Battery Electric Vehicle Adoption and the Importance of Free Parking

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Abstract

In this thesis, we use market level sales data from the Norwegian automobile market to investigate the effect of free parking privileges for battery electric vehicles (BEVs) on sales of BEVs. Following a decision in 2016, municipalities were allowed to charge BEVs for parking as of January 1 2017. Although a small share of the Norwegian municipalities acted on the possibility to change parking policy, we find that the effect on BEV sales was negative. We estimate that the number of BEVs sold in 2017 would have been higher had the policy change not been introduced at all. In addition, we find that the number of charging points in a municipality has a positive effect on market shares of BEVs. These findings are statistically significant at the 1% level after controlling for fixed effects across markets and time, in order to account for unobserved car characteristics and individual consumer preferences for the characteristics across markets and temporal demand chocks.

Key words: battery electric vehicles, policy, parking, automobile industry, Norway
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Contents

Battery Electric Vehicle Adoption and the Importance of Free Parking 1
1. INTRODUCTION 4
2. BACKGROUND 6
2.1 The Norwegian Market 6
2.2 Other BEV markets 7
2.3 Institutional background 8
2.2.1 Free parking 11
2.4 Range 12
2.5 Charging stations 14
3. PREVIOUS LITERATURE 16
3.1 Vehicle choice 16
3.2 Government initiatives and alternative fuel vehicles 16
4. DATA 18
4.1 Car sales 18
4.2 Car characteristics 18
4.3 Charging stations 18
4.4 Fuel and electricity prices 19
4.5 Free parking 19
4.6 Demographic variables 19
4.7 Additional data 19
4.8 Summary statistics 19
5. METHOD 20
5.1 Background 20
5.2 Model definition 20
5.3 Regression Equation 22
5.4 Variables 22
5.4.1 Charging stations 22
5.4.2 Fixed effects 23
5.4.3 Car characteristics 23
5.4.4 Population characteristics 23
5.4.5 Parking fee for BEV's 23
5.5 The market 24
5.6 Instrumental variables 24
5.7 Nested logit 25
6. EMPIRICAL RESULTS 26

6.1 Ordinary Least Squares logit regression 26
6.2 Instrumental variables logit 28
6.3 IV Nested Logit 32
6.5 Results from counterfactuals 33
7. INTERPRETATION & IMPLICATIONS 36
8. LIMITATIONS 38
9. CONCLUSION 39
9.1 Suggestions for further research 40
10. REFERENCES 42
10.1 Literature 42
10.2 Electronic 42
10.3 Data 44
10.4 Other 44
A. APPENDIX 44
A.1 Data adjustments 44
A.1.1 Car characteristics and price 44
A.1.2 Parking fee 45
A.1.3 Income 45
A.2 Estimation results 45
A.3 NOK/USD Monthly exchange rates 57

1. INTRODUCTION

Environmental issues have become a top priority in politics all over the globe. Despite the global environmental focus, carbon dioxide emissions (CO_2) continue to grow, as 2017 set a new record in emission levels from fossil fuels (International Energy Agency, 2018). This results from a small number of sectors emitting high levels of CO_2, where transportation accounts for a significant part (26% in Europe 2015). In the transport sector, cars are mainly responsible: 12% of total CO_2 emissions within the EU came from cars in 2016. As a result, the EU has set several targets to decrease emissions. In 2010, the EU launched the Europe 2020 Strategy*,* with a target of 20% lower greenhouse gas emissions compared to 1990 levels. In 2030, the goal is a 40% reduction compared to 1990, according to the EU's 2030 climate & energy framework. In 2015, 196 countries agreed to the Paris Agreement – an agreement within the United Nations Framework Convention on Climate Change (United Nations, 2018). Similarly, several nations have set individual goals. Sweden aims to eliminate greenhouse emissions by 2045 and Norway's goal is to cut net emissions to zero by 2030 (European Commission, 2017).

New technologies in the automobile industry have allowed cars to become less CO_2 emissive. Hybrid vehicles became commercially available for the first time in 1997, when Toyota introduced the Prius and Honda the Insight. While internal combustion engine vehicles (ICEVs) are fueled with either gasoline or diesel, hybrids run on two different power sources. Although hybrids achieve lower emissions than ICEVs on average, they do not necessarily guarantee lower emissions. It is still possible to drive hybrids entirely fueled by diesel or gasoline, which is often why consumers choose to purchase hybrids. Battery electric vehicles (BEVs) are entirely driven by electricity, thus they are completely free from emissions from driving. Yet, the net environmental benefit of driving BEVs depends on the country in which the vehicle is used, and specifically that country's electricity production. With carbon intensive electricity production, lifetime CO_2 emissions can be far from zero for BEVs. A recent study has, however, found that BEVs emit less than diesel cars even when powered by the most carbon intensive electricity (European Federation for Transport and Environment, 2017). The study shows that BEVs emit 25% less CO_2 than diesel cars using the average Polish energy mix, which is the highest CO_2 emissive example in the study. In Sweden, BEVs emit 85% less than diesel vehicles on average.

