a clear picture of what this mean, let's take Oslo and its surrounding and reference time of 2011. In the 2011, the total population was 1.167 million and the unemployment rate was  $\approx 2.5\%$ . Reducing unemp by 0.1% means giving a new job for 1167 people who were unemployed before. This implies, as we discuss above, higher willingness and ability of firms to hire many workers which will result in a large lift in the purchasing power of the population in the city. Thus, a massive EV sales is expected.

Like unemp, the city municipality may use average before tax income to enhance the sales of EVs in the city. Of the three cities considered, Oslo and its surroundings and Stavanger have consistently higher average before tax income in each year of 2010–2015, predicting higher EV sales, if everything else is equal. In general, one can see that an increase in average before tax income of 10,000 NOK, will boost EV car sales by  $\approx 36$  cars, keeping all other factors constant. This amount of income surge is not uncommon, since in Norway salary increment scales are larger than this figure. However, here it should be noted that such kind of analysis do not consider inflation. It may be the case that a nominal increase in salary do not correspondingly reflect a higher disposable income, if inflation is considerably high.

Of all the significant variables, vkm is the one where the city municipality has the least control over. As we saw in the data section of our thesis, people in Oslo and its surroundings drive long distance in all times of 2010–2015. In addition, people drive less and less km in later years than in 2010 and 2011. Considering only these facts, we can deduce that EV demand in Oslo and its surroundings will be lower than other cities but people in all three cities demand/buy more and more EVs over time. This is true because electric cars are short range as compared to non-electric cars and if people drive long distances, they prefer non-EV cars as compared to EVs and vice versa. The regression result shows that if the average vehicle kilometer traveled in a city is raised by 10 km, the sales of EV cars will be dropped by  $\approx 18$  cars, keeping all other factors the same. To illustrate this with the example, let's take Oslo again. In 2011, the average vkm is 12,778 km and in 2012 the average vkm is raised to 13,055 km. Considering only this change, the sales of electric cars in the city will be dropped by  $\approx 500$  cars.

In addition to significant and insignificant variables, the regression equation also contains a constant, which itself is significant. But for our case the constant has no relevant interpretation except it shows that EV sales will not be zero even without all incentives for EVs. In other words, there will always be people who buy electric cars for reasons other than EV incentives. For instance, people will buy EVs because it is environmental friendly and/or because it is convenient and saves time etc.

## 8.4 Main result

The main result of our thesis is that EV sales are not sensitive to EV toll exemptions in the three cities we consider. This is true whether you as a driver estimate user's saving/cost from EV or non-EV perspectives. In addition, we find that charging stations, unemployment, income and vehicle kilometer are significant predictors of the sales of EVs, a result which is also confirmed by previous studies, for instance a research by Mersky et al (2016). However, in contrary to our suspicion (EV users drive unnecessarily more since they don't pay for road use and hence may excessively contribute to congestion), we did not find any significant

rebound effect in relation to change in consumer driving behavior. But, this result is also in agreement with previous survey studies on rebound effect<sup>11</sup>.

## 8.5 Limitations

The main limitations of our study relate to the way average toll value is estimated for a city. First, average traffic is estimated for a representative toll station. Hence, the monthly traffic variation between the different toll stations is ignored which may cause our result to be biased. Second, average monthly toll price is estimated for a city. Thus, monthly toll charges variation between the different toll stations, including variation between rush hour and out of rush hour charges is ignored. Though this variation is very minimal, it may cause a bias to our conclusion. Third, after a vehicle has passed a toll station and charged for toll, it can freely pass any other toll station without paying within the next one hour. When we calculate the independent variable, that is the cost of traffic through toll stations, we do so by multiplying the traffic volume with associated cost. Our dataset does not differentiate between paying passes and those that pass for free because of the one-hour rule. This means that when calculating the cost of traffic through toll stations this variable could become larger than it should be and thus influence our analysis. Fourth, when analyzing the effects of toll road exemption on electric vehicle sales, it is important that the data associated with sales and traffic is coherent. Since we are trying to see the impact of toll road exemption, it is necessary that the vehicles that generate traffic through stations are in fact sold in that area. We assume that for most cases this is true but we cannot guarantee that all part of the sales complies with this. It is quite likely that some of the vehicles that are sold in one area will generate traffic in entirely different areas, and vice versa. Thus, this may create some issues (upward or downward bias) on our analysis since there may not be a perfect geographical overlap. Fifth, the data for charging stations also have some limitations. A charging station may have at its creation only a few charging points, while it can later be developed and expanded to have several charging points. Our data does not show the proper development of them. While it shows when the different charging stations were created, how many charging points they have

