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The Adverse Effects of the Norwegian Electric Vehicle Incentive Scheme

With Emphasis on Congestion and Public Funding

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NORWEGIAN SCHOOL OF ECONOMICS

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Abstract

Norway is one of the countries in the world with the highest market share of electric vehicles per capita. Much of this is due to a comprehensive incentive scheme to facilitate the purchase and use of electric vehicles. The purpose of the incentive scheme is to reduce emissions, which is an externality of road traffic. However, road traffic also causes other externalities, which the incentive scheme does not take into account.

The purpose of this thesis is to identify and estimate the adverse effects that arise with increasing shares of electric vehicles. The adverse effects are associated with the externalities that emerge from road traffic. In particular, this thesis emphasizes the adverse effects of toll exemption for BEVs, which are related to congestion and public funding

Existing literature on the incentive scheme focuses on the importance and cost-effectiveness of the incentives, and the characteristics of electric vehicle owners. Some discuss the potential adverse effects of the incentives, but fail to provide evidence and take the whole cost into account. Therefore, this thesis will try to empirically estimate how demand for driving changes with higher numbers of electric vehicles, and discuss what externalities this may cause.

The demand for driving is estimated through three different models using two data sets, where the first model uses annual mileages per vehicle for all municipalities and the second and third model use toll passages in the five largest cities in Norway. All three models suggest that demand for driving increases with increasing shares of electric vehicles. This thesis argues that because demand for driving increases, the externalities from road traffic increase.

Acronyms

BEV	Battery Electric Vehicle
FE	Fixed Effects
ICEV	Internal Combustion Engine Vehicle
MCF	Marginal Cost of public Funds
NOK	Norwegian Krone
OLS	Ordinary Least Squares
PMC	Private Marginal Cost
POLS	Pooled Ordinary Least Squares
RE	Random Effects
SMC	Social Marginal Cost
SSB	Statistics Norway
TØI	Institute of Transport Economics
VAT	Value Added Tax
VKMT	Vehicle Kilometres Travelled
2SLS	Two-stage Least Squares

Contents

1. Introduction

Norway has committed itself to reduce emissions of greenhouse gases with 40% by 2030 compared to the level of emission in 1990 (Ministry of Climate and Environment, 2016). The transport sector produces roughly one third of the emission in Norway, where road traffic contributes to a significant part (Ministry of Transport and Communications, 2017). Switching to zero emission vehicles may contribute to Norway reaching the goal of emission reductions. To facilitate the use of Battery Electric Vehicles (BEV), Norwegian authorities have introduced a comprehensive incentive scheme to reduce the costs of purchase and usage of BEVs, resulting in Norway becoming one of the countries with highest BEV per capita in the world (Aasness & Odeck, 2015).

In terms of the high BEV market share, the Norwegian BEV incentive scheme is a story of success. However, alongside the generous incentives, some adverse effects arise that potentially offset some of the emission reductions. This paper will emphasize the adverse effects of toll exemption for BEVs.

1.1 Motivation and purpose

The purpose of the BEV incentive scheme is to gradually replace internal combustion engine vehicles (ICEVs) with BEVs to reduce emissions. Emissions are an external cost, or externality, of road traffic. That is, an unintended and uncompensated side effect of one person's action, which affect others (Sterner, 2003). Even if BEVs are zero emissions vehicles, other externalities from road traffic are practically the same for BEVs and ICEVs. Some of these externalities are wear and tear of road infrastructure, noise, accidents and barrier effects (Thune-Larsen, Veisten, Rødseth, & Klæboe, 2014).

In this thesis, we emphasise the external cost of congestion, which is the opportunity cost of time spent in traffic. Congestion occurs when the density of cars surpasses the capacity of the road causing cars to slow down and increase travel time (Evans, 1992). A regulatory measure to cope with congestion and reducing this externality is by introducing congestion pricing. Norway has an extensive use of toll projects to finance roads and infrastructure, but congestion pricing is used to a less extent (Welde, Bråthen, Rekdal, & Zhang, 2016). We enunciate that when BEVs do not face toll charges, BEVs will drive more on tolled roads, thereby causing more congestion, which in turn constitutes a cost to society

As a consequence of the incentive scheme, toll revenues might decline significantly. In Norway, toll projects are mainly used for financing road infrastructure and works as a supplement to government funding (Aasness & Odeck, 2015). The loss in toll revenue is not a cost to society but a transfer from government to consumers. However, loss in toll revenue may cause a larger need for government funding, which has a cost to society.

There is a large literature on the efficacy and cost-effectiveness of the incentive scheme in terms of emission reductions (Bjerkan, Nørbech, & Nordtømme, 2016; Figenbaum, 2016; Holtsmark & Skonhoft, 2014). Extensive research has also been done on some of the externalities of road traffic identified above, however, there is little empirical evidence on the magnitude of these externalities. This thesis will contribute to the existing literature by discussing the adverse effects that occur from BEV incentives, empirically estimate the magnitude of these effects, and discuss the influence on congestion and toll revenues.

We enunciate that increased demand for driving increase the magnitude of all externalities related to road traffic. Furthermore, we assume that higher demand for driving leads to more congestion in urban areas, because a large fraction of the increased demand for driving will take place during hours where congestion normally occurs.

We use two sets of data to empirically estimate the change in demand of driving when the share of BEVs increases. The first data set is used for estimating the demand for driving using vehicle kilometres travelled (VKMT) for all municipalities in Norway. The second data set is used for estimating how increasing shares of registered BEVs contribute to the share of BEV toll passages. We propose three models, each meant to add value to our results. The first model estimates change in VKMT with increasing shares of BEVs, disregarding if roads are subject to toll charging. Because we emphasize the BEV incentives' influence on congestion and toll revenues, the second model looks only at cities with toll rings, and estimates the effect on toll passages. Moreover, this model displays a more direct relationship between congestion and the number of toll passages, since cities a more likely to experience congestion in the first place. To assess the economic impact of reduced toll revenues, the third model estimates the contribution of one additional BEV on number of passages per toll station, which could be viewed as a measure of potential revenue loss.

None of the three models estimate external costs directly. They do, however, estimate the change in demand for driving, either measured as vehicle kilometres travelled or as toll passages. These estimates can in turn be used as approximations to analyse the magnitude of the externality.

This paper provide evidence in favour of higher levels of traffic, where a one percentage point increase in share of registered BEVs yields a 0.63% increase in vehicle kilometres travelled (VKMT). Furthermore, a 1% increase in the share of registered BEVs corresponds to a 1.42% increase in the share of BEV toll passages.

1.2 Research Question

This thesis aims at answering the following question:

What are the adverse effects of the electric vehicle incentive scheme?

The thesis continues as follows: in section 2 we discuss the historical development of BEVs in Norway, and the government's motivation to allow BEVs to be exempted from road charging. In section 3 we discuss the previous literature and review its implication for our study. Section 4 analyses the costs associated with toll road exemption from a theoretical point of view. Section 5 presents the data used for our empirical analysis, whereas section 6 elaborates on the empirical specification of our models. Section 7 and 8 present the results and a discussion of our results respectively, before we conclude in section 9.

2. Historical background

This section will present a brief historical overview of the Norwegian BEV incentive scheme as well as a description of the extent of toll charges and toll projects in Norway.

2.1 Norwegian EV Incentives

In Norway, electrical vehicles have been high on the political agenda since the 1990s (Figenbaum & Kolbenstvedt, 2013). BEVs are more energy efficient and have lower driving costs than ICEVs (Lindberg & Fridstrøm, 2015), but still suffers a competitive disadvantage to ICEVs due to higher production costs and lower driving range (Figenbaum & Kolbenstvedt, 2013). To equalize the competitiveness, BEVs were exempted from the value-based initial registration tax (purchase tax) in 1990. Several other BEV incentives followed, displayed in table 2.1.

Consequently, Norway has the highest BEV market share per capita globally (Bjerkan et al., 2016). From a negligible amount of BEVs, the number has increased rapidly the last couple of years, reaching almost 100,000 vehicles in 2016. The development from 2008 to 2016 is shown in figure 2.1. With a total vehicle fleet of 2.7 million, the share of BEVs still only corresponds to less than 4% in 2016.

Because of the high share of BEVs in Norway, authorities will start phasing out the some of the incentives in the years to come. As from January 1 2017, local authorities may decide on the degree to which local incentives, such as free parking, reduced rates on ferries, exemption from toll charges and access to bus lanes, are put into force in each municipality (Meld. St. 33 (2016-2017), 2017, p. 56). Several of the largest cities in Norway responded to the policy revision, by introducing parking fees for BEVs (Flatlandsmo & Løland, 2017). Nevertheless, zero emission vehicles cannot be charged by more than 50 % of the charges for conventional vehicles (Meld. St. 33 (2016-2017), 2017, p. 56). The exemption of VAT and purchase tax was planned terminated in 2017, but has prolonged until 2020.

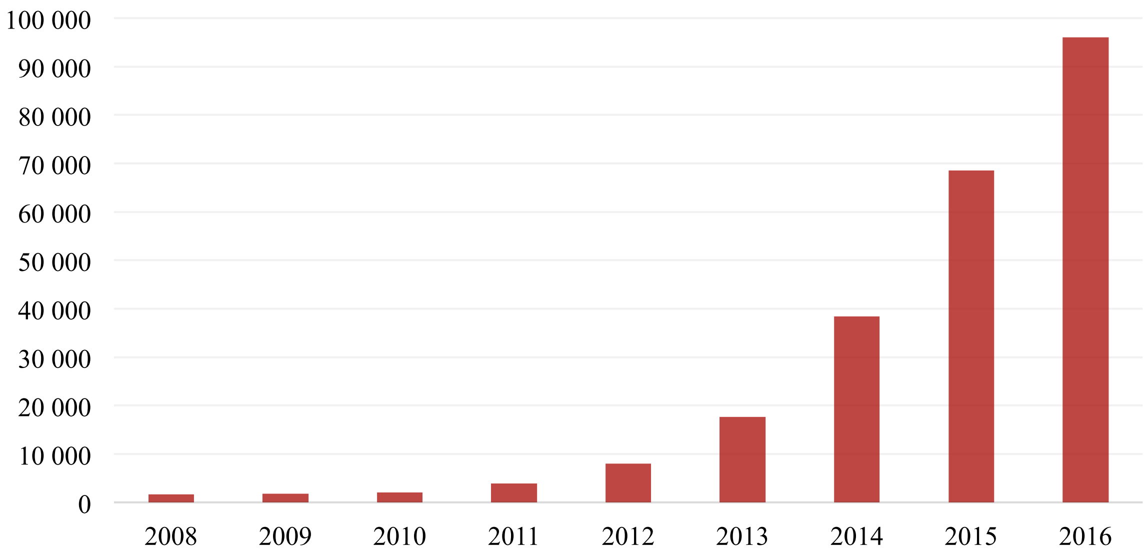
Table 2.1: Overview of Norwegian BEV incentives

Incentive	Year of introduction
Exemption from registration tax	1990* / 1996
Reduced annual vehicle licence fee	1996* / 2004
Free toll roads	1997
Free parking	1999
Reserved EL number plates	1999
Reduced imposed taxable benefit on company cars	2000
VAT exemption	2001
Access to bus lanes	2003* / 2005
Reduced rates on ferries	2009
Financial support for charging stations	2009
Fast charge stations	2011

*) *Incentives were introduced as temporary measures before becoming permanent*

Based on table by Figenbaum and Kolbenstvedt (2013, p. V)

Figure 2.1: Number of registered Battery Electric Vehicles in Norway, 2008 - 2016. Source: Statistics Norway (SSB, 2017c).



2.2 Toll road projects in Norway

Financing of road projects has been a common supplement to government funding in Norway for more than a century (Odeck & Bråthen, 2002). Even before the arrival of private cars, roads and bridges were built privately and the costs covered through user fees. For example, the bridge between Tønsberg and Nøtterøy in 1735 and Nygårdsbroen in Bergen in 1851, practised user fees to finance the investment (Welde et al., 2016).

Historically, toll financing was used where tunnels or bridges replaced ferries, but in the 1980s urban toll rings emerged. In 1986, the first toll ring opened in Bergen, followed by Oslo in 1990 and Trondheim in 1991, based on the increasing need for public road funding. Toll financing of road investments outside the large cities became common during the 2000s. Today, toll charges in urban areas are used for financing urban road projects as well as public transport (Odeck & Bråthen, 2002). In non-urban areas, toll charges are used for financing road investments only.

Norway is among the countries in the world with the most extensive use of toll charges. As of today, there are about 75 toll road projects in operation or passed by Parliament, whereas 60 of these are collecting toll charges from 230 toll stations, including ferries (Statens Vegvesen, 2017a). Despite the high number of toll projects spread across the country, most the of revenue is collected in the largest cities. Of total revenue collected in 2013, approximately half of it was collected at the toll stations in Oslo, Bergen, Trondheim, Stavanger and Kristiansand (Welde et al., 2016, p. 18). The toll revenues from Oslo alone constituted about one third of it.

Traditionally, financing of road networks has been the main purpose of toll projects in Norway. However, increased road capacity may increase the demand for driving, resulting in more congestion. A way of coping with these problems is to turn toll rings into congestion pricing systems, where the main objective is to regulate the traffic and facilitate efficient use of the existing infrastructure (Welde et al., 2016). From a theoretical perspective, congestion pricing is an effective solution to reduce the excessive use of roads. Still, political will and public opposition against congestion pricing has postponed the implementation. A possible explanation is that people accepts being charged when they benefit from it, but do not like paying for something they want to avoid, such as congestion (Odeck & Bråthen, 2002). In Norway, only three cities have introduced congestion pricing: Trondheim in 2010 (Yttervik, Henriksen, & Langset, 2016), Kristiansand in 2013 (Myklebust, 2013) and Bergen in 2016 (Haaland, 2016).

3. Literature Review

This section will present literature on the Norwegian BEV incentive scheme where the importance of the incentives on BEV adoption, characteristics of BEV owners and the adverse effects will be discussed. Finally, we discuss the contribution of this thesis.

3.1 Norwegian BEV incentives and BEV owners

A consumer survey on vehicle owners about the motivation for purchasing a BEV showed that Norwegian BEV owners attach the highest value to the low operating costs and toll exemption (Lindberg & Fridstrøm, 2015). In other surveys, exemption from purchase tax and VAT were the most critical incentives for more than 80% of the BEV owners asked, which suggests that upfront price reductions are most powerful (Bjerkan et al., 2016). Nevertheless, in the same survey, 49% of the respondents answered that exemption from toll charges was critical for purchase, clearly showing a diversity among consumers' valuation of the incentives.

A reason for why the incentives differs in importance among BEV owners, is that the value of the local incentives depends on location. Yet, the BEV adoption is also spreading into smaller municipalities and areas with few local incentives, indicating that the local incentives are not the only factor influencing the choice of purchasing BEVs (Fearnley, Pfaffenbichler, Figenbaum, & Jellinek, 2015).

When comparing vehicle owners, BEV owners are often younger, live in larger households with more children, have higher education, higher income and have longer distances to work than other vehicle owners (Figenbaum & Kolbenstvedt, 2016). BEV owners tend to live in urban areas, while ICEV owners are more dispersed. Moreover, the BEV often operates as a second car for many households, either as supplement or as substitute for a second ICEV. In these multicar households the BEV is often used for everyday use, while the ICEVs are used for non-routine trips (Figenbaum & Kolbenstvedt, 2016). On the other side, BEVs are becoming increasingly common for single vehicle households as well (Lindberg & Fridstrøm, 2015).