Norway is the country with the highest share of electric vehicles in the world, both when it comes to BEVs and plug-in hybrid electric vehicles (PHEVs). This makes it an interesting market to study. Norway's success can be linked to the country's political decisions. BEV incentives are many; they are varied and generous, and were established in the early 1990s, long before the first commercially marketed BEVs were introduced. Norwegian incentives eliminate the price differences between BEVs and ICEVs. The BEV option often becomes cheaper than the corresponding ICEV. Norway is in many ways an ideal place to introduce BEVs: the population is wealthy, a large share of the households owns multiple vehicles and speed limits are low, leading to longer range for BEVs (Institute of Transport Economics, 2018). Furthermore, access to home parking is good, and electricity is relatively cheap and supplied by a robust grid.

Since BEVs are less CO_2 emissive than hybrid vehicles, and as Norwegian political initiatives target BEVs rather than PHEVs or hybrid vehicles, BEVs are the most interesting vehicles to study from an environmental perspective. The Norwegian tax exemptions for PHEVs and hybrid vehicles have been drastically reduced in 2018 compared to 2017 (Norwegian Tax Association, 2018). Norwegian initiatives target BEVs specifically, and so does this thesis.

Two types of incentives are traditionally used to stimulate BEV demand. Price incentives are used to make electric vehicles cheaper: e.g. rebates, tax and VAT exemptions. In Norway, BEVs are exempted from purchase tax and VAT. Besides, there are other sorts of incentives that do not affect consumer prices of electric vehicles. These include free parking, toll roads and ferries exemption and bus lane access (Institute of Transport Economics, 2018). Until 2017 free parking for BEVs was mandatory within all municipalities. This was, however, changed: from January 1 2017 municipalities could choose to introduce parking fees for BEVs (Norwegian Electric Vehicle Association, 2016). Only 38 out of 418 municipalities introduced parking fees for BEVs. How the option of removing free parking affected BEV sales in 2017 is indeed interesting, and something we aim to answer in this thesis.

Price subsidies have previously been shown to have a positive effect on electric vehicle purchases, by Springel (2016), among others. This is neither surprising nor revolutionary; subsidies have been used since the Industrial Revolution to promote certain products or manufacturers. However, the effect of other policies - i.e. policies not related to product price – on BEV sales has not been studied as thoroughly. Nevertheless, according to a survey conducted by the Norwegian Electric Vehicle Association (NEVA) in 2017, such policies are deemed important to electric vehicle (EV) owners. In the survey, with around 12 000 EV owners, c. 1500 respondents claimed that free parking was one of the three most important factors for choosing an EV. We argue that the free parking policy, coupled with other non-price related policies, is important in order to increase BEV sales in three ways: (i) it increases the relative advantage for BEV owners, (ii) it decreases lifetime costs of owning a BEV and (iii) it sends important signals to consumers of the government's attitudes regarding BEVs relative to other vehicles.

The main purpose of this thesis is to understand the relationship between the non-price related policy of free parking, and the sales and market shares of BEVs. We will use counterfactual simulation in order to understand the efficiency of the free parking incentives, on BEV sales. We have structured this thesis to answer the following research question:

1. How does the change of the free parking policy for BEVs affect the sales of BEVs?

We contribute to previous research by studying the change in free parking policy in Norway 2017. To our knowledge, the connection between free parking policy and BEV sales has not been studied before. Since the policy was revised in 2017 we are allowed to isolate the policy's effect on BEV sales. Our ambition is to be able to indicate the relevance of free parking, which hopefully can provide guidance on incentives in a fast-growing market.

2. Background

2.1 The Norwegian Market

Norway is well known for its high BEV adoption. With BEVs reaching a market share of 21% in 2017, Norway is the leading country worldwide in terms of BEV adoption. The success of the Norwegian BEV market is often attributed to the country's policies. Norwegian BEV incentives date back to the 1990s, even though the BEV market did not evolve until the introduction of the Mitsubishi i-Miev in 2010 and Nissan Leaf in 2011 (Lorentzen et al, 2017). Figure 1 shows the development of new BEV and non-BEV sales in Norway, from 2010 to 2017.