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<sup>11</sup> One example is a mail-back survey conducted on buyers of second generation Toyota Prius in Switzerland (367 buyers). From two possible kinds of direct rebound effect: people switch from small/more fuel efficient to hybrids and average household vehicle ownership could increase, the result shows that it is not possible to reject the null hypothesis of direct rebound effect is **not** present (Haan, 2006).

today, and when they were last modified, it does not show the step-by-step development of them. While it does give us an overview of the evolution of the infrastructure, it does result in an imperfect picture of the expansion of charging stations. Our analysis includes only cumulative number of charging stations not charging points (by assuming charging stations developed in earlier years will keep working at least until 2015). This means, our result will be biased downward as compared to considering charging points. In overall, future studies should focus on one or more of the limitations mentioned above to have a better picture of the policy incentive.

## 8.6 Suggestion for future research

In addition to what is said above, there are a number of interesting suggestions for future studies. Our research focuses only on the three major Norwegian cities Oslo, Bergen and Stavanger due to the difficulty of obtaining data. Though the omitted cities have very little EV sales, as compared to the three cities of our consideration, including them will highlight a more complete picture of the impact of toll on EV sales. In addition, rather than performing city level regression, one could do the same analysis at the municipality level. Changing the scale to the municipality level may be important since some of city level factors may have different values per municipality<sup>12</sup> and thus, municipality level analysis will give a more detailed effect of factors on EV sales. The main difficulties in performing municipality level regression will be the small number of EV sales for many municipalities and the challenge of delimiting toll station for a particular municipality (if the goal is primarily to estimate the impact of toll exemption on EV sales). However, these challenges can be tackled by grouping different municipalities together (of course at a scale lower than city level) either based on geographic location and/or socioeconomic conditions.

Our analysis covers a period where EV sales in Norway has gone from marginal to experiencing incredible growth. It has allowed us to identify and capture the effects of the different factors responsible for EV adoption. In the near future, it is expected that most of these incentives will be phased out, or at least changed drastically. We have also seen that EVs have gone from a limited means of transportation to technological advanced vehicles that are

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<sup>12</sup> For instance, income, unemployment, charging stations, EV sales, vehicle kilometer, toll value.... if some demographic factors are not available for municipality level, it is possible to use population weighted average value of the city

more able to compete with ICE vehicles. It is expected that the technology for EVs will continue to develop and become closer to being a reasonable substitute for ICE vehicles. It will therefore be interesting to conduct a similar analysis in the years to come. However, the analysis will have a different approach, as incentives are removed and EVs and ICE vehicles are close substitutes. This means, rather than identifying what drives and promote an early technology, it will then be relevant to investigate what drivers are maintaining the sales of EVs.

Since incentives will be removed in the years to come, it will also be interesting to conduct an analysis which compares two time periods of EV sales, one period with incentives and one period without. Doing an analysis over this timespan will be of great interest as it will identify the differences and evolution of drivers for EV sales. Through such an analysis one can identify clearly which drivers have always been present and which have changed over the years. Especially interesting is to identify any potential drivers which have always been present regardless of governmental incentives since this will uncover characteristics of the EVs themselves that consumers appreciate.

As described in the data description and limitation section of our thesis, due to limitations in our dataset our analysis employ cumulative number of charging stations, not charging points. Charging points may reflect more accurate magnitude (significance) of the charging infrastructure to EV sales than charging stations. This is because a charging station with one charging point serve only one EV at a time, while a charging station with 35 charging points serve at least 35 vehicles at a time. In a city where there is already a high number of EVs and limited charging infrastructure, this difference may seriously affect customer buying decisions. Consequently, it will be more useful and recommended for future studies to rely on the number of charging points than the cumulative number of charging stations as one of the independent variable which determine EV sales in an area.