3.2 Adverse effects and cost effectiveness

Halvorsen & Frøyen (2009) asked BEV owners about their travelling behaviour before and after purchasing a BEV, and compared the answers to the general population. The survey concludes that BEV owners drive more and use less public transport prior to purchasing a BEV. A second finding suggests that BEV owners use toll roads more frequently than the general population which can be ascribed to two effects. First, it could be that people choosing to buy a BEV initially used toll roads more often than the general population and consequently use the toll roads as frequently as before. The second effect is that because BEV owners no longer have an incentive to avoid toll roads, they will drive more on toll roads than before.

Aasness and Odeck (2015) examine the issue of increased BEVs on toll roads, by further discussing the adverse effects of toll exemption and access to bus lanes. They use data from Oslo toll ring company, and estimate that the revenue loss in 2012 due to BEV exemption amounted to more than NOK 24 million. These results depend on the assumption that 100% of these passages would otherwise be done by ICEVs. Furthermore they do not reflect on the fact that decreased toll revenue is not a cost to society, but a cross-subsidy between payers and non-payers (Fearnley et al., 2015). To increase the toll revenue, either the rate per paying vehicle must be increased or the period of payment be extended, or alternatively subsidised by public authorities. The displacement of other vehicles due to a higher price is a cost to society or to spend public funds, which is referred to as the marginal cost of public funds (Lindberg & Fridstrøm, 2015).

Holtsmark & Skonhoft (2014) question the cost efficiency of the BEV incentives as opposed to other emission mitigating acts. Bjerkan et al (2016) also criticises the BEV incentives of favouring the most affluent individuals, whereas (2015) strongly advocates against replicating the Norwegian incentive scheme due to its costly and ambiguous effects on emissions.

3.3 Contribution of this thesis

The aim of this paper is to contribute to the existing literature by empirically estimating the BEVs influence on the demand for driving. Furthermore, we discuss how the change in demand affects the external costs of road traffic to a larger extent than previously done. To our knowledge, no literature

This section has shown that the existing literature focuses on the importance of BEV incentives, the characteristics of BEV owners and discusses the cost-effectiveness. Some of the literature discusses the potential adverse effects of the incentives, but fail to provide evidence and take the whole cost into account. This thesis will contribute with a more detailed discussion.

4. Economic framework

This section will identify and analyse the expected adverse effects of the BEV incentives from a theoretical point of view. First, we discuss the market failures in terms of public goods and externalities, before we provide a detailed framework to analyse the costs of congestion to society. With declining revenues for toll companies, we elaborate on the social cost of public funding, before we review the expected rebound effect for passenger vehicles that occur with increasing shares of BEVs. Finally, we draw the line between economic theory and our empirical strategy to estimate the magnitude of the identified adverse effects.

4.1 Market failures

Market failures refer to situations where the free market does not produce optimal welfare for society (Sterner, 2003). There can be several causes of market failures, in which two of them are public goods and externalities that are relevant when analysing roads and road traffic in an economic framework. Especially the concept of externalities is relevant in terms of explaining the adverse effects from toll exemption for BEVs, and public goods may explain why these externalities occur.

4.1.1 Public goods and open access resources

A public good is used collectively by the society and not consumed by individuals as with a private good (Sterner, 2003). Market mechanisms fail in providing public goods, and it is thus a main responsibility for the governments to provide and regulate these goods.

Public and private goods are distinguishable in terms of two characteristics: excludability and rivalry. A good is "excludable if it is feasible and practical to selectively allow for consumers to consume the good" (Kolstad, 2011, p. 90), meaning that one have to ensure that a consumer pay to consume a good. Non-excludable goods can be accessed and consumed by everyone without being charged for it, and it is therefore not profitable for a private actor to provide the good. The second characteristic is rivalry, meaning that "consumption reduces the amount of the good that might be available for others to consume" (Kolstad, 2011, p. 94).

A public road can in most cases be accessed by everyone without charge, thus it satisfies the non-excludable condition. The non-rivalry condition is satisfied if one additional motorist entering the road will not diminish the ability for other motorist to use the road. In this way, one can argue that a road is a pure public good.

The assumption of non-rivalry will often hold for roads in rural areas. For urban areas however, this assumption may only be true until a certain threshold of traffic. Beyond this threshold, each additional motorist will reduce the "amount" of road left for other motorists, and reduce the speed of all motorists on the road. In this way, the road is non-rival for low levels of consumption and rival for high levels of consumption. This is often referred to as a congestible good (Kolstad, 2011).

As the example of congestible good shows, a good does not have to be either private or pure public, and can hold different varieties of rivalry and excludability. These different forms of goods are shown in Table 4.1.

Table 4.1: Various forms of goods

	Excludable	**Non-excludable**
Rival	*Private goods*	*Open access resource*
Non-Rival	*Club goods*	*Pure public goods*

When a road is rival and non-excludable, which it typically is during peak hours, it can be analysed as an open access resource. If the road is accessible to everyone without charge, all those wanting to reach a destination by using this road will benefit. However, because of rivalry, the entrance of one motorist will diminish the amount of road for the other motorists. When many motorists enter the road and create congestion, the benefit across all the motorists is lower than if fewer motorists used the road, and everyone is worse off. This phenomenon is referred to as "the tragedy of the commons", which was first presented by Garrett Hardin (1968). All open access resources are subject to the risk of overuse, which is the tragedy of the commons.

A club good is excludable and non-rival, and implies that users of the good must pay a charge to use it. A public road can be turned into a club good by using toll charges, which makes it possible to effectively exclude those not willing to pay for the good. However, if the road is congestible, the toll charge will lead to inefficient outcomes for low levels of use

(Daly & Farley, 2011, p. 117) To facilitate efficient use of the road, a solution is treating the road as a private good during peak hours and as a public good during off-peak. This practice is referred to as congestion pricing, and involves different charges for different times or users.

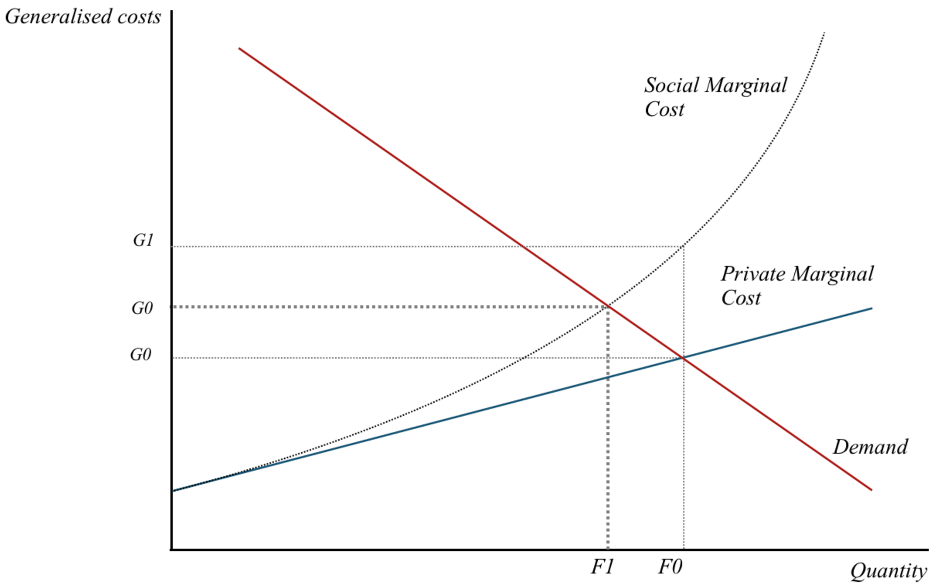
4.1.2 Externalities

An externality is defined as "an unintended and uncompensated side effect of one person´s or firm´s activities on other" (Sterner, 2003, p. 23). Negative externalities, or external costs, refer to more specific cases where the action of one agent inflict costs upon other, without this cost being the purpose of the action (Thune-Larsen et al., 2014). A central aspect of external costs is that a part of the cost caused by the agent is not borne by himself but by others (Mayeres, Ochelen, & Proost, 1996).

In the context of road traffic, the agent is a motorist and the action is driving. When a motorist chooses to drive and how much to drive, he takes into account the private marginal costs (PMC). The PMC includes fuel and maintenance costs, as well as the opportunity cost of time spent on driving. However, the motorist is not taking the marginal external cost to society into account when choosing how much to drive. The PMC of driving is therefore lower than the social marginal cost (SMC) by the size of the externality (Sterner, 2003). Figure 4.1 displays the cost curves, resulting in more than optimal quantity of driving (F_0).

Road traffic causes several external costs. The most common examples of externalities due to road traffic are local and global emissions, congestion costs, noise pollution, wear and tear of infrastructure, the cost of accidents and barrier effects (Thune-Larsen et al., 2014). Local pollutants contribute to increasing respiratory health problems in areas where congestion is substantial. Furthermore, the emission of CO_2 contributes to anthropogenic climate change that could significantly harm future generations.

Figure 4.1: Private marginal cost and social marginal cost curves



However, the other externalities are also important to take into consideration. Congestion costs constitutes a large problem in urban areas, especially during peak hours. This externality is particularly relevant for this paper, as it is highly relevant for the incentive regarding toll exemption for BEVs. The next subsection will explain the mechanisms behind congestion more in detail.

4.2 Congestion

Congestion occurs when the density of cars on the road surpasses a certain threshold causing cars to slow down and thereby increasing travel time. Evans (1992) analyses the externality that occurs with increasing levels of traffic. The model by Evans is discussed throughout this thesis and is preferred over more generalised models, due to its desirable characteristics which is advantageous for our discussion in section 8.

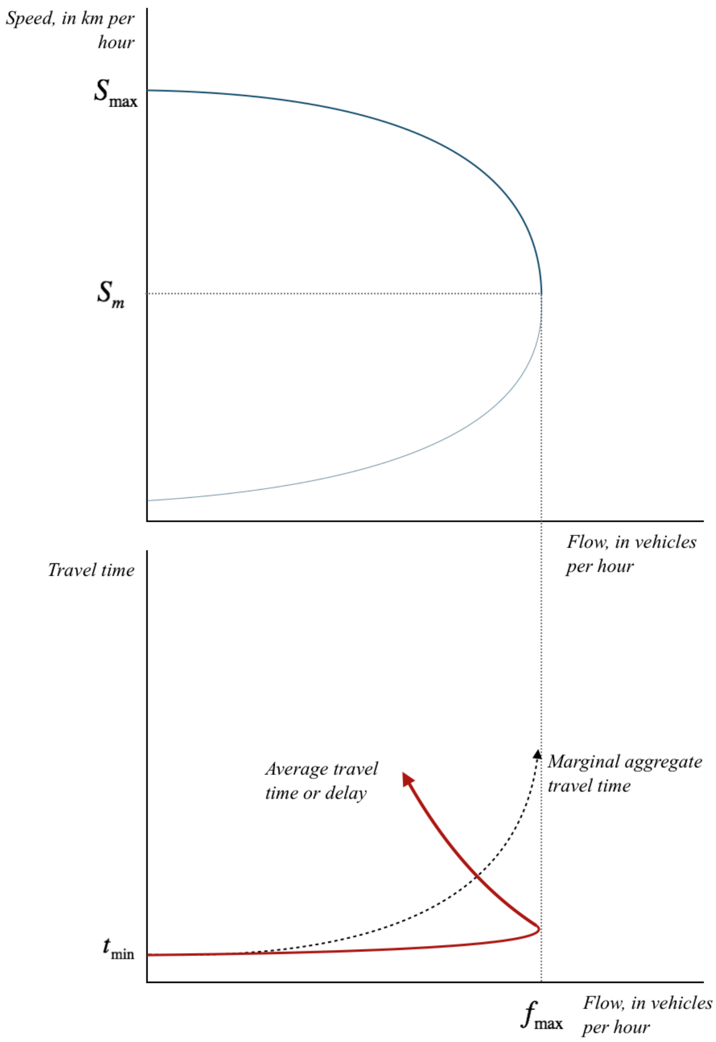
A road network will experience an increasing traffic flow[1] up until a point where one additional car's contribution to flow is offset by the reduced availability for the existing cars

[1] $flow = density \cdot speed = \frac{vehicle}{km} \cdot \frac{km}{hour}$, (Parry, 2009).

due to reduced speed and increasing travel time. Figure 4.2 displays the speed-flow relationship graphically, where f_{max} is the maximum of the road´s carrying capacity.

When maximum capacity is reached, adding more cars to the road network decreases the speed significantly. The bottom graph displays travel time as an upward sloping function of flow, since travel time is assumed to be the reciprocal of speed. The backward bending part of the curve represents hyper-congestion, which occurs because traffic flow has reached its maximum capacity, and adding more cars will reduce speed and increase travel time significantly.

Figure 4.2: Speed-flow relationship and its effect on travel time



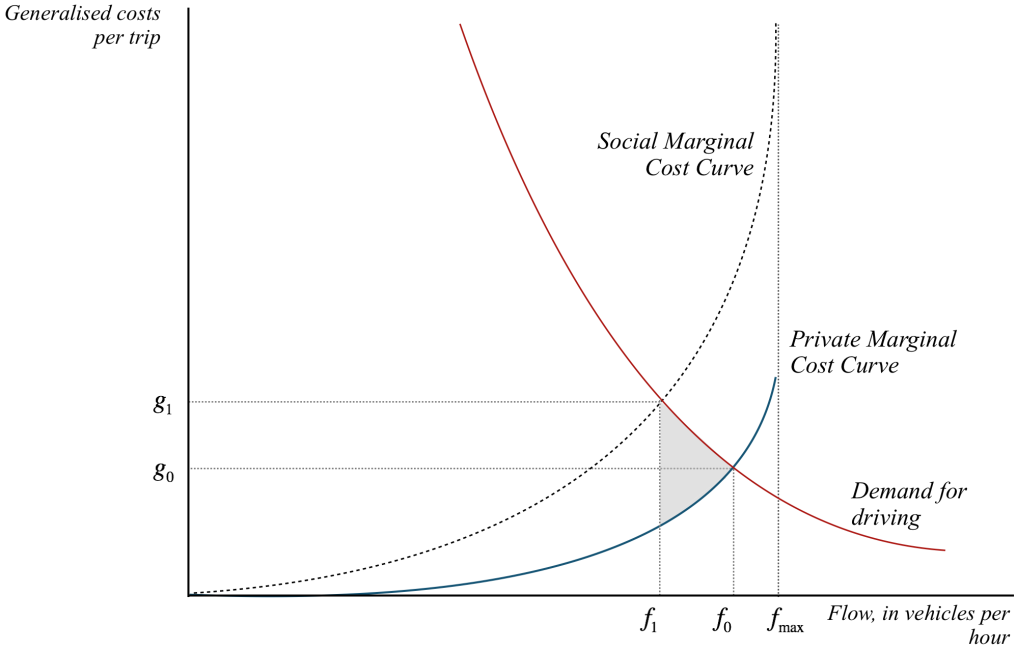
To assess the impact on economic welfare, the model can easily be transformed to represent costs to the driver by assuming that travel time is the constant value of time. The value of time then represents the shadow price for the driver, or the drivers´ willingness to pay to avoid an extra hour of travel. As travel time increases, the cost of time increases, implying a downward-sloping demand for travel as the corresponding costs increase.