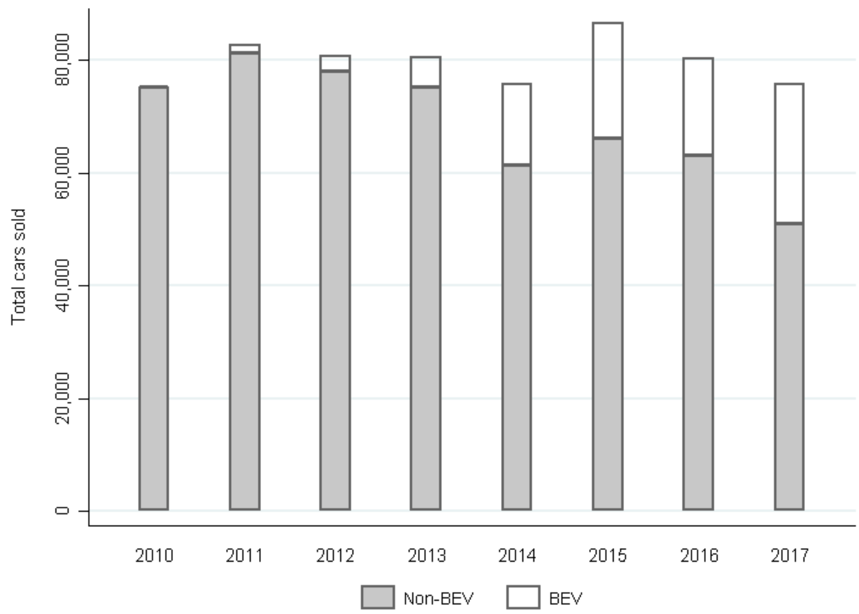


Figure 1: New vehicle sales of BEVs and non-BEVs in Norway (2010-2017), source: OFVAS

From 2010 to 2017 hybrid vehicle sales have increased, from 1 502 in 2010 to 20 184 in 2017. During the same time period gasoline car sales have remained fairly stable, while diesel car sales have dropped every year since 2011. In 2015 diesel cars were the most sold cars among all fuel categories, in 2017 it was the least popular fuel type, except for natural gas and hydrogen. Figure 2 shows sales per fuel type in Norway.

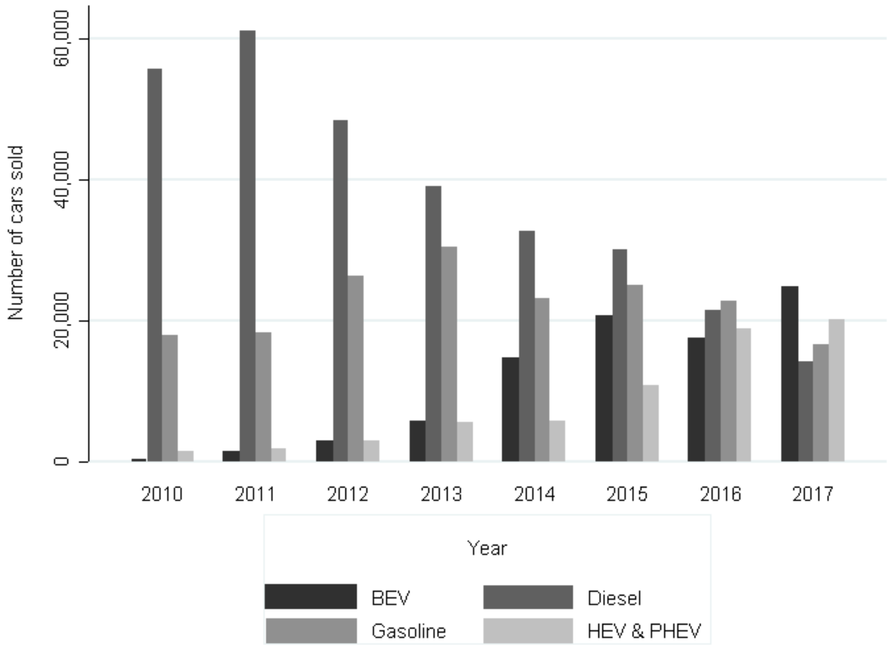


Figure 2: New vehicle sales per fuel type in Norway (2010-2017)[1], source: OFVAS

2.2 Other BEV markets

Other countries with high BEV market shares include Iceland (3.3%), the Netherlands (1.9%), Sweden (1.3 %) and France (1.2%). In terms of volume, China is the largest BEV market worldwide, accounting for more than 55% of the total BEVs sold in 2016 (257 000 BEVs). The total number of BEVs sold was 86 730 for the U.S. and 96 470 for all European countries (International Energy Agency, 2017). Figure 3 shows market shares of BEVs in Norway and in other leading BEV markets in 2016. In Norway, BEV adoption rates are in the double digits. Most other countries have rates shy of 1%.