## 8.7 Policy implication

As stated in the problem background section of our thesis, some local municipalities already removed free parking and access to bus lane. In addition, as the National Transport Plan 2018–2029 (NTP) of the Norwegian Public Roads Administration makes it clear, EVs will move from free toll to low toll fare around cities. Based on our analysis, we argue that the NTP is

aiming towards the correct direction since toll road exemption is not significantly contributing to the sale of EVs. This means, free EV toll (public subsidy) for reducing emission from transport sector (through higher EV sales) may be better spent in another area which is more efficient<sup>13</sup>. However, there is no guarantee that our period of analysis (2010–2015) will reflect the complete picture of the policy effect. Even though we feel confident that we included both the period of low and high EV sales, this couldn't guarantee that the market is mature (in equilibrium) and will not show any change. In fact, it may be true that the market will not show any drastic changes as it shows in earlier periods, but still we cannot be sure that it remains stable. In addition, for our result to be conclusive, the joint significance of toll charges with other EV incentives should be tested. For instance, the significance of toll charges with free parking or toll charges with ferry expense and bus lanes. It might be the case that jointly these incentives are significant, in which case our recommendation for policy makers will not hold. Similarly, our result may not be irrefutable since our model doesn't include fuel price as we assume that it will on average be constant across cities (and hence captured by the city fixed effect). But, fuel price slightly varies across cities which may lead our result to be biased.

Unlike toll road exemptions, there is less doubts regarding the role of charging infrastructure, unemployment, income and vehicle kilometer in promoting the sales of EV. Though it is difficult to infer causality, it is true that charging infrastructure has a significant positive role in boosting EV sales. Thus, future policy may direct EV adoption by controlling the development of charging infrastructure. Future policy may also be directed toward reducing unemployment rate. Because a unit percentage change in unemployment rate may result in a massive boost in EV sales, it is very compelling to use unemployment rate as a factor to affect EV sales. However, it may be difficult (may be out of local government autonomy and capacity) to affect unemployment rate in a desired direction, at least in the short run. A highly related factor to unemployment is income. Bjerkan et al (2016) conclude that when the purchase cost of BEV and ICEV are similar (similar RFC), people in the low-income category prefer an alternative which also reduce the use cost (RUC). BEV fulfill such condition because, among others, (at present) it pays no toll and enjoy free parking. This implies that (contrary to our conclusion); if the goal of the policy is to specifically encourage low-income people to buy and use BEV, then toll exemption and free parking should not be removed. However, income is not as compelling as unemployment rate with regard to promoting EV

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<sup>13</sup> Note that the efficiency of EV in reducing greenhouse gases (GHG) is debatable and out of the scope of this thesis (Holtmark, 2014).



sales. A 10,000 NOK increase in before tax income result in only  $\approx 36$  cars, while a reduction of unemployment rate by 0.1% will boost EV sales by  $\approx 334$  cars, keeping all other factor constant.