To determine the full set of costs inflicted on society in the case of externalities, costs are separated into two parts. First, each driver deciding to use the road will encounter private costs such as fuel costs, maintenance costs, value of time, and other costs associated with driving. These costs are represented by the PMC curve in figure 4.3, and are the costs the driver takes into account when deciding its demand for driving, where higher costs will decrease the demand.

A second set of costs occur in the presence of a public goods which are costs drivers do not take into account when deciding its demand for driving. These costs are associated with the added travel time each driver imposes on others by using the road. These costs are represented by the SMC curve in figure 4.3. As figure 4.2 displays, adding more cars to the network will lead to increasing travel time, thereby increasing the associated cost of travel.

When drivers do not take into account the full set of costs associated with using a public good, the market fails to clear optimally, resulting in a higher than optimal quantity of driving, as shown in figure 4.3. The SMC curve incorporates the full set of costs, causing it to lie above the PMC curve. The optimal level of driving is at the point where SMC curve intersects with the demand for driving (f_1). A higher demand for driving causes a market failure and less than optimal social economic outcome. Both cost curves increase sharply as number of cars approaches the threshold (f_{max}), the point where hyper-congestion starts to form.

Figure 4.3: Generalised costs per trip as a function of flow, in vehicles per hour



The difference between the PMC curve and the SMC curve represents the external costs of driving. According to theory, the optimal tax should be set equal to the marginal external cost each driver imposes on all other drivers for any level of traffic, referred to as the Pigouvian tax. By introducing this tax, the demand for driving will be such that it corresponds with the driver incorporating all costs. The demand for driving will fall from initial levels (f_0) to optimal level (f_1). The shaded area represents the efficiency loss, and is the cost associated with some drivers being priced out of the road.

BEVs have lower marginal costs of driving than ICEVs, resulting in a lower PMC curve, and consequently higher demand for driving. The SMC curve will also be lower, but because BEVs demand more driving, the external cost will increase and the equilibrium will be further away from the optimum[2].

Evans (1992) assesses the market failure described above, taking into account that a road network has a fixed capacity c, with q number of vehicles, and that at a point moving toward

[2] Note that the denominator term for the marginal external costs in equation (1) is squared, whereas it is not for PMC. Consequently, a change in the demand for driving will cause the marginal external cost to increase relatively more than the PMC.

this capacity $\left(\frac{q}{c}\right)$, the road starts to get congested. Equation (1) displays the social marginal costs of congestion including both private marginal costs and the marginal external cost:

(1) $$SMC = \underbrace{\beta\left(\frac{1}{1-\left(\frac{q}{c}\right)} - 1\right)}_{PMC} \quad + \quad \underbrace{\frac{\beta q}{c}\frac{1}{\left[1-\left(\frac{q}{c}\right)\right]^2}}_{Marginal\ external\ cost}$$

β is the cost of travel in uncongested conditions, i.e. the initial value of time. Assuming that demand is given as a function of the generalized costs, the optimal demand for driving can be expressed as:

(2) $$q = \alpha e\left(-\frac{1}{\mu}\left(p + \frac{\beta}{\left[1-\left(\frac{q}{c}\right)\right]} - 1\right)\right)$$

where the variable p represents a road fee. The parameter $\frac{\beta}{\left[1-\left(\frac{q}{c}\right)\right]}$ is the associated value of travel time, and when $q \to c$, the cost of travel reaches infinite values, implying that as the road reaches its maximum capacity, cost of congestion increases sharply due to considerable delay. The variable μ represents the marginal utility of driving, where individuals who have a high utility of driving relative to the value of time will have higher demand.[3] In general, drivers decide the demand by considering both the utility and costs of driving.

To achieve the socially optimal equilibrium, the driver must take into account all costs associated with driving, including the costs imposed on others. To accomplish this, the road fee (p) should be set such that it corresponds to the external cost. From equation (1), the external cost is defined, and by substituting this term into equation (2), optimal demand q^* is given as:

(3) $$q^* = \alpha e\left(-\frac{\beta}{\mu}\left(\frac{1}{\left[1-\left(\frac{q^*}{c}\right)\right]^2} - 1\right)\right)$$

In equation (3), the driver adjusts demand such that the increased travel time imposed on others is included, thereby internalizing the externality.

[3] For the complete mathematical derivation of the model, see Evans (1992).

Consequently, improved economic welfare is achieved in two ways. First, the government now earns income from the road fee (p), the Pigouvian tax that optimally corrects for the market failure. Second, drivers experience a change in economic outcome of utilizing the road, which moves in two directions. Drivers will now have to pay a fee to enter the road network. Assuming that drivers have different willingness to pay for driving, some individuals are now pushed out of the road network because the costs exceed the benefits. Others will have increasing costs of driving, but value driving higher than the added costs. Those drivers who continue to drive will experience an economic surplus through time savings since the road network is much less congested.

As a consequence of the model, BEV incentives such as toll road exemption cannot be an optimal policy from a theoretical point of view. Equation (2) implies that the fee (p) is set equal to the full set of externalities, hence a zero fee corresponds with zero externalities. Even though BEVs are zero emitters, they contribute to many other externalities as shown in table 4.2.

4.3 Provision and funding of public goods

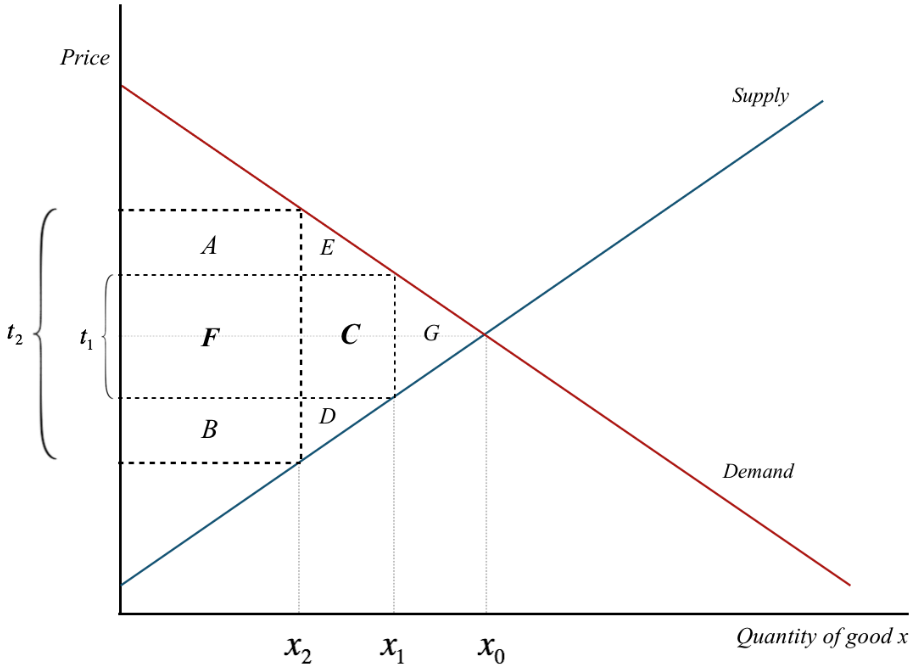
Toll exemption for BEVs causes a toll revenue loss. In Norway, public roads are normally financed through general taxation and user payments. Both general taxation and user payments create costs to society, which will be illustrated. These costs are relevant when investigating the adverse effects of toll exemption for BEVs. The following section analyses the potential added costs to society, which occurs through a higher general taxation.

4.3.1 Taxes and marginal cost of funds

Governmental revenue used for funding private goods is usually collected through taxation of goods and services. When imposing a tax, consumers and producers are faced with different prices, which affect the resource allocation. In a perfect market without taxes, the “invisible hand” will provide an efficient allocation of resources, but when levying a tax, the allocation is less efficient (Dahlby, 2008).

The efficiency loss resulting from increased taxes will be illustrated through a simple example in figure 4.4, based on Holtsmark and Bjertnæs (2015, p. 5). This illustrates the market for good x, which is assumed to be perfectly competitive with no external effects and distributional effects can be ignored.

Figure 4.4: Efficiency loss caused by taxation



The efficiency loss occurring when imposing a tax t_1 per unit of x compared to a situation in absence of taxation, is given by the size of the are G in figure 4.4, while the government revenue is given by the area F + C. Assume now that the government is funding a new public road, and thus needs to increase the government revenue through general taxation of good x. The tax is now increased to t_2, which reduces both consumer and producer surplus, but increases government revenue, which is now given by the area A + F + B. However, there is an overall reduction in welfare as the efficiency loss has increased, to the area E + C + D + G.

The cost of the tax increase is referred to as the marginal cost of public funds (MCF). MCF represents the costs to society of increasing public funding through general taxation. The MCF is equal to the welfare loss of the consumers and producers per dollar of tax revenue, or

$$MCF = \frac{A+B+D+E}{A+B-C} \tag{4}$$

Here, the welfare loss is given by $\Delta W = A + B + C + E$, and the change in tax revenue is given by $\Delta R = A + B - C$. When the demand curve is downward sloping and the supply curve is upward sloping, it follows from the equation that MCF is greater than one (Holtsmark & Bjertnæs, 2015).

For all public projects funded through general taxation, a tax funding cost must should be calculated (NOU 2012:16, 2012, p. 20). Having a standardised point estimate of MCF is especially important when comparing different public projects with regards to costs and benefits. In Norway, the practise is to use MCF = 1.2 (0.2 + 1), which is decided by the Ministry of Finance[4] (NOU 1997:27, 1997, p. 95). This means that NOK 1 collected through taxes and spent on public projects, costs NOK 1.2 to society on average (Hagen & Pedersen, 2014).

4.3.2 User payments

The other common form of funding public goods, such as road projects and infrastructure, is through user payments. In contrast to general taxation where all tax paying individuals contribute to funding the good, user payments only affect those individuals consuming the good (NOU 2012:16, 2012, p. 20). Nevertheless, user payments also have economic effects that are comparable to those of general taxation. The trade-off between these effects and the efficiency gain of reducing the level of taxes will be explained through a stylized example based on Hagen and Pedersen (2014, p. 15-25)

The figures 4.5 and 4.6 represents a road project that needs public funding. The generalized costs are the motorists´ direct costs of using the road. For simplicity it is assumed that there are no externalities in terms of congestion, pollution, wear and tear of the road and so on. For a model that includes congestion costs, see in subsection 4.3.1 where this is discussed.

[4] There is much insecurity around the point estimate of 1.2, as it is based on a variety of empirical studies with diverse results. For a comprehensive discussion of this point estimate, see for example Holtsmark and Bjertnæs (2015).

Figure 4.5: Road project fully financed through general taxation

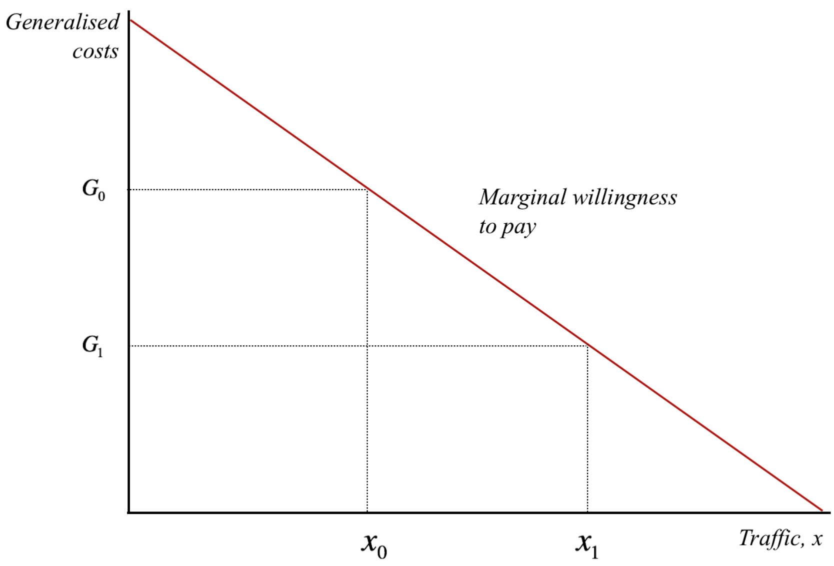
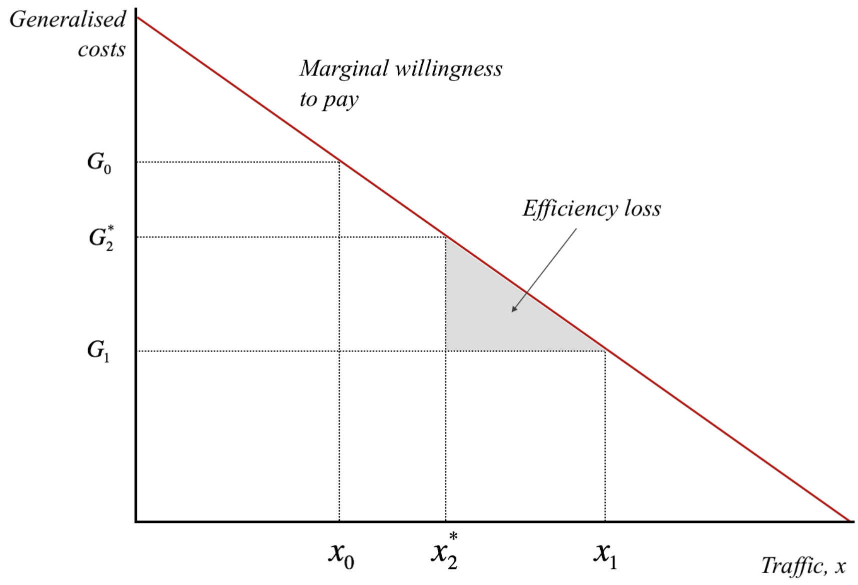


Figure 4.5 illustrates an example where a road is improved so that the general costs of the drivers are reduced, for example through reduced travel time. The result is more traffic on the road. In this case, the project is fully funded through general taxation the cost to society is the cost of collecting taxes, as explained in subsection 4.3.1.

Figure 4.6 illustrates the same road improvement, but here a user payment (*difference between G_2^* and G_1)* in terms of toll charges is introduced. As motorists using the road have to pay this toll charge, the general costs increases by the size of the user payment. Because of the higher costs compared to figure 4.5, some road users are displaced and a efficiency loss emerges.

As these examples illustrate, both general taxation and user payments will create efficiency losses. The practice in Norway is to use a combination of general taxation and user payments when funding road projects (Odeck & Bråthen, 2002). The optimal solution is to find the toll charge that minimizes the efficiency loss for the economy as a whole. This is where the efficiency loss due to increase in user price, i.e. an increase in generalized costs, is equal to the efficiency gain due to reduced taxation (Hagen & Pedersen, 2014). In other words, the efficiency loss on the margin from collecting toll road charges is equal to the efficiency loss on the margin from collecting tax. As the point estimate of MCF is considered to be 1.2 in Norway, it means that NOK 1 spent by the government is equivalent to NOK 1.2 spent privately. This means that NOK 1 collected through user payments, such as toll charges, reduces the need for tax collection, and the increases the gain for society by NOK 1.2.