[1]Hydrogen and natural gas cars have been excluded in this graphic as amount of sales was trivial

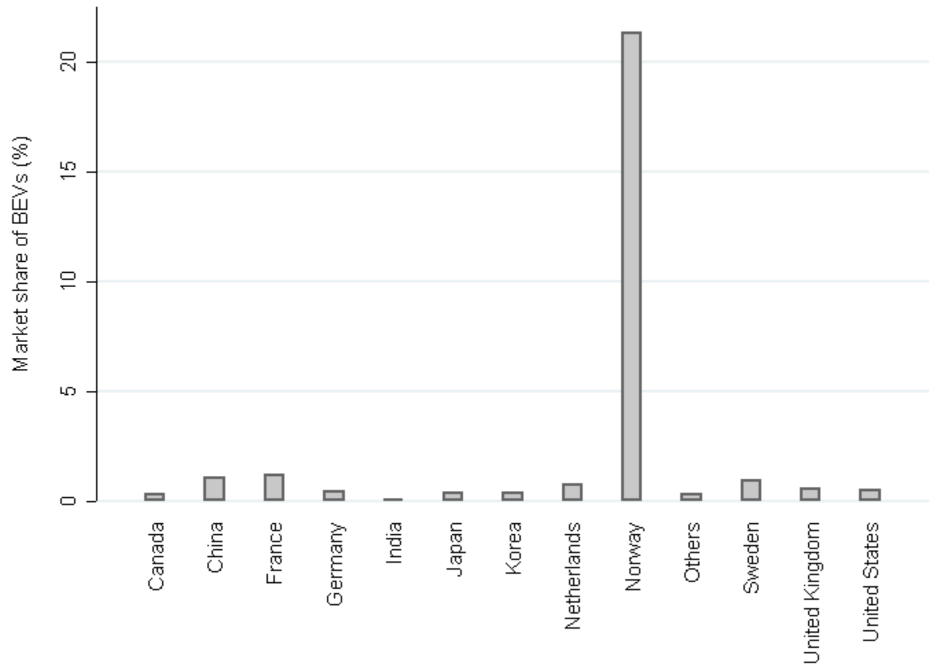


Figure 3: Market Shares of BEVs in 2016, source: International Energy Agency

Political BEV incentives differ between countries. In China, policies include acquisition tax and excise tax exemption (EUR 4 600 to 7 900) as well as circulation and ownership tax exemption. Locally, BEV owners have access to bus lanes, free charging and free parking. In the U.S., BEV consumers enjoy a tax credit, ranging from \$2 500 to \$7 500 (EUR 2 000 to 6 300). In addition, some states have purchase discounts and registration tax exemptions. In Sweden, BEV prices are subsidized with SEK 40 000 (EUR 3 900). In June 2018 a "bonus-malus" scheme will be introduced. The BEV rebate will then be increased to SEK 60 000 (EUR 5 800) and gasoline and diesel cars will be taxed higher (Government of Sweden, 2017). France also has a bonus-malus scheme: BEVs enjoy bonuses of EUR 6 300. The Netherlands offers exemption from registration tax for BEVs as well as ownership tax exemption of EUR 400 to 1 200 (International Energy Agency, 2018).

2.3 Institutional background

In Norway, BEV incentives are officially divided between fiscal incentives, direct subsidies and user privileges. Fiscal incentives aim to reduce purchase prices and yearly costs for consumers. Direct subsidies reduce variable costs and help solving range challenges, while user privileges reduce time costs and provide users with relative advantages. Table 1 shows the universe of BEV incentives in Norway in 2017.