## 9 Conclusion

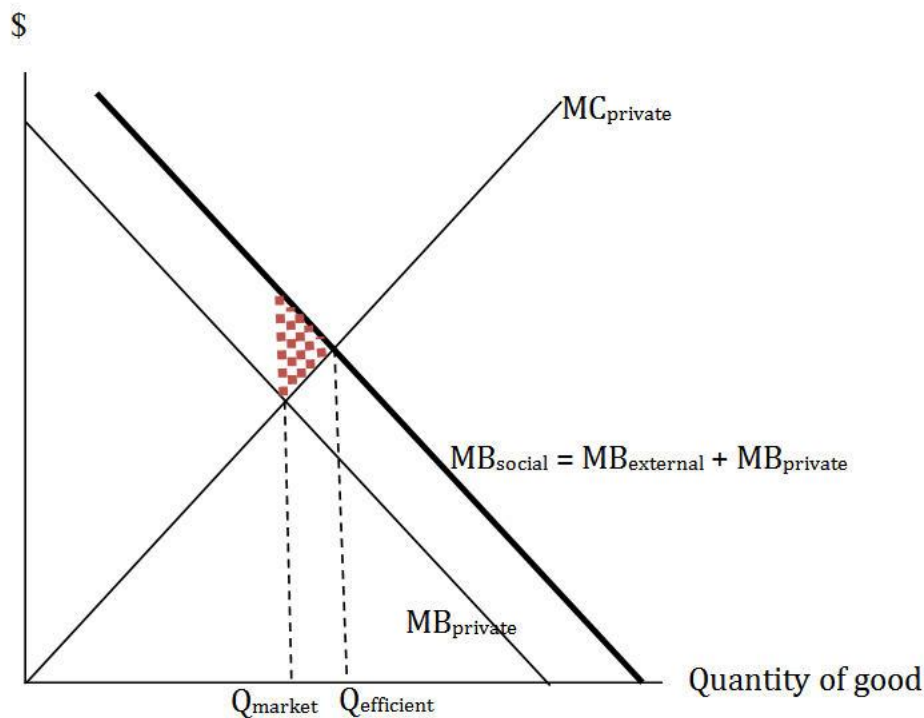
In our thesis, we answer the research question “what is the impact of EV toll exemption towards the sales of EV?” To do so we primarily use data on the sales of EV, toll cost, traffic, charging station, vehicle kilometer, income and unemployment. Our time range for the analysis is 2010–2015. By employing panel data technique with city, year and month fixed effects (to capture the unobserved city or time constant), we arrive at a conclusion: EV toll road exemption is insignificant to the sales of EV. This result holds true whether you split customers as EV and non-EV users and analyze the toll exemptions or toll cost they save/incur respectively. In addition to this main result, we find that charging stations, income, vehicle kilometer and unemployment are significant predictors of EV sales. From our main model, we predict that increasing the cumulative number of charging stations by 4 will boost EV sales by  $\approx 8$  cars, keeping all other factor constant. On the other hand, unemployment has a very huge economic significance in promoting the sales of EV. For instance, if a city unemployment rate is reduced by 0.01%, sales of EV car will be enhanced by  $\approx 33$  cars, keeping all other factor the same. Income is also economically significant, as increasing the average before tax income by 5,000 NOK lift EV sales by  $\approx 18$  cars, if all other factors remain unchanged. Here again readers must note that in such kind of analysis inflation (which changes the purchasing power of income) is not considered. Our main model also predicts that if the average distance people drive yearly increases by 10 km, then EV sales will drop by  $\approx 18$  cars, if everything else is kept unchanged.

As the Norwegian Public Roads Administration makes it clear in its NTP, EVs will move from no toll to paying low toll fare. Our result also suggests a move in that direction. As EV toll exemptions are insignificant to EV sales, we argue that the free toll (public subsidy) could be better spent in another area (technology, investment) where the benefit cost ratio is higher than the case in EV toll subsidy. However, our result should be interpreted carefully with the following limitations into considerations. We ignore monthly toll variations across the various toll stations when we estimate the average traffic for a representative station. The same goes for average toll charges which may bias our conclusion. We don't account for the one hour rule; hence our result is biased upward. We assume charging stations built in years 2010 and afterwards continued to be operational at least until end of 2015. And finally, there is no guarantee that the sales and traffic have the exact same geographic location (minor geographic divergence can occur).

Our policy recommendations contradict with the result of Bjerkan et al (2016), as they argue that to encourage low-income group of people to buy and use BEV, incentives like toll exemptions and free parking are indispensable. However, readers should note that our approach is completely different from theirs. As noted in the literature section of our thesis, they employ a survey approach of BEV owners with the main goal to describe and identify critical incentives for buying BEV.

Our research has significance in that it gives a clearer understanding of the EV toll exemptions subsidy. Previous research attempts to analyze toll exemptions only as binary variable. Hence, our research adds to the literature because it estimates toll values as a discrete variable before estimating its impact on the sales of EV. We believe that our way of approach is more valuable for policy makers who demand detailed input to design effective and efficient future EV policies.