Figure 4.6: Road project partly financed through user payments



4.4 Rebound effect

Environmental policies are implemented to reduce the emissions of greenhouse gas emissions and local pollutants. Normally, such externalities have been mitigated by imposing fuel tax on the consumption of fossil fuels, or through fleet wide fuel economy standards. While a fuel tax provides incentives for the consumer to drive less due to increasing costs of driving, fuel economy standards demands car manufacturers to produce more efficient cars to comply with regulations. This fuel efficiency improvement provides incentives for the consumer to drive more due to decreasing costs of driving. This effect is referred to as the rebound effect.

The magnitude of the rebound effect is paramount in public policy analysis to assess the efficiency of policies. A large rebound effect implies that a policy is highly cost inefficient, due to a reduction in the expected gains. Most empirical research on the magnitude of the rebound effect for passenger vehicles arrive at estimates between 5% and 40% (Greene, 1992; Jones, 1993; Linn, 2013; Small & Van Dender, 2007).

The rebound effect is normally divided into three categories, direct rebound effect, indirect rebound effect and general equilibrium effect. The rebound effect for passenger vehicles is defined as a direct rebound effect, since the response to reduced costs of driving is increased demand, also referred to as a substitution effect. The indirect rebound effect implies that as the cost of driving declines, individuals can allocate consumption towards other goods that also contribute to emissions. The general equilibrium effect describes a situation where a new technology significantly changes the price of a service or good, causing the market equilibrium itself to shift (Throne-Holst, 2003).

4.5 Quantifying the adverse effects

Road traffic is the source of many externalities, and the introduction of BEVs has not made these externalities less significant. Even though BEVs, motivated by environmental policies, are subject to generous incentives to encourage its proliferation, it might cause other externalities to increase in magnitude. Table 4.2 compares externalities that occur for BEVs and ICEVs, where emissions are the only externality that distinguish BEVs from ICEVs.

Table 4.2: Externalities from vehicle use

Externality	*BEVs*	*ICEVs*
Emissions		X
Congestion costs	X	X
Noise pollution	(X)	X
Wear and tear	X	X
Accident costs	X	X
Barrier effects	X	X

This thesis discusses externalities of BEV incentives, and brings special attention to the cost of congestion and public funding. We postulate that because the marginal cost of driving associated with BEVs are lower than ICEVs, consumers will have higher demand for driving. This phenomenon is referred to as the rebound effect, and our empirical strategy tries to estimate if such a rebound effect has emerged as the number of BEVs has increased sharply the past five years.

To estimate the increased demand for driving, we propose three models. In the first model, we estimate how the general demand for driving changes with increasing shares of registered BEVs across all municipalities. Because this model looks at all municipalities, a higher demand for driving would indicate that all externalities will increase in magnitude. Moreover, externalities occur when cars are driving, explaining why we look at vehicle kilometres travelled. However, because we want to bring special attention to BEVs influence on congestion, model 2 uses city data to see if increasing shares of registered BEVs influence the number of BEV passages in city areas where congestion is likely to form. Despite the relationship between toll passages and congestion being ambiguous, we expect it to be highly correlated, which we discuss further in section 8. Model 3 looks at the contribution from BEVs and ICEVs through toll stations, making it easier to estimate possible revenue losses that occur with toll exemption for BEVs and relate this to the cost of public funding.

5. Data

This section will present the two panel data sets used for the empirical analysis. The first subsection will describe how the data sets are built and the variables included, while the second subsection will provide a detailed summary statistics of the data sets. Finally, we discuss the relationship between the variables.

5.1 Panel data sets

The first data set contains annual observations of 424 Norwegian municipalities[5] over the time period 2012-2016, obtained from Statistics Norway (SSB). This time period was chosen as this is when the number of BEVs in Norway started to increase substantially. As table 5.1 show, from 2012-2013 the number of BEVs increased by almost 10,000 vehicles (SSB, 2017b).

Table 5.1: Development of BEVs in Norway 2010 – 2016

	2010	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*
Number of BEVs	2,035	3,849	7,961	17,670	38,422	68,516	96,086
As share of total vehicle fleet	0.09%	0.16%	0.33%	0.72%	1.54%	2.68%	3.80%

Source: SSB (2017b).

For the second data set "city regions" were created, consisting of the five biggest cities: Oslo, Bergen, Trondheim, Stavanger and Kristiansand, and their surrounding municipalities[6]. These units are from now on referred to as cities, and form the cross-sectional dimension of this panel. These five cities are chosen, as the majority of the toll revenue is collected from the toll rings in these cities (Welde et al., 2016, p. 18). The share of BEV toll passages is of particular interest in this data set, and figure 5.1 shows the

[5] Four municipalities are not included in the data set due to municipality mergers and missing values, which are (706) Sandefjord, (719) Andebu, (720) Stokke and (1903) Harstad.

[6] An overview of the municipalities grouped into city regions can be seen in appendix A.1.

development in the five cities from 2013-2016[7]. As the figure shows, the BEV share was close to zero through the first half of 2013, which explains why 2012 is not included in this data set.

Figure 5.1: Battery Electric Vehicle, share of toll passages

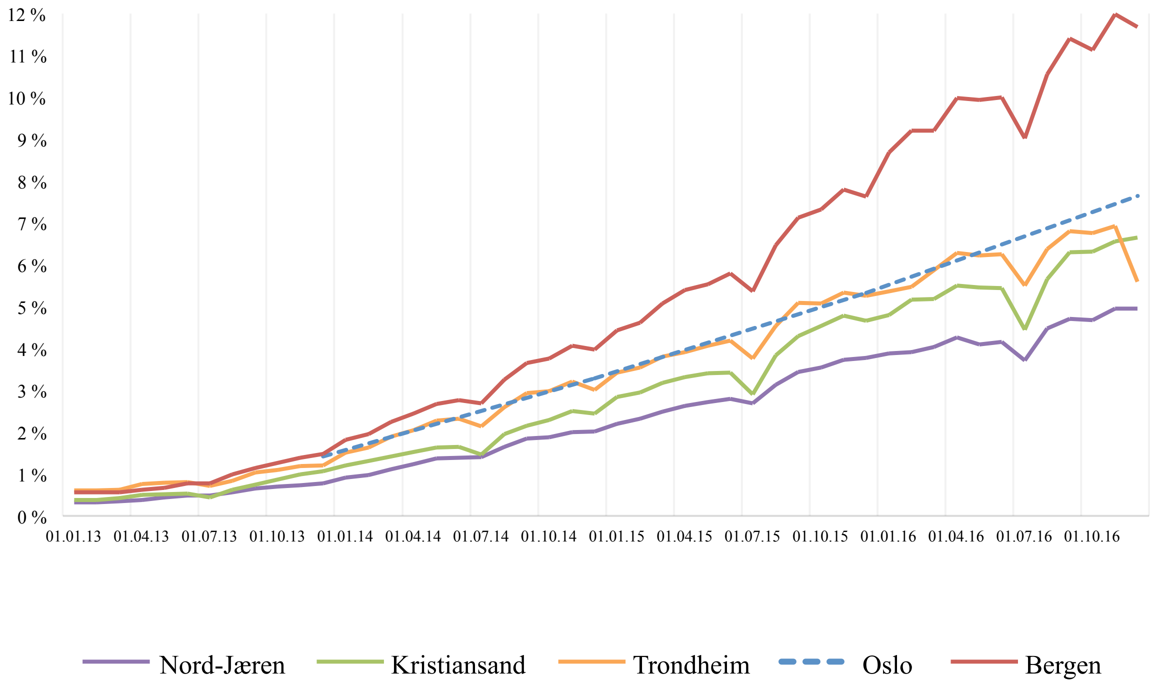


Table 5.2 presents a brief overview of the variables included in the two data sets. A more detailed description the variables follow in the next subsections.

[7] Figures for all cities except for Oslo are displayed as monthly observations. In the data set however, annual observations are used for all cities. Sources of the figure: (Agder Bomdrift, 2017; BT Signaal, 2017; Nord Jæren Bompengeselskap, 2017; Statens Vegvesen, 2017b; Vegamot, 2017) .

Table 5.2: Overview of the variables included in the data sets

Variable name	**Description**	**Unit**
VKMT per car	Average mileage per vehicle in each municipality	Thousand kilometres
BEV reg	Number of BEV registered	Vehicles
ICEV reg	Number of ICEVs registered	Vehicles
Share BEV reg	BEVs registered as share of the total vehicle fleet	Share
BEV pass	Annual numbers of toll passages done by BEVs	Passages
ICEV pass	Annual number of toll passages done by ICEVs	Passages
Share BEV pass	BEV passages as share of total toll passages	Share
Income	Median household income, real	NOK, 2015 values
Fuel price	Annual average of fuel price per litre, real	NOK, 2015 values

5.1.1 Municipality data set

Road traffic is the variable we want to explain, and is measured through vehicle kilometres travelled (VKMT) in the municipality data set. The data on VKMT is originally obtained in total numbers for each municipality (SSB, 2017c). However, as municipalities vary in terms of size and population, the total VKMT does not give a representative impression of how much people drive on average in each municipality. To create a more comparable variable, we divide total VKMT by the size of the vehicle fleet registered in each municipality (SSB, 2017b).

For the data describing the vehicle fleet, we have only utilized data on passenger cars for private use, classified by fuel type (2017b). In the data set, those vehicles fuelled by electricity are classified as BEVs while those fuelled by petrol or diesel are classified as ICEVs. We did not include those vehicles using paraffin, gas or “other fuel” as these are very few and thus not relevant for our analysis. To get an impression of the importance of BEVs in different municipalities, the share of BEV registrations was calculated by dividing the number of BEVs on the total vehicle fleet, which is the number of BEVs and ICEVs combined.

The two last variables included in the municipality data set, are income and fuel price. The income variable is measured as the median income after taxes for all households, measured in NOK (SSB, 2017a). The income figures for 2016 be published by SSB towards the end of 2017, and we therefore had to make estimates of the median incomes for 2016. We used a prediction by SSB in income growth of 2.3% for 2016 (SSB, 2017f). The fuel price variable is calculated based on based on monthly prices per litre (SSB, 2017e). Both median income and fuel prices are adjusted for inflation, using the consumer price index (CPI) with 2015 as basis (SSB, 2017d).

5.1.2 City data set

For the city data set, road traffic volumes are measured as the amount of toll passages. The data is received from the toll companies operating in Oslo (Statens Vegvesen, 2017b), Bergen (BT Signaal, 2017), Trondheim (Vegamot, 2017), the Stavanger area (Nord Jæren Bompengeselskap, 2017) and Kristiansand (Agder Bomdrift, 2017), and distinguishes toll passages done by ICEVs and BEVs. The data for all cities was reported as monthly passages, except for Oslo, which was reported annually. As the data on registered vehicles were also reported annually, this panel only reports annual data.

The number of toll passages depends on the number of toll stations in the cities. A good example of this is the case of Trondheim, where the number of toll passages increased massively from 2013 to 2014. The reason for this was that where the number of toll stations increased from 13 to 24, and not because the amount of traffic increased. The number of toll stations in the different cities varies from 5 to 27, which also affects the number of toll passages in the cities. In order to control for this, all the variables for toll passages are per station passages.

5.2 Summary statistics

This subsection will show a detailed summary statistics of the two data sets, in table 5.3 and 5.4. The two data sets differ in number of units and number of time periods, which results in large differences in the number of total observations, whereas the municipality data set contains 2,120 observations and the city data set 20.

As the data sets are panel data, we find it appropriate to report the summary statistics tables with three types of variation: overall, between and within variation, as this provides a more detailed insight of the data. The overall mean shows the mean value for the variable over time and units. In the same way, the overall standard deviation, the minimum and maximum value shows how the variable varies over time and units.

The between variation shows how a variable for one unit vary compared to other units, which is comparing the mean of one unit to the overall mean. The time dimension is removed from this variation. Variables with zero between variation are unit-invariant, which means that they take the same value for all units for a given time period.

The within variation shows how a variable for a unit vary over time, which is comparing the value of the variable to the unit´s mean for this variable. The within minimum value can sometimes be negative, and the interpretation of this is that the lowest value a variable takes for a unit is lower than its own mean. If a variable has a low within variation, it means that units do not change much over time. If a variable has zero within variation, the variable is time-invariant and is constant over time. Note that the within variation does not give an indication of the level of the values of the variables, whether the values are high or low, only how the values vary compared to the unit mean.

5.2.1 Municipality data statistics

Table 5.3 show the summary statistics for variables included in the municipality data set. Because the total VKMT for each municipality will vary depending on the size of the vehicle fleet in each municipality, the only variable for VKMT displayed in table 5.3 is VKMT per car. Across time and municipalities, the average distance a vehicle travel annually is 14,020 kilometres, and this varies from an average of 7,460 kilometres in one municipality to almost 18,700 kilometres in another municipality.

Over the time period 2012-2016 and across all municipalities, the average number of BEVs registered is 106. For some municipalities during this time period, there were no BEVs registered while the most registered BEVs within a municipality over this time period was over 16,000. This variable varies both between municipalities and within, which implies that the size of the BEV fleet varies across municipalities as well as it develops within municipalities during this time period. The variable has a negative within minimum value.

As explained in subsection 5.2, this means that the lowest value this variable takes for a municipality is lower than the municipality´s own mean throughout the time period.

Table 5.3: Summary statistics for municipality data set

Variable		Mean	St. Dev	Min	Max
VKMT per car	Overall	14.02	1.29	7.46	18.70
	Between		1.23	8.94	17.24
	Within		0.39	12.54	16.61
BEV reg	Overall	106.62	598.03	0	16015.00
	Between		488.35	0	7831.60
	Within		345.85	- 6198.98	8290.02
Share BEV reg	Overall	0.0094	0.016	0	0.190
	Between		0.012	0	0.121
	Within		0.010	-0.068	0.093
Income	Overall	485.74	51.56	343.07	656.79
	Between		50.88	363.68	642.96
	Within		8.64	423.22	529.20
Fuel price	Overall	14.64	0.97	13.08	15.71
	Between		0	14.64	14.64
	Within		0.97	13.08	15.71

To increase the insight of the development of BEVs registered in the municipalities, it is valuable to look at the number of BEVs registered as share of the total vehicle fleet. This is shown in table 5.3 as “Share BEV reg”. The interpretation of the overall mean is that the average BEV share over time and over municipalities is 0.9%. This share ranges from 0% to 19%, and this share varies across both time and municipalities.

Fuel price is equal for all municipalities for each time period, and is thus an individual-invariant variable. This is confirmed by the standard deviation of the between variation being zero in table 5.2. The income variable is given in thousands, meaning that the overall household income mean is NOK 485,740, measured in 2015-NOK.

5.2.2 City data statistics

The summary statistics for the variables included in the city data set is shown in table 5.4. The table provides a detailed overview of annual BEV and ICEV toll passages divided by the number of toll stations. What is interesting when comparing the ICEV and BEV passages is to look at the difference in between and within variation.

Table 5.4: Summary statistics for city level data set

Variable		Mean	St. Dev	Min	Max
BEV pass	Overall	132581.5	103859.70	9215.68	362348.8
	Between		56975.98	46215.54	185760.8
	Within		89739.34	-15489.50	312359.1
ICEV pass	Overall	3357831	792290.1	1840648	4149471
	Between		842795.0	1921737	4018506
	Within		171969.2	2994465	3639308
Share BEV pass	Overall	0.036	0.026	0.005	0.103
	Between		0.011	0.023	0.051
	Within		0.024	-0.005	0.089
BEV reg	Overall	6043.25	5876.74	621.0	22971.0
	Between		4830.62	2070.5	13802.8
	Within		3858.19	-2352.5	15211.5
ICEV reg	Overall	150867.3	98776.39	57057.0	340779.0
	Between		107551.70	57935.0	334649.0
	Within		3978.82	138570.3	156997.3
Share BEV reg	Overall	0.0366	0.022	0.009	0.088
	Between		0.008	0.026	0.049
	Within		0.021	0.001	0.076

For ICEV passages per station, the between variation is dominating, while for BEV passages per station on the other hand, the within variation is largest. This means that the number of BEV passages varies much from year to year, while the number of ICEV passages may be relatively more stable over time. Overall, BEV passages constitute 3.6% of all toll passages, as shown by the variable “share BEV toll pass”. This variable varies from around 0.5% to more than 10% over time and cities, as the overall minimum and maximum values show. This variation is also reflected in Figure 5.1.

The city data set also contains variables of vehicle registrations. These are aggregated numbers for the municipalities included in each city, and show the number of BEVs and ICEVs registered. The number of BEVs registered varies from 600 to almost 23,000 over time and cities, in which most of the variation is between the cities but a large part is also within variation. This is interesting when comparing to ICEV, where within variation constitutes a much smaller portion of the overall variation.

5.3 Analysing the data

For the variables in the municipality data sets, a correlation matrix is shown in table 5.5. The table shows that VKMT is negatively correlated with the share of registered BEVs and income, while positively correlated with fuel price. The sign of the correlation coefficients for income and fuel price are unexpected, as we assume than generally people will drive more with increasing income and drive less with increasing fuel prices. For the relationship between VKMT per car and share BEV reg, there are two opposing effects. On one hand, share of BEVs could be negatively correlated with VKMT per car because of the limited driving ranges. On the other hand, because of lower variable driving costs for BEVs could explain a positive correlation. However, none of the correlation coefficients are of a substantial size.

The share of registered BEVs is positively correlated with income and negatively with fuel price. The correlation coefficients are the highest in this table, but still not considered to create issues regarding multicollinearity. The correlation matrix displayed in table 5.5 does not provide insight to whether there might be non-linear relationships between the variables, which a graphical correlation matrix will show. A graphical correlation matrix is reported in appendix A.2.

Table 5.5: Correlation matrix for municipality data set

	VKMT per car	*Share BEV reg*	*Income*	*Fuel price*
VKMT per car	1.0000			
Share BEV reg	- 0.1167	1.0000		
Income	- 0.1237	0.4653	1.0000	
Fuel price	0.1045	- 0.4218	- 0.0333	1.0000

For the city data set, the correlation between share of BEV passages and share of BEV registered is 0.9897, meaning that they are highly correlated. Appendix A.3 displays the graphical correlation between the variables.

6. Empirical framework

Both data sets exhibit time and cross-sectional dimensions allowing us to apply panel data estimation methods. This section presents three panel data estimators: the simple pooled ordinary least squares estimator (POLS), fixed effects (FE) and random effects (RE). How to choose between these estimators will be shown before tests for heteroscedasticity and serial correlation are presented. Finally, the structural and functional forms of our three models are discussed.

6.1 Pooled ordinary least squares

Pooled ordinary least squares estimation is the simplest form of utilizing panel data, treating each observation independently and using ordinary least square (OLS). This method pools all observations together and treats one observation of unit[8] (i) at time (t) independently of unit (i) at time $(t+1)$.

Formally, the POLS model can be written as:

$$y_{it} = \beta_0 + \beta_j x_{itj} + \delta t + v_{it}, \tag{5}$$

where v_{it} is the composite error term $v_{it} = a_i + u_{it}$

In equation (4), β_j is the coefficient for the variable x_j, and δt represents a time trend. The error term v_{it} is composed of a time-invariant factor a_i and the idiosyncratic error term u_{it}.

To produce unbiased and consistent estimates, the zero conditional mean assumption must not be violated, meaning that the unobserved effects a_i and u_{it} must be uncorrelated with any of the independent variables. With panel data, this is a strong assumption, and challenges the consistency of our estimates. For example, municipalities may have demographic or geographic distinctness that persists over time and influences the demand for driving in two different periods in time.

[8] Municipalities and cities are the units we observe in our models.

Different cities may also have varying local incentives, which could influence the number of toll passages or the kilometres travelled. Furthermore, even if incentives are similar between cities, inhabitants may weigh local incentives differently since traffic patterns will differ across cities and regions. As an example, in the Oslo region, commuters from neighbouring municipalities may value access to bus lanes and toll exemption higher compared to Stavanger or Bergen.

6.2 Fixed effect estimator

In many applications, the assumption of zero correlation between a_i and the independent variables is not likely to hold. The fixed effect estimator overcomes this issue by allowing a_i to correlate with the independent variables through fixed effect transformation. This transformation is also referred to as the within-estimator, because the model now uses the time variation in our dependent variable and independent variables *within* each cross-section.

The fixed effects transformation eliminates a_i. equivalently, fixed effects can also be controlled for by including a dummy for each unit; thus, a_i is a parameter we estimate for each unit (i).

Formally, the model can be written as:

$$y_{it} = \beta_0 + \beta_j x_{itj} + \delta t + a_i U_i + u_{it} \tag{6}$$

where $a_i U_i$ is a dummy for each unit (i).

The key difference from the pooled OLS model is that composite error term is now substituted by the idiosyncratic error u_{it}, which is the unobserved variation. The fixed effect estimator is unbiased if the idiosyncratic error term satisfies the assumption of strict exogeneity

Even though the fixed effect estimator is more robust than pooled OLS in the presence of unobserved specific effects, completely neglecting the between variation available in panel data could remove some of the explanatory value of toll passages or vehicle kilometres travelled.

6.3 Random effect estimator

While the fixed effect estimator controlled for time-invariant effects specific for each unit we observe, the random effects model does not remove a_i, but hinges on the assumption that the time-invariant effects are randomly distributed and strictly exogenous. Under this assumption, OLS will produce consistent estimates. It does so, however, at the risk of estimating incorrect standard errors and test statistics, due to the likelihood of serial correlation in the error term. The RE estimator corrects for serial correlation through the random effects transformation, thereby producing efficient and consistent estimates, given that the assumptions discussed above holds.

The assumption of zero correlation between a_i and the independent variables also imply that the coefficients for β_j can be estimated consistently using a single cross section. However, using a single cross section when we have longitudinal data, neglects useful information in other time periods.

The key advantage of the fixed effects estimator is that it allows for arbitrary correlation between the independent variables and the individual-specific effect a_i, whereas the random effect estimator imposes a strong assumption of zero covariance between x_{ij} and a_i. Consequently, the fixed effect estimator is considered to be more applicable in estimating causal relationships (Wooldridge, 2015).

On the other hand, an advantage of random effects models is that it enables the possibility to analyse the effect of time-invariant factors, which the FE estimator removes. Furthermore, given that the assumptions discussed above holds, RE is more efficient than FE.

6.4 Choosing between estimators

Given the information in our data concerning all municipalities and the five cities, we expect the assumption of zero covariance between a_i and the independent variables to be violated. As already explained, demographic and geographical differences may have an influence on the demand for driving, factors which are difficult to fully control for.

Hausman (1978) proposed a test, to discern between fixed effects and random effects estimators by formally test if the estimates of the two models are significantly different from each other. The RE model is preferred unless the test rejects the null hypothesis of no practical difference. Rejection implies that some unobserved time-invariant effect has a significant influence on the estimates. Failing to reject the Hausman test, either implies that the estimates are practically inseparable, or that the variance in the FE model is so large that one cannot conclude if the difference is statistically significant.

6.5 Testing for heteroscedasticity and serial correlaction

For OLS regressions to produce efficient estimates, the assumption about homogeneity in the residuals of the variance must hold, meaning that the variance of the error term given any value of the independent variable in all periods must equal zero. If we have heteroscedasticity in our model, statistical inference is biased. As an example, if the variance of the residuals in the share of BEV toll passages is increasing with the share of registered BEVs, our model suffers from heteroscedasticity and we cannot make conclusions about the statistical significance. However, the presence of heteroscedasticity does not bias the estimates.

In our data sets, there were few BEVs registered in the first year, and the share of BEV passages was close to zero. During the period we observe, the share of BEVs registered and the share of BEV passages increases significantly. As the share of BEVs increase, we also expect the variation in the share of BEV passages to increase.

Another example is to look at the municipality data set. Even though we expect people driving a BEV to drive more due to low marginal costs of driving, we do not expect all people to exhibit the same change in behaviour. Moreover, we believe people to change behaviour differently. Some people might take additional trips, others might drive less due to other factors. This increasing variance, due to behavioural distinctiveness could cause a higher variation in the vehicle kilometres travelled as the share of BEVs on the market increase, thereby causing heteroscedasticity.

Plotting the fitted values against the residuals, will in many cases reveal if our models suffer from heteroskedasticity. Additionally, linear forms of heteroskedasticity can formally be tested using the Cook-Weisberg test. The White's test is applied to test for more general forms of heteroskedasticity, which allows the residuals to deviate with extreme values of the independent variables in either direction. The White's test consumes more degrees of freedom; thus, the test is more likely to produce less significant test statistics.

As with longitudinal data, serial correlation is often a problem making the estimates inefficient. We test for serial correlation using the test proposed by Wooldridge (2010). The null hypothesis assumes no first-order serial correlation in the idiosyncratic error term. A significant test statistic requires us to reject the null hypothesis and correct for serial correlation by clustering our standard error at the unit level.

6.6 Structural models

This subsection will elaborate on the main specification of the models. Three models are provided to estimate the demand for driving when the share of electric vehicles increases.

Model 1 uses data for all municipalities and estimates how an increase in the share of BEVs across all municipalities on average affects the demand for driving, measured as vehicle kilometres travelled (VKMT). Model 2 and 3 uses the city data set where toll passages measures demand for driving. Model 2 estimates how increasing shares of registered BEVs influences the share of BEV toll passages in the five cities in the data set, while model 3 investigates the contribution on toll passages of an additional BEV or ICEV, through a set of linear equations. The empirical specification of the three models are as follows:

Model 1

$$log\ (VKMT\ )_{it} = \beta_o + \beta_1 log\ (VKMT)_{it-1} + \beta_2 Share\ BEVreg_{it} + \beta_3 income_{it} + \beta_4 fuel\ price + \delta t + \underbrace{[v_{it}]}_{POLS\ /\ RE} + \underbrace{[a_i M_i + u_{it}]}_{FE}$$

Model 2

$$log\ (Share\ BEVpass)_{it} = \beta_0 + \beta_1 log(Share\ BEVreg)_{it} + \delta t + \underbrace{[v_{it}]}_{POLS/RE} + \underbrace{[a_i C_i + u_{it}]}_{FE}$$

Model 3

$$BEV\ pass = \theta_1(BEVpass + ICEVpass) + \theta_2 BEVreg + \varepsilon_1$$

$$ICEV\ pass = \theta_3(BEVpass + ICEVpass) + \theta_4 ICEVreg + \varepsilon_2,$$

Model 1 includes a lagged dependent variable, as it is reasonable to assume vehicle owners exhibits behavioural inertia in demand for driving due to friction in life-styles. On average, people will use their vehicles for approximately the same trips as the year before, and it is therefore reason to believe that the demand for driving in year $t + 1$ is dependent on the demand in year t. In model 1 and 2, v_{it} is the error term used in the POLS and RE effects model, whereas $[a_i C_i + u_{it}]$ is the composite error term in the fixed effect model[9].

The key independent variable in model 1 is the share of BEVs registered. There is some concern regarding endogeneity in this variable through reverse causation, which is the case if the demand for driving influences the decision to purchase a BEV. For example, people who drive long distances will probably not purchase a BEV due to its range issues, meaning that the share of registered BEVs are determined by demand for driving. On the other hand, as shown in section 3, the choice of purchasing a BEV is often motivated by economic incentives. Consequently, the demand for driving does not influence the purchasing decision to a large extent. Based on the latter argument, we find it plausible to believe that the share of BEVs is exogenously given. Nevertheless, we acknowledge that possibility of reverse causation. The other variables, income and fuel price are not influenced by the demand for driving and are therefore exogenous.

Model 2 regresses the share of BEV passages on the share of registered BEVs, and the independent variable is considered to be exogenous. This variable is expected to explain a large amount of the variation in the dependent variable, because of the high correlation between these variables. A time trend is included in this model to account for the general trends in the share of BEV passages.

Model 3 approaches the relationship of registered BEVs´ influence on the share of BEV toll passages through a set of linear equations. The number of BEV passages is explained partly by the general level of total number of toll passages ($BEV\ pass + ICEV\ pass$) and the number of BEVs registered. As model 3 contains the dependent variable on both sides of the equation, the model can be transformed to estimate the θs.

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[9] $a_i M_i$ and $a_i C_i$ are the error terms for model 1 and 2 respectively, where M denotes municipalities and C denotes cities.

(7) $$BEV\ pass = \frac{\theta_1}{1-\theta_1} ICEV\ pass + \frac{\theta_2}{1-\theta_1} BEV\ reg + \varepsilon_1$$

(8) $$ICEV\ pass = \frac{\theta_3}{1-\theta_3} BEV\ pass + \frac{\theta_4}{1-\theta_3} ICEV\ reg + \varepsilon_2$$

For simplicity, we denote

$$\beta_1 = \frac{\theta_1}{1-\theta_1}, \beta_2 = \frac{\theta_2}{1-\theta_1}, \beta_3 = \frac{\theta_3}{1-\theta_3}, \beta_4 = \frac{\theta_4}{1-\theta_3},$$

and rewrite equation (7) and (8) as:

(9) $$BEV\ pass = \beta_1\ ICEV\ pass + \beta_2\ BEV\ reg + v_1$$

(10) $$ICEV\ pass = \beta_3\ BEV\ pass + \beta_4\ ICEV\ reg + v_2$$

Equation (9) and (10) illustrate the expected relationship between BEVs and ICEVs, where the decision to drive the BEVs is determined by the level of traffic of ICEVs ($ICEV\ pass$) and naturally the number of BEVs on the road. Equation (10) displays the same relationship for ICEV passages.