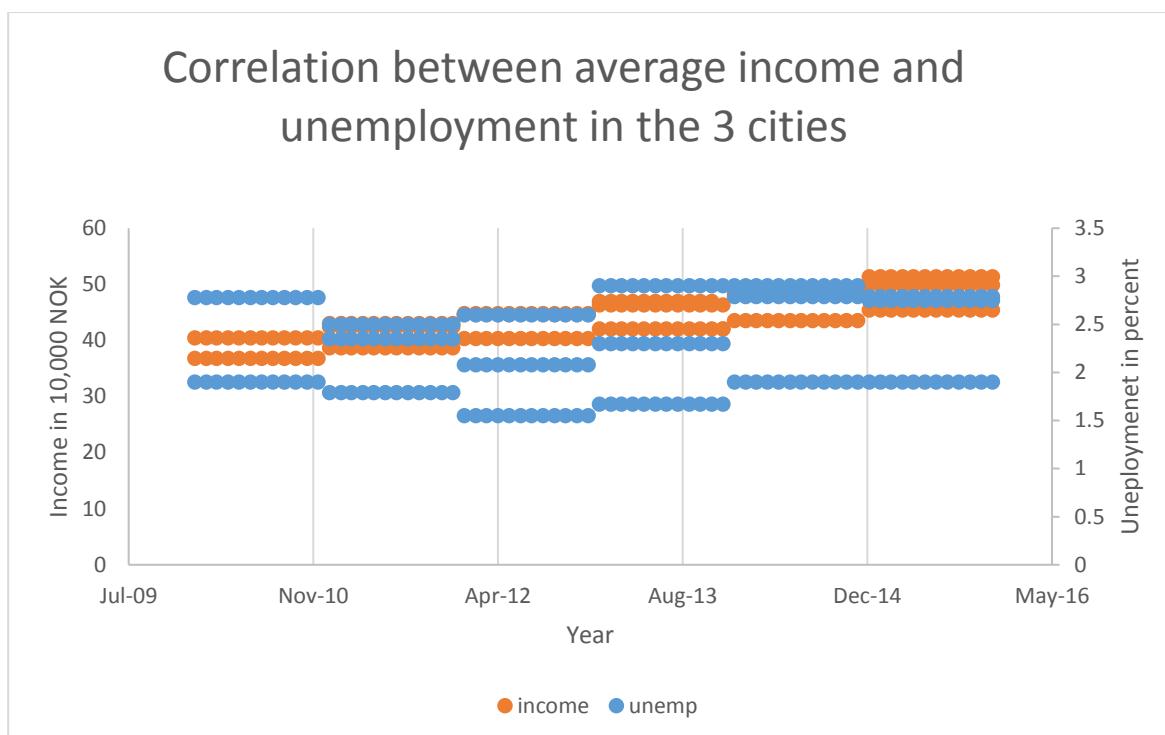
## Appendices



*Figure A.1: Market failure: public good*

Source: Tragedy of the Common (2017)

Figure 14 above shows the market failure to efficiently allocate public goods. This happens because the market allocates private MC to private MB. However, the social MB of public good is much higher than private MB, hence the efficient allocation is achieved when social MC equals social MB. The shaded area represents welfare loss due to inefficient allocation of public goods.



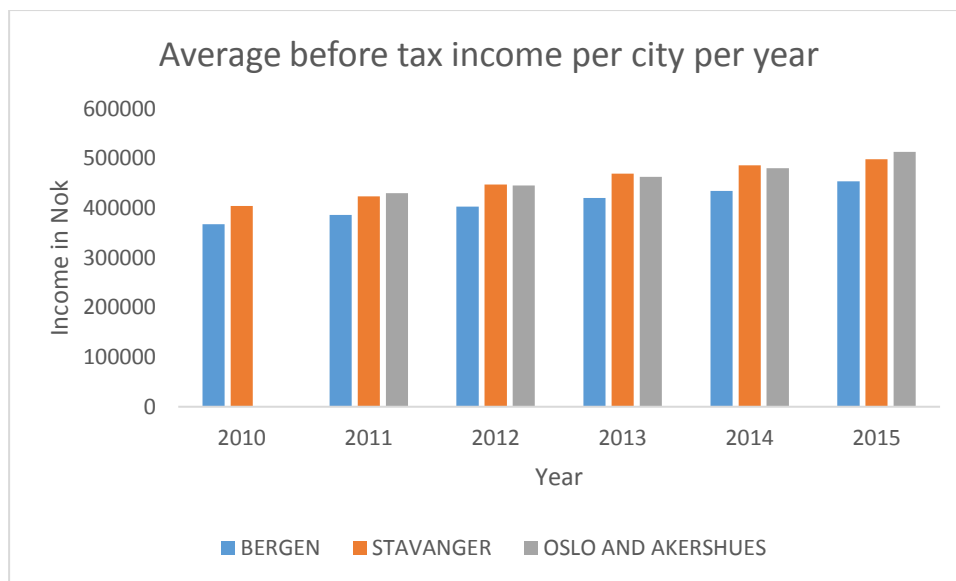
Correlation coefficient 0.647929

*Figure A.2: Income and unemployment correlation*

*Table A.1: Yearly income (NOK) per city 2010–2015*

CITY/YEAR	2010	2011	2012	2013	2014	2015
BERGEN	367700	386800	403200	420500	435100	454200
STAVANGER	404300	424100	447600	469600	486200	498400
OSLO AND AKERSHUES		430250	446100	463050	480600	513550