We can solve this system of linear equations through two-stage least squares (2SLS) estimation and we need an instrument for $BEV\ pass$ and $ICEV\ pass$. A good instrument for $BEV\ pass$ and $ICEV\ pass$, are variables that are good predictors for these variables, meaning that a large variation in $BEV\ pass$ is explained by the variation in the instrumental variable. Furthermore, the instrument must be exogenous in the initial equation to produce unbiased and efficient estimates. Formally these two conditions can be written as:

(11) $$Cov([BEV\ reg, ICEV\ reg], \widehat{BEV\ pass}) \neq 0$$

(12) $$Cov([BEV\ reg, ICEV\ reg], v_3) = 0$$

and

(13) $$Cov\big([BEV\ reg, ICEV\ reg], \widehat{ICEV\ pass}\big) \neq 0$$

(14) $$Cov([BEV\ reg, ICEV\ reg], v_4) = 0$$

The covariance between the instrumental variables and the instrumented variable must be non-zero. Equation (12) and (14) are similar to the zero conditional mean assumption, where the instrumental variables are uncorrelated with the error term in the initial equation. The first-stage regression is:

(15) $$\widehat{BEV\,pass} = \beta_5\, BEV\,reg + \beta_6\, ICEV\,reg + v_3$$

(16) $$\widehat{ICEV\,pass} = \beta_7\, BEV\,reg + \beta_8\, ICEV\,reg + v_4$$

We use the number of registered BEVs and ICEVs as instruments for the number of passages. The validity of the assumption in equation (11) is formally tested in the first stage regression displayed in appendix A.5. Furthermore, we believe that number of registered vehicles satisfy the assumption of exogeneity. We do not identify any possible omitted variables correlated with number of registered cars that simultaneously has an influence on our dependent variable. It is reasonable to assume that the variance in the error term only influences toll passages through our independent variables, $BEV\,reg$ and $ICEV\,reg$. The first-stage regression estimates are then used in the second-stage regression, and our IV estimation is then:

(17) $$BEV\,pass = \beta_1 \widehat{ICEV\,pass} + \beta_2\, BEV\,reg + v_1$$

(18) $$ICEV\,pass = \beta_3 \widehat{BEV\,pass} + \beta_4\, ICEV\,reg + v_2$$

We assume that the number of registered ICEVs only affect the BEV drivers' decision to drive, through the number of ICEVs that are on the road, since a higher level of traffic will discourage driving.

We now have estimates for β, and can calculate θ, meaning that we can measure by how much an additional BEV or ICEV contribute to the number of toll passages.

6.6.1 Functional forms

Different functional forms of the models were considered. For model 1, a log-form of the dependent variable was preferred over a level-form. This is because a level-form would show the absolute change of VKMT when changing the independent variable, while a log-transformation would be interpreted as a percentage change. The log-form was evaluated as more intuitive and easier to interpret than the level form. Additionally, an advantage of log-transforming the dependent variable is that it normalises its distribution. For the independent variable, a log-transformation would provide a coefficient that could be interpreted as a constant elasticity. However, some municipalities have zero registered BEVs and a log-transformation for these observations is not possible and would exclude many variables.

For model 2 we log-transform the dependent and independent variable, to interpret the estimated coefficient as a constant elasticity. Compared to model 1, there are no zero values of the independent variable and log-transformation is therefore not an issue.

In model 3 we want to estimate the contribution on total passages in absolute values from BEVs and ICEVs respectively; thus, we consider the level-level form as most appropriate for this purpose.

7. Results

This section will present the results from the three models, before testing whether the models exhibit heteroskedasticity and serial correlation. Sensitivity analysis of the three models will also be presented and finally a summary of the results.

7.1 Main findings

The results from the three models are shown in the tables 7.1, 7.2 and 7.3, which all display the FE, RE and POLS estimates. The results in table 7.1 and 7.2 are reported with standard errors clustered at either municipality or city level. Table 7.4 shows the test statics from the Hausman test.

Table 7.1: Results from model 1

Dependent variable: Log VKMT	(1) FE	(2) RE	(3) POLS
Log VKMT $(t-1)$	0.193***	0.955***	0.955***
	(0.0295)	(0.00751)	(0.00896)
Share BEV reg	0.631***	0.299***	0.299***
	(0.0914)	(0.0524)	(0.0603)
Income	-0.000239*	-0.0000356*	-0.0000356*
	(0.0000929)	(0.0000162)	(0.0000180)
Fuel price	-0.0260***	-0.0227***	-0.0227***
	(0.00312)	(0.00349)	(0.00410)
Trend	-0.0246***	-0.00769**	-0.00769*
	(0.00264)	(0.00285)	(0.00333)
Constant	2.763***	0.501***	0.501***
	(0.107)	(0.0719)	(0.0803)
R^2	0.163		
N	1699	1699	1699

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In model 1, the dependent variable is the log of VKMT per vehicle. As we have used a lagged dependent variable, the number of observations is lower than the full data set of 2,120 observations. Table 7.2 displays the results for the model 2, where the share of BEV toll passages is the dependent variable.

Table 7.2: Results from model 2

Dependent variable: Log Share BEV pass	(1) FE	(2) RE	(3) POLS
Log Share BEV reg	1.427***	1.422***	1.397***
	(0.0733)	(0.0826)	(0.142)
Time Trend	-0.101	-0.0986	-0.0847
	(0.0492)	(0.0543)	(0.0866)
Constant	1.536**	1.517***	1.409
	(0.328)	(0.402)	(0.654)
R^2	0.997		0.986
N	20	20	20

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7.3: Results from Model 3

		(1) FE	(2) RE	(3) POLS
ICEV passages	β_1	0.0604	- 0.174	- 0.174
		(0.422)	(0.153)	(0.153)
BEVs registered	β_2	22.00 **	18.99 ***	18.99 ***
		(7.476)	(4.421)	(4.421)
BEV passages	β_3	- 0.488	- 0.654	- 0.654
		(0.0728)	(0.585)	(0.585)
ICEV registered	β_4	8.941	3.301	3.301
		(14.83)	(3.232)	(3.232)
	θ_1	0.057	- 0.21	- 0.21
	θ_2	20.74	22.99	22.99
	θ_3	- 0.95	- 1.89	- 1.89
	θ_4	17.48	9.54	9.54

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For model 3, which is the set of linear equations, the estimated βs from the 2SLS estimation are shown in table 7.3, as well as the calculated θs. See appendix A.5 for the first stage regression output.

Table 7.4: Hausman test results

	Model 1	Model 2	Model 3
Test statistic	751.64	0.02	0.25 / 0.14
Prob > Chi2	0.0000	0.9922	0.8832 / 0.9314

Table 7.4 provide the Hausman test statistics for the three models. The Hausman test clearly rejects the null hypothesis for model 1, implying that the FE estimator is preferred. For model 2 and 3, the Hausman test fails to reject the null hypothesis. The Hausman test statistic is reported twice for regression 3, due to the system of linear equations.

7.1.1 Results from Model 1

We interpret the fixed effect estimates, where one percentage point increase in the share of BEV registrations, leads to a 0.63% short run increase in the average VKMT per car. The long run effect[10] is 0.78%. The estimates on the lagged dependent variable suggest that people change behaviour quite rapidly, implying that people adjust their travel behaviour with approximately 80% of the ultimate response to a permanent change.[11] Our results suggest that as the share of electric vehicles increase, people will increase the demand for driving.

The coefficient on income is significant but in the unexpected direction. However, the effect is small and the coefficient suggests that if median income is increased by NOK 1000, the demand for driving decreases by approximately 0.002%.

The results for fuel price indicates that if the cost of fuel increases with NOK 1 per litre of fuel, then we would expect that people decrease the demand for driving by 2.6%. The estimate is statistically significant at the highest level and in the expected direction.

[10] The long run effect is given as $\frac{\beta_2}{1-\beta_1}$ for AR(1) models, (Wooldridge, 2015).

[11] The coefficient on Log VKMT(t-1) is 0.193, indicating that past values of log VKMT has a small influence on the present values of log VKMT. Consequently, (1 - 0.193 = 0.807) is the individuals' response to a permanent change.

The coefficient on time trend is statistically significant at the highest level and suggests that VKMT decreases annually by approximately 2.46% from 2012 to 2016. The gradual decline in demand for driving can be ascribed to unobservable factors such as environmental awareness. The Hausman test clearly rejects the null hypothesis of no systematic difference; thus, the assumptions behind the RE and POLS model is violated.

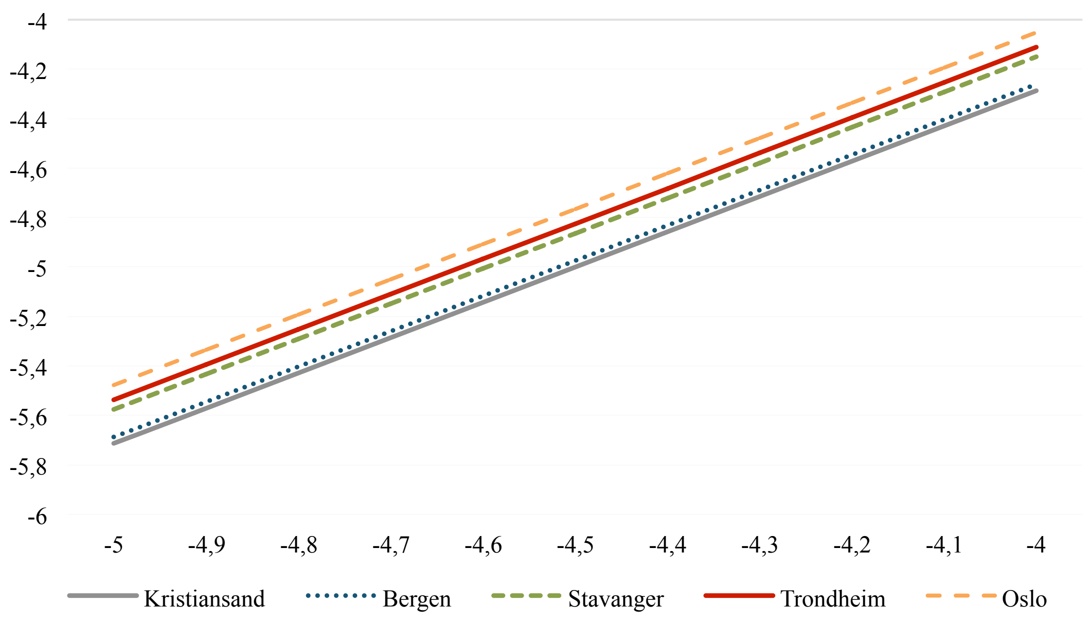
7.1.2 Results from Model 2

For model 2, the Hausman test fails to reject the null hypothesis. However, the validity of the test can be questioned because the city data set only contains 20 observations. The Hausman test statistic is calculated from the estimated coefficients and corresponding standard errors. Consequently, few observations in the data set may lead to high standard errors, which could cause the test statistic to become relatively small, and fail to reject the null hypothesis.

The fixed effect estimator is the equivalent of running a regression with a dummy for each city, thereby estimating different estimates for each city, as explained in subsection 6.6. The dummies capture the city specific effects, by allowing each city to have its own intercept. Figure 7.1 displays the estimated coefficient with separate intercepts for the five cities we observe. All city-specific intercepts, are statistically significant at the highest level, except for Bergen. Consequently, even though the Hausman test fail to reject the null hypothesis, we recognize that city-specific factors exist, and will emphasize the FE estimator in the interpretation of the coefficients. On the contrary, the estimates do not differ significantly from each other, making the interpretation much the same.

The coefficient of 1.42 means that increasing the share of registered BEVs by 1% increases the share of BEV toll passages by 1.42 %. The coefficient is also significantly different from 1. The trend variable is not statistically significant for any estimator, and in the unexpected direction. We expected the trend variable to be positive even if it represents the residual trend after the trend in BEV registrations is controlled for. For example, unobservable factors such as environmental awareness and the increasing diversity in BEV models might explain certain trends in our data, which we anticipated to be positive.

Figure 7.1: Regression output with city-specific dummies (Log transformed variables)



7.1.3 Results from Model 3

Table 7.3 reports both the estimated βs and the calculated θs for model 3, where θ_2 and θ_4 are the coefficients of interest. Only β_2 is statistically significant in the FE and RE model. As with model 2, the Hausman test fails to reject the null hypothesis, partly because the standard errors are high.

When comparing the RE estimator to the FE, the coefficient β_1 has changed sign from 0.06 to - 0.17. A negative sign is expected, as it must be true that if the share of BEV passages increase the share of ICEVs must decreases. β_3 is negative for both FE and RE. Because of the difference in sign of β_1 for the RE and the FE estimators, the calculated estimate of interest, θ_2, is very different for the two estimators. The FE estimator suggests that one additional BEV contributes to approximately 21 passages per station annually. Since the number of stations varies across cities, the contribution to total passages will also vary between cities. In comparison, one additional ICEV contributes to 17 passages per station annually. The RE estimates display a greater difference between BEVs' and ICEVs' contribution to passages, with approximately 23 and 10 passages respectively.

Even though the FE and RE estimators demonstrate the same effect of BEVs passing toll stations more often than ICEVs, the difference in magnitude is significant. With the RE estimators, the standard error on β_1 is substantially less than in the FE estimators, even though it is not statistically significant within reasonable confidence levels. The difference in standard errors might come from the fact that the FE estimator only uses the within variation, where we have four years of observations for each city. Furthermore, the first stage regression indicates that $BEV\ reg$ and $ICEV\ reg$ are unsuitable instruments for $ICEV\ pass$, which could result in biased and inefficient estimates.

The high level of uncertainty in the estimates from model 3 forces us to review the results with caution. The results are further discussed in section 8.

7.2 Dealing with heteroscedasticity and serial correlation

The estimated results discussed above, all rely on the assumption of homoskedasticity to produce efficient coefficients and corresponding test statistics. We ran post-regression tests to check for the presence of heteroscedasticity, and used robust estimators when required. Figure 7.2a and 7.2b exhibits the plot of fitted values on the residuals in model 1 and 2 respectively.

Figure 7.2a: Residual plot for model 1

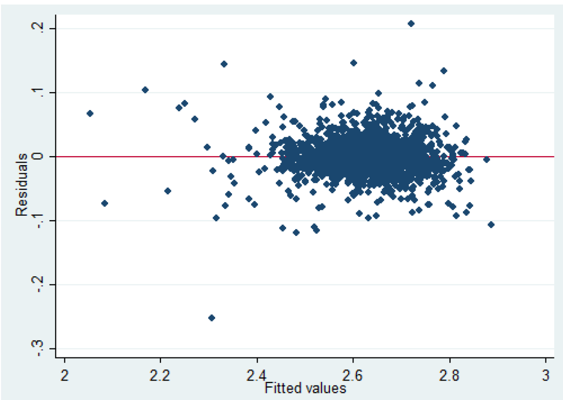


Figure 7.2b: Residual plot for model 2

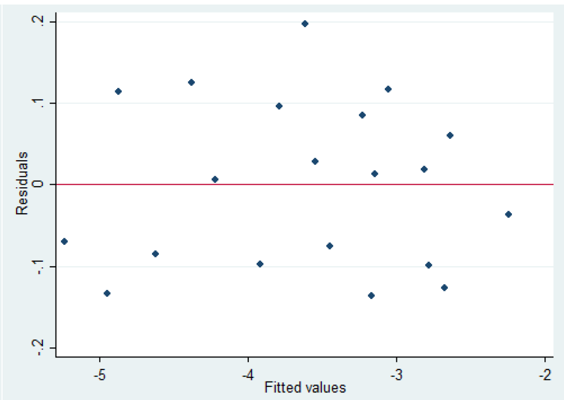


Figure 7.2.a does not show a clear pattern of any linear form of heteroscedasticity, but it shows sign of nonlinear forms of heteroscedasticity, with the variance increasing at the centre of the cluster of observations. Figure, 7.2b does not show any clear sign of heteroscedasticity, since the residuals seem to be distributed evenly around zero across

increasing levels of the fitted values. Formal tests of heteroscedasticity are displayed in table 7.5 below.

Table 7.5: Formal tests for heteroscedasticity

	Cook-Weizberg Test	**White's Test**
Model 1, FE		
Test-statistic	115.77	220.85
Probability > Chi2	0.0000	0.0000
Model 2, FE		
Test-statistic	1.75	4.87
Probability > Chi2	0.4167	0.4321

In model 1, both tests reject the null hypothesis very clearly suggesting that our model does suffer from heteroscedasticity. Therefore, we should use robust estimates to correct for the interdependency between the error term and the independent variables. In model 2, both tests fail to reject the null hypothesis, whereas the heteroskedasticity test for IV-estimation provides evidence in favour of heteroskedasticity[12].

The serial correlation tests rejected the null hypothesis of no serial correlation in model 1 and model 3, whereas it failed to reject the null hypothesis for model 2. Clustering the standard errors at unit-level normally eliminates the problem, but as Wooldridge (2010) points out, it depends on fairly long time series, unless the number of cross sectional observations is high. The municipality data set has a fairly large number of observations, even though the number of years is low. Consequently, we expect that clustering the standard error at municipality levels corrects for any serial correlation. In model 3, we use the data set on cities, which has relatively few cross-sectional and longitudinal observations. Even if we use clustered standard error, we cannot conclusively assume that we have eliminated the problem entirely.

[12] Testing for heteroskedasticity in IV estimation procedures requires a different approach. The squared residuals from model 1 are regressed on the independent variables, and tested for joint significance. We reject null hypothesis of no serial correlation.

7.3 Sensitivity analysis

To check the robustness of our empirical specification, we run a series of alternative regressions to expose any weakness. The results from our sensitivity analyses are displayed for model 1 in table 7.6 and for model 2 in table 7.7. For model 3, we have limited opportunities to vary the set of linear equations and the variables we use. We considered using model 3 on different subsamples, but found it unsuitable due to the small data set.

7.3.1 Sensitivity analysis for Model 1

In many applications, it is desirable to include nonlinear representations of a variable if we suspect that the change in the dependent variable follows a nonlinear trend (column (2) in table 7.6). The dependent variable is not anticipated to follow a nonlinear trend based on the nature of the parameter we are trying to measure. In a developed country like Norway, we would suspect relatively linear trends in the kilometre travelled mainly driven by the car stock. Including the squared of the trend does not cause dramatic shifts in the main model.

We excluded the lagged dependent variable to see if our main specification was sensitive to the exclusion of dynamics. The coefficients change substantially, where the key independent variable now suggests a 6.9% increase in VKMT. The sign of the coefficients remains the same as in the preferred model and all variables are statistically significant at the highest level expect for income. Nevertheless, our main specification in column (1) is still preferable due to the opportunity of assessing both short run and long run effects.

To control for geographical differences between cities and rural areas, we considered adding a variable on population density. We expected that vehicle kilometres travelled in rural areas would be higher per vehicle than in densely populated areas due to longer travel distances. However, we suspected that population density would be highly correlated with our key independent variable on registered BEVs, since most BEVs are sold in urban areas. Adding density could results in collinearity issues between our independent variables and bias our estimates. Furthermore, density is captured by the municipality-fixed effect.

Table 7.6: Sensitivity analysis for Model 1

	(1) Preferred model	(2) Squared trend	(3) Excluding lagged dependent variable
Log VKMT $(t-1)$	0.193^{***}	0.142^{**}	
	(0.0557)	(0.0520)	
Share BEV reg	0.631^{***}	0.659^{***}	6.967^{***}
	(0.0998)	(0.102)	(1.412)
Income	-0.000239	0.000122	-0.000693
	(0.000135)	(0.000155)	(0.00143)
Fuel price	-0.0260^{***}	0.0162^{***}	-0.451^{***}
	(0.00290)	(0.00392)	(0.0326)
Trend	-0.0246^{***}	-0.0507^{***}	-0.453^{***}
	(0.00251)	(0.00359)	(0.0249)
Trend^2		0.0117^{***}	
		(0.000903)	
Constant	2.665^{***}	1.994^{***}	21.80^{***}
	(0.163)	(0.168)	(0.628)
r2	0.163	0.253	0.326
N	1699	1699	2124

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.3.2 Sensitivity analysis for Model 2

We added a lagged dependent variable for model 2, to see if the main results were sensitive to a dynamic specification. Adding this variable change the coefficient on $share\ BEV\ reg$ significantly to an elasticity of 0.546, suggesting that higher shares of BEVs in the city corresponds to a less than proportionate increase in total passages. Thus, increasing shares of BEVs would yield less demand for driving, and fewer toll passages, evidence against our hypothesis of increased driving. The coefficient on $share\ BEV\ reg$ is also less significant than in the preferred model and this model is not desirable due to the loss of efficiency.

To account for macro shocks that occur across all cities, we substituted the trend variable with year dummies. As the results in table 7.7 displays, none of the dummies turn out to be statistically significant at any reasonable level, but our estimates indicate a negative development over time. The coefficient on our key independent variable does not change significantly, but the standard error has increased.

Table 7.7: Sensitivity analysis for Model 2

	(1) Preferred model	(2) Including lagged dependent variable	(3) Year dummies
Log Share BEV pass $(t-1)$		0.378^{*}	
		(0.0859)	
Log Share BEV reg	1.427^{***}	0.546^{*}	1.453^{***}
	(0.0733)	(0.160)	(0.186)
Trend	-0.101	-0.0378	
	(0.0492)	(0.0215)	
Dummy 2014			-0.0931
			(0.150)
Dummy 2015			-0.255
			(0.251)
Dummy 2016			-0.331
			(0.312)
Constant	1.536^{**}	0.0804	1.646
	(0.328)	(0.253)	(0.830)
N	20	15	20
R^2	0.997	0.996	0.998

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

All the models displayed in table 7.7 are FE estimators, since adding a lagged dependent variable to the random effects estimator violates the crucial assumptions of unbiasedness. The unobserved error term is correlated with the lagged dependent variable by specification, which violates the assumption of zero covariance between the error term and the independent variable. Consequently, the FE is the only unbiased estimator.

7.4 Summary of results

All three models support our hypothesis of higher demand for driving when the stock of BEVS increase relative to ICEVs. Model 1 and 2 produce statistically significant estimates on our key independent variable, and in the expected direction. Model 3 produce estimates in the expected direction with the random effects estimator, but only β_2 is statistically significant.

In model 1, increasing the share of registered BEVs yields a 0.63% increase in VKMT and is significant at the highest level, suggesting that people do have higher demand for driving as they make the transition from fossil fuels to BEVs. In model 2, we find a constant elasticity of 1.42, indicating that if the share of BEVs registered increase by one per cent, the share of BEV passages increases by 1.42%, indicating a small but statistically significant rebound effect of driving. Model 3 produce estimates in the expected direction, where an additional BEV pass the toll system more often than an additional ICEV, again suggesting that increasing shares of electric cars contribute to more toll passages.

We have performed a variety of robustness tests. In conclusion, including or excluding variables in model 1 and 2 did not alter the estimates significantly. Model 3, however, suffers from low efficiency caused by the weak instrument of $ICEV\ pass$ and because the underlying data does not exhibit enough variation to produce efficient estimates on most variables. Several tests were performed to identify structural weakness in our model such as heteroscedasticity and serial correlation. Model 1 suffers from heteroscedasticity, and we use robust standard errors. Model 2 did not display any evidence of heteroscedasticity, but since the city data are aggregated form municipality data, we cluster these standard errors too. Model 3 has clustered standard errors at city levels since heteroskedasticity is present.

8. Discussion

Generally, the results from the three models produce estimates in the expected direction, and display a relationship according to our hypothesis. In the following subsections, results from the empirical analysis will be discussed in relation to the adverse effects identified in section 4. We start out by analysing how higher demand for driving yields higher external costs, and look particularly on the level of congestion, before we discuss the implications on toll revenues and the corresponding cost of funds. Furthermore, we discuss the limitations of our data set and caveats of our empirical approach, before we present suggestions for future research and policy implications.

8.1 Implications of the results

8.1.1 Effects on externalities

Section 4 presented the externalities that arise from road traffic, and showed that most of the externalities are the same from use of BEVs as ICEVs (see Thune-Larsen et al., 2014). The results from the three models all indicate that increasing levels of BEVs increase the demand for driving. It is therefore reasonable to assume that external costs from road traffic also increase.

Noise pollution from road traffic is a local externality and will therefore vary depending on location, as well as the type of vehicle. A quiet-running engine creates less noise, but this is only valid for low speeds as it is factors such as tyres types, drive shafts and the road surface that creates noise for high speeds (Thune-Larsen et al., 2014, p. 19). Therefore, the difference in the magnitude of noise externality created by BEVs and ICEVs is marginal, as most of the road traffic measured through VKMT or toll passages is most likely high-speed driving.

Wear and tear of infrastructure depends on the size and weight of the vehicles. When comparing BEVs to other vehicles of the same size and weight, the external cost is of the same magnitude. The same reasoning can be used for the externalities of accident costs and barrier effects, as there are no obvious differences between BEVs and ICEVs in these matters.

As a consequence, we argue that increasing shares of BEVs leads to higher externalities from road traffic in general. This is a result of the BEV incentive scheme, where the owners of BEVs do not face the full cost of driving.

8.1.2 Effects on congestion level

The results from our empirical estimation indicate that a rebound effect emerges as the share of BEVs increases. While the effect is quite small in model 1, a constant elasticity of 1.42 in model 2 is an indication of a small, but significant effect and evidence in favour of higher demand for traffic, analogous to more congestion. Model 3 also provides evidence in favour of more congestion, since a higher level of BEVs suppress ICEVs, shown through a negative coefficient in the RE model. With increasing shares of BEVs, and a higher demand for driving among BEV drivers, the level of traffic and congestion is likely to increase significantly.

Under the assumption of the model in section 4, congestion occurs at any level of traffic (Since $\left(\frac{q}{c}\right) > 0$). Consequently, drivers of BEVs contribute to a negative change in the economic welfare, since they drive more than their opposing ICEV drivers. Furthermore, this implies that deviations from the optimal economic equilibrium increase the social cost exponentially. Since only a fraction of the entire vehicle stock today is BEVs, the social costs will escalate as the number of BEVs increase. This is seen from figure 4.3, since a 1.42% increase of toll passages at high levels of traffic increase the social marginal costs relatively more, than a 1.42% increase in toll passages at low levels of traffic. This can be seen by the increasing deviation between the PMC and SMC curve.

It is important to notice that figure 4.3 applies for all vehicles. The important difference lies in the corrective measures of toll charging, which reduces the magnitude of the external costs for ICEVs but not for BEVs. As a consequence, BEVs have lower marginal costs and are motivated to use the car more often. Toll costs are substantial in many cities, and the exemption from toll charges is considered to be of large importance for approximately 50% of the respondents when buying a BEV (Figenbaum & Kolbenstvedt, 2016).

The mathematical model in section 4 includes the parameters on utility of driving (μ) and the value of time (β), where a higher value of time implies less demand and a high utility of driving yields higher demand. Figenbaum and Kolbenstvedt (2016), find that the share of people driving BEVs increase with income, indicating that BEV ownership is a luxury good. In economic theory, high-income individuals have a higher value of time, relative to lower income individuals. In our model, this implies that high-income individuals have a higher private marginal cost of congestion, since the disutility of delay is valued highly (high β). When BEV owners have a higher disutility of congestion and at the same time contribute relatively more than ICEV owners, the cost to society will increase substantially as the share of BEVs increase. The net effect on congestion depends on which of the two factors that dominates, either the incentives to drive more, or the cost of congestion that occurs.

Consequently, those who contribute relatively more to congestion also carry the highest cost of it, and as a result, the amount of traffic will be more than the optimal equilibrium, and the associated external costs will increase substantially.

In model 2, some uncertainty in the interpretation of the causality between registered BEVs and share of BEV passages are questionable. Because the dependent variable is the share of BEV passages $(Share\ BEV\ pass = \frac{BEV\ pass}{Total\ pass})$, and we do not control for the partial effect of these variables, the actual effect is ambiguous. Two factors drive the variation in the share of BEV. Either, the absolute number of BEV passages increases relatively more than the total passages, or, the number of total passages decreases relatively more than the number of BEV passages. We expect that the variation in the dependent variable is a combination of the two factors, which could influence our expectations of the relationship between traffic level and congestion. If a large fraction of the variation in the dependent variable comes from decreasing total passages, whereas the share of BEV passages remains relatively constant, then most ICEV trips are substituted by BEV trips; thus, traffic levels remains the same and consequently, congestion levels. Appendix A.4 suggests that a change in the total passages surpasses that of BEV passages, a clear indication that much of the variation in the variable share BEV pass is driven by total passages, rather than BEV passages. On the contrary, the figure only displays the aggregated number and not the within-city change, which could have a substantial influence on our estimates.

8.1.3 Effects on toll revenue loss

To illustrate how loss in toll revenue may cause adverse effects in terms of cost of public funds, results from model 3 will be used. The results displayed in table 7.3 show that when adding one BEV to the vehicle fleet, the number of BEV toll passages will on average increase by 20.7 or 22.9 passages, depending on whether the FE or RE estimations is preferred. For the purpose of illustrating the cost of public funds, an increase of 21 passages per station will be used.

In the paper by Aasness and Odeck (2015), observations from the toll ring in Oslo are used for estimating of the revenue loss caused by exemption for BEVs. The revenue loss is found by multiplying the number of BEV toll passages with the toll price. They find that for 2012, the calculated revenue loss was NOK 24,421,210 (2015, p. 7). A weakness of this calculation is that the authors indirectly assume that 100% of the BEV passages is substituted by ICEVs. However, it is possible that BEVs will drive more on toll roads than ICEVs because of the BEV incentive scheme. Thus, a more realistic assumption would be that only a part of these BEV passages would otherwise be ICEV passages. Based on this reasoning, we have calculated the average toll revenue loss for each additional BEV added to the vehicle fleet, assuming that 20%, 50%, 80% and 100% of the BEV passages would otherwise be ICEV passages. We use a toll price of NOK 20, as done by Aassness and Odeck (2015) together with our findings saying than an increase by one BEV will increase the number of BEV passages with 21 per station. As toll prices and the number of stations varies in the different cities, the cost of an additional BEV will also vary. The calculation calculated loss revenue per additional BEV is shown in table 8.1.

Table 8.1: Calculated loss in toll revenue per additional BEV

Passages per station 21
Toll charge NOK 20

Share of BEV passages that would otherwise be ICEV	**20%**	**50%**	**80%**	**100%**
Loss in toll revenue per BEV	NOK 84	NOK 210	NOK 260	NOK 429
Social cost of funds per BEV	NOK 16.8	NOK 41	NOK 72	NOK 84

Another shortcoming of Aassness and Odeck´s paper is that they automatically assume that this toll revenue loss is an adverse effect and a cost to society. However, loss in toll revenue is not directly an economic cost, but a transfer or subsidy to BEV owners at the expense of the toll companies (Lindberg & Fridstrøm, 2015). However, as the toll revenue is used for funding road infrastructure and public transport, the loss must be compensated for, and as subsection 4.3 showed, this comes at a cost.