*Source: Statistics Norway 2017*



*Figure A.3: Average before tax income per city per year*

*Table A.2: Estimates from regression with three different models of EV sales on Price (P), Price and Traffic (PT) and Price, Traffic and Toll (PTT) with fixed effect*

	(1) (P)City FE	(2) (P)Year FE	(3) (P)Month FE	(4) (P)All FE	(5) (PT)City FE	(6) (PT)Year FE	(7) (PT)Month FE	(8) (PT)All FE	(9) (PTT)City FE	(10) (PTT)Year FE	(11) (PTT)Mont hFE	(12) (PTT)All FE
price	7.364 (2.562)	6.087 (5.128)	-1.834 (8.533)	9.447** (0.846)	8.711 (3.725)	6.060 (5.742)	-1.772 (7.932)	11.21* (2.474)	-70.07 (26.72)	-86.27 (65.30)	-23.46 (44.33)	-54.41 (24.31)
lagtraffi c	0.000523* (0.00003 50)	0.00016 9 (0.00015 3)	0.000207 (0.000368 )	0.00027 1 (0.00024 8)	- 0.000016 2 (0.00011 5)	0.000011 2 (0.000026 8)	0.000359* (0.000161)	0.00020 3 (0.00031 1)	- 0.0000209 (0.000110 )	- 0.0000148 (0.000058 7)	0.000387* (0.000190)	0.000206 (0.00028 0)
charst	2.532** (0.240)	1.035*** (0.0421)	1.486*** (0.197)	2.151*** (0.0296)	2.692** (0.258)	0.930*** (0.0991)	1.624*** (0.294)	2.204*** (0.0333)	2.397* (0.269)	0.875*** (0.142)	1.539*** (0.356)	2.009** (0.102)
unemp	-589.0* (80.97)	- 5837.5*** (982.2)	-634.4* (271.5)	- 3461.6** (270.1)	-556.0* (72.74)	-5926.0*** (936.0)	-627.3* (268.6)	-3962.4* (520.3)	-564.6* (79.60)	-6005.2*** (1026.8)	-627.9* (278.4)	-3340.4** (228.4)
income	0.00486 (0.00148)	0.00106* (0.00043 4)	0.00308** (0.00111)	0.00373* (0.00043 7)	0.00464 (0.00144)	0.00126 (0.000739 )	0.00283* (0.00118)	0.00208 (0.00080 4)	0.00499 (0.00149)	-0.000134 (0.00133)	0.00275** (0.00103)	0.00364* (0.00066 9)
buslane	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
vkm	-0.0700 (0.0848)	-3.768*** (0.501)	-0.432* (0.183)	-1.837** (0.147)	-0.0571 (0.0929)	-3.812*** (0.470)	-0.426* (0.176)	-2.335* (0.355)	-0.0726 (0.0719)	-4.080*** (0.613)	-0.444* (0.198)	-1.806** (0.176)
avgtraffi c					0.00167 (0.00083 2)	0.000315 (0.000350 )	-0.000364 (0.000334)	0.00181 (0.00158 )	-0.00338 (0.00169)	-0.00522 (0.00400)	-0.00157 (0.00204)	-0.00251 (0.00099 4)
avtoll									0.000272 (0.000097 6)	0.000318 (0.000217)	0.0000746 (0.000127)	0.000227 (0.00008 86)
_cons	-131.6 (1457.5)	63762.5* (9234.4)	5874.1* (2623.6)	30902.6* (2677.6)	-628.9 (1803.6)	64453.9** (8800.1)	5917.0* (2465.3)	38939.3* (5859.2)	920.1 (825.5)	70359.5*** (11658.4)	6546.8* (3307.0)	30998.1** (2928.4)
R <sup>2</sup>	0.834			0.885	0.846			0.889	0.857			0.896
N	166	166	166	166	166	166	166	166	166	166	166	166

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

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