One way to compensate the loss in toll revenue is through general taxation. As shown in subsection 4.3.1, the marginal cost of public funds is 0.2 for each NOK collected. The cost to society of replacing the loss of toll revenue per additional BEV is also shown in table 8.1 as the cost of funds per BEV.

Another way to compensate for the loss in toll revenue is to increase the toll charge for all the other vehicles. Subsection 4.3.2 shows that an increase of the user payment will displace some vehicles form the road, and an efficiency loss is created. The size of the efficiency loss will depend on the slope of the demand curve and the size of the increase of the toll charge. Finding the optimal toll price, which minimizes the efficiency loss of the economy as a whole, is a more complex process when the exemption for BEVs must also be included.

As this discussion show, there are large insecurities in estimating the cost of toll revenue and it is difficult to find precise estimates. Nevertheless, we conclude that based on the social costs of compensating for the loss in toll revenue there are adverse effects from toll exemption for BEVs.

8.2 Limitations of the data sets

As section 5 show, two panel data sets have been used for the empirical strategy of this paper. The first data set contained information on 424 units over five years, and leaves us with 2,120 observations, which is a strength of this data set. However, the variable of interest is the share of BEVs registered in each municipality and this is zero or very close to zero for many municipalities over this period. As a result, despite having many observations, some of these observations do not provide us with much information.

The dependent variable in model 1 is vehicle kilometres travelled (VKMT) per vehicle. This is a measure of how much the average vehicle drives during a year, but it does not provide any information of differences between vehicles such as BEVs and ICEVs. Neither does the variable provide any information of the time of the driving, i.e. the variable does not provide information of congestion directly.

A weakness of the fuel price variable used in the data set, is that it is individual variant, i.e. it only varies over time and not across units in our data set. In reality, fuel price do vary within municipalities as well as from day to day, even hour to hour. This variation is not reflected the data set, and can be a possible explanation for why this variable is less significant than others.

The city data set has a lot fewer observations than the municipality data set. The number of units is five compared to 424, while the time period is one year shorter for this data set than the municipality data set. It can be argued that a longer time period should have been utilized, but as figure 5.1 show the share of BEV passages was very low at the beginning of 2013. Thus, using data on toll passages prior to this would probably not provide much relevant information.

The data on toll passages provided by the toll companies were for all cities except Oslo reported as monthly data. An improvement would be utilising this monthly variation, but as the data on registered vehicles were not available on a monthly basis this was not available to us.

Whether the city regions created for this data set is appropriate can be discussed. It is a possibility that some of the municipalities belonging to a city should not be included, and that other municipalities that does not directly border on the municipality in which the toll ring is located in should be included. To capture the full effect of BEVs passing using toll roads on congestion, more units could have been included. There are other municipalities where toll stations exist, and including these could have strengthened the results.

8.3 Limitations of the empirical approach

The results from our empirical estimation suggest that over time we should experience increasing levels of traffic with higher shares of electric vehicles. Even though we do find indications of more traffic, we fail to unambiguously conclude that more traffic from electric vehicles leads to higher levels of congestion than otherwise would have occurred. Our empirical strategy does not control for the time of day, which could have a substantial influence on our hypothesised effect on congestion. It is reasonable to assume that in regions with toll roads, individuals buy BEVs due to the cost benefit it provides relative to ICEVs, suggesting that they drive more.

At the same time, it is reasonable to believe that individuals who previously passed toll stations, also did so after buying a BEV, suggesting that the level of traffic during the hours of day when congestion normally occurs, has not increased as much as our estimate indicates, because people to some degree follow the same behaviour over time. Consequently, the added trips caused by BEVs are possibly distributed across the day, also during off-peak hours, thereby contributing less to congestion.

Model 2 fails to control for the two factors that influence the dependent variable: BEV passages and total passages. Therefore, we cannot causally determine if the share of BEV passages is caused by an actual increase in the number of passages by BEVs, or due to the declining number of total registered passages. This implies that we cannot discern if we observe a substitution effect of people shifting from ICEVs to BEVs, or if we observe an actual increase in the number of BEV passages.

From the empirical estimation, we do find evidence in favour of a rebound effect, suggesting that owners of BEVs have a higher demand for driving than ICEV owners. In previous studies on the rebound effect, the effect is measured as the causal effect on vehicle kilometres travelled, when the per-kilometre fuel costs declines (see for example Small & Van Dender, 2007). Even though our main interest is to look at the effect of increasing shares of BEVs in municipalities, failing to control for the effect ICEVs have on the demand for driving, could possibly bias our estimates. On the contrary, our data set is relatively short ranged, where we believe the average fuel efficiency of cars has improved only by small amounts between 2012 and 2016.

As discussed in section 6.6, the possibility of reverse causation between the dependent and key independent variable could lead to biased estimates. We could not find any suitable instruments for the key independent variable, and acknowledge that our estimates may be influenced to some degree.

8.4 Suggestions for future research and policy implications

Our empirical models measure the increase in demand for driving due to higher levels of BEVs. This is in itself not a measure of the externalities or the adverse effects directly, but we argue that through increased demand for driving the externalities will also increase. Future research could directly target the externalities through using measurements of the externalities. An example would be to use observation of the congestion during peak hours for some road stretches in Oslo and Bergen over time, and see how the travel time changes with increasing levels of BEVs.

An improvement of Model 1 would be to include area-fixed effects to control for demographic and geographic differences. This could explain some of the variation in the shares of BEVs registered between municipalities. As an example, the adoption rates in the northern regions of Norway are generally lower than in the southern.

As an obvious limitation of the data sets are few time periods, it would be interesting to perform a similar analysis in the future. As of now, including more years prior to the chosen time periods would not be expedient as the share of BEVs registered only started expanding from 2012. For future research it would be particularly interesting to investigate increasing shares of BEVs´ influence on demand for driving, as the incentives are gradually phased out.

As this discussion has shown, increasing externalities with higher shares of BEVs is a result of the Norwegian incentive scheme. Because of this, we recommend the government to revise the incentives and take the externalities of road traffic into account.

Based on the results and the discussion in this thesis, it seems reasonable to phase out the incentives due to the increasing external costs. On the contrary, the process of dissolving the incentives should be done gradually as several surveys show that the incentives are important for the adoption of BEVs.

9. Conclusion

This thesis has aimed at analysing and estimating the adverse effects that arise with increasing shares of BEVs. The adverse effects of the incentive scheme are the associated externalities that emerge with road traffic. We enunciated that a generous incentive scheme for BEVs would cause higher levels of traffic, since the marginal costs related to BEV driving are lower than ICEVs. We proposed three models, each contributing to our research question from different perspectives. Model 1 uses annual municipality data to see if the general demand for driving increases with increasing shares of registered BEVs. Model 2 uses data from city regions to see if the demand for driving increases in urban areas by measuring the "demand" for tolled roads, areas where congestion is likely to occur more frequently. Model 3 looks at the contribution from one additional BEV and ICEV on toll passages to assess the potential revenue loss for toll companies.

All models indicate that increasing number of BEVs on the roads cause higher demand for driving. Model 1 suggests that the vehicle miles travelled per car increases by 0.63% if the share of BEVs increase with one percentage point. Model 2 suggests that a 1% increase in the share of registered BEVs yields a 1.42% increase in the share of toll passages by BEVs. Model 3, indicates that one additional BEV contributes to approximately 23 passages per station, compared to approximately 10 for ICEVs. In general, the results demonstrate that the external costs associated with road traffic is likely to increase with the proliferation of BEVs. In most cases, our results are robust to changes in the empirical specification.

To our knowledge, no paper has previously studied the influence of increasing shares of BEVs on the demand for driving in Norway, and its corresponding external costs. The novelty of the recent BEV proliferation may partly explain why such literature is absent to this day. Nonetheless, the importance of such research is paramount if the incentive scheme for BEVs accomplishes its goal of a technological shift toward zero emissions vehicles. Our thesis contributes to the literature by looking at the change in demand for driving as more individuals make the transition from fossil fuels to electricity.

Our thesis has implications for policy makers in the sense that the current incentive scheme may not only motivate a wanted transition toward zero emission vehicles, it also causes the external costs of driving to increase significantly. Consequently, a revision of the incentives scheme is recommended.

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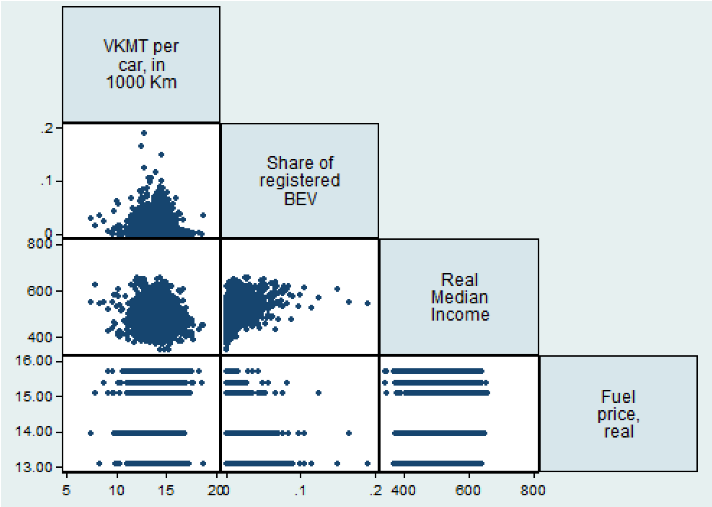
11. Appendix

A.1: Municipalities belonging to each city region in city data set

OSLO		BERGEN	
216	Nesodden	1201	Bergen
217	Oppegård	1243	Os (Hord.)
219	Bærum	1245	Sund
220	Asker	1246	Fjell
226	Sørum	1247	Askøy
228	Rælingen	1251	Vaksdal
229	Enebakk	1256	Meland
230	Lørenskog	1259	Øygarden
231	Skedsmo		
233	Nittedal		
301	Oslo kommune		
STAVANGER (NORD-JÆREN)		**TRONDHEIM**	
1102	Sandnes	1601	Trondheim
1103	Stavanger	1653	Melhus
1120	Klepp	1657	Skaun
1121	Time	1662	Klæbu
1122	Gjesdal	1663	Malvik
1124	Sola	1714	Stjørdal
1127	Randaberg		
1130	Strand		
1142	Rennesøy		
KRISTIANSAND			
926	Lillesand		
928	Birkenes		
935	Iveland		
1001	Kristiansand		
1014	Vennesla		
1017	Songdalen		
1018	Søgne		

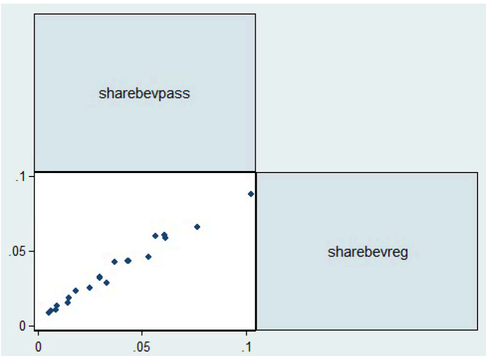
Note: Appendix A.1 shows which municipalities that belong to the city regions Oslo, Bergen, Stavanger, Trondheim and Kristiansand. These municipalities are chosen as these borders with the municipality (the city) where the toll ring is present.

A.2: Graphical correlation matrix of variables in mucipality data set



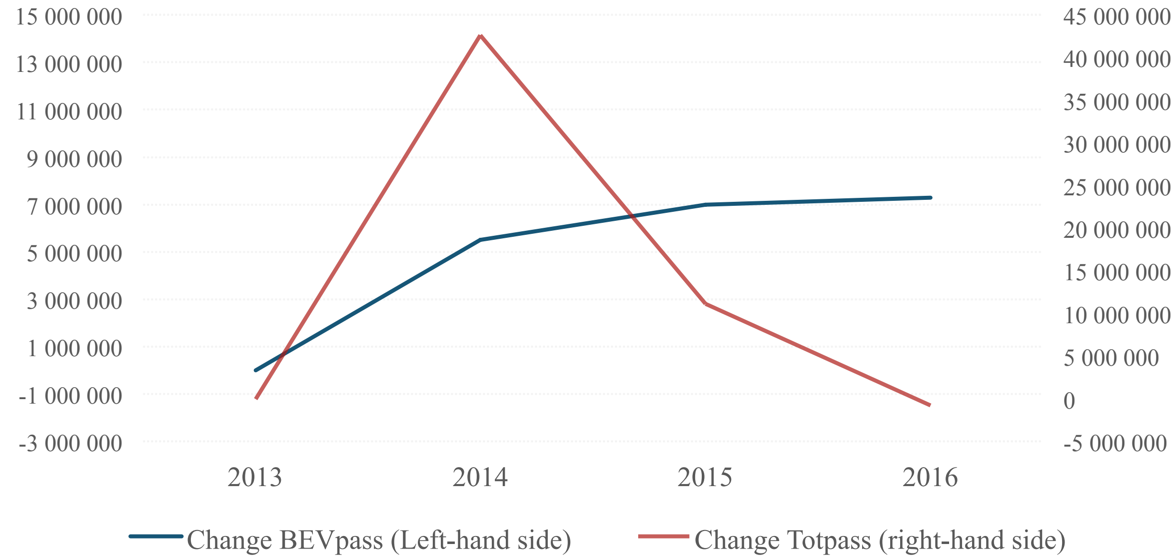
Note: A.2 shows a graphical correlation matrix for the variables in the municipality data set to identify any non-linear relationships between the independent variables.

A.3: Graphical illustration of correlation between share BEV pass and share BEV reg



Note: A.3 shows the correlation between the share of BEV passages and share of BEV registrations graphically. The figure does not show any signs of non-linearity.

A.4: Aggregated change in total toll passages and BEV passages over time for all cities



Note: A.4 shows the change of toll passages (measured on the right-hand side axis) and BEV passages (measured on the left-hand axis) for all cities over the time period 2013 – 2016.

A.5: First stage regression output for model 3

	(FE)		(RE)		(POLS)	
	BEVpass	ICEVpass	BEVpass	ICEVpass	BEVpass	BEVpass
BEVreg	21.37***	-10.44	21.40***	-13.62	21.61***	10.50
	(3.735)	(15.30)	(2.635)	(11.06)	(2.697)	(43.80)
ICEVreg	0.525	8.685	-0.613***	3.836	-0.622**	2.393
	(3.622)	(14.83)	(0.165)	(3.913)	(0.160)	(2.606)
Constant	-75744.5	2110632.7	95669.6***	2861449.3***	95826.3***	2933393.3***
	(561969.4)	(2301517.8)	(21878.7)	(723649.5)	(20042.2)	(325505.9)
r2	0.816	0.158			0.808	0.128
N	20	20	20	20	20	20

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: All first stage regression coefficients were tested for joint significance using the standard F-test. In all regressions, BEVreg and ICEVreg were jointly significant when regressed on BEVpass. Equally, the coefficients were not jointly statistically significantly different from zero, making BEVreg and ICEVreg poor instruments for ICEVpass. This surely has an impact on the consistency and efficiency of the estimates in the initial equation.