Incentive	Introduction year	BEV buyers: relative advantage	Future plans
Fiscal incentives: Reduction of purchase price/yearly cost gives competitive prices			
Exemption from registration tax	1990/1996	The tax is based on ICEV emissions and weight. Example taxes: VW Up 3000 €. VW Golf: 6000-9000 €	To be continued until 2020
VAT exemption	2001	Vehicles competing with BEVs are levied a VAT of 25% on sales price minus registration tax	To be continued until 2020
Reduced annual vehicle license fee	1996/2004	BEVs and hydrogen vehicles 52 € (2014-figures). Diesel rate: 360-420 €	To be continued indefinitely
Reduced company car tax	2000	The company-car tax is reduced but BEVs are rarely company cars	Incentive may be revised in 2018
Exemption from the re-registration tax	2018	A tax is imposed on the change of ownership of ICEVs and PHEVs. 0-3 year old vehicles above 1200 kg: EUR 610, 4-11 years EUR 370. Older: EUR 160. BEVs have an exemption	Will be introduced from 2018
Direct subsidies to users: Reduction of variable costs and help solving range challenges			
Free toll roads	1997	In Oslo-area saved costs are EUR 600-1 000 per year. Some places exceed 2 500 €	Law revised so that rates for BEVs in toll roads and ferries will be decided by local governments, up to a maximum rate of 50% of the ICEV rate
Reduced fares on ferries	2009	Similar to toll roads; saving money for those using car ferries	
Financial support for normal charging stations	2009	Reduce investors risk, reduce users range anxiety, and expand usage	A national plan for charging infrastructure will be developed
Financial support for fast charging stations	2011	More fast-charging stations increase BEV km driven & market share	ENOVA support program to establish fast charging along major transport corridors. City fast charging is left to commercial actors
User privileges: Reduction of time costs and providing users with relative advantages			
Access to bus lanes	2003/2005	BEV users save time driving in the bus lanes during rush hours	Local authorities have given the authority to introduce restrictions if BEVs delay buses
Free parking	1999	Users get a parking space where these are scarce or expensive and save time looking for a space	Local authorities will be given the authority to introduce rates up to 50% of the ICEV rate (2018)[2]
Free charging (some places)		Not regulated by national law, but often bundled with free municipal parking	Local authorities and parking operators decides whether this incentive will continue.

Table 1: Norwegian BEV incentives in 2017, relative advantages and future plans, source: Institute of Transport Economics

[2] It was decided that, starting in 2018, zero-emission vehicles will not pay more than a maximum of 50% of the tariffs for conventional vehicles for tolls, ferries and parking (Stortinget, 2017).

The Norwegian fiscal incentives started in 1990 with the exemption from registration tax, based on emissions and weight (Institute of Transport Economics, 2018). From 1996 onward, reduced annual vehicle license fees apply to BEVs and hydrogen cars. Company car tax was reduced for BEVs in 2000. Since 2001 BEVs are exempt from VAT. Two examples of how these tax components affect retail prices for BEVs and ICEVs are given in tables 2 and 3. In 2018, exemption from re-registration tax when changing the ownership of a car will be introduced. Both registration tax and VAT exemption will continue until 2020, at least. The reduced annual license fee will continue indefinitely while the reduced company car tax may be revised already in 2018.

Tables 2 and 3 present examples of price differences between BEVs and ICEVs due to Norwegian incentives. In Table 2 Volkswagen Golf and Volkswagen e-Golf are compared. Even though the import price is 44% higher for the e-Golf, its retail price is lower than the corresponding ICEV Golf.

	Volkswagen Golf	**Volkswagen e-Golf**
Model	1,0 TSI 110hk Business line	Exclusive
Import price (NOK)	180 624	259 900
CO2 tax (NOK)	31 827 (109 g/km)	0
NOx tax (NOK)	2 263 (31.9 mg/km)	0
Weight tax (NOK)	21 526 (1162 kg)	0 (1510 kg)
Scrapping fee (NOK)	2 400	2 400
VAT (25%)	59 660	0
Retail price (NOK)	298 300 (EUR 31 263)	262 300 (EUR 27 446)

Table 2: Price differences due to BEV policies: Volkswagen Golf vs e-Golf, 2017, source: OFVAS

In a more extreme example, Figure 3 shows the difference in prices between an Audi A7 and a Tesla S 75D in 2017. Despite the Tesla being nearly twice as expensive in terms of import price, its retail price is cheaper than that of the Audi A7. As can be seen, Norwegian incentives eliminate the price differences between BEVs and ICEVs.

	Audi	Tesla
Model	A7 2,0 TFSI 252hk Quattro aut	Model S 75D 4WD
Import price (NOK)	319 464	636 000
CO2 tax (NOK)	125 253 (157 g/km)	0
NOx tax (NOK)	1 525 (21.5 mg/km)	0
Weight tax (NOK)	109 198 (1720 kg)	0 (1510 kg)
Scrapping fee (NOK)	2 400	2 400
VAT (25%)	139 460	0
Retail price (NOK)	697 300 (EUR 73 017)	638 400 (EUR 66 849)

Table 3: Price differences due to BEV policies: Audi A7 vs Tesla S75D, 2017, source: OFVAS

Direct subsidies were introduced in 1997, when toll roads became free of charge. In 2009 fares on ferries were reduced for BEVs. The same year, financial support for normal charging stations was introduced. In 2011 similar support was introduced for fast chargers, which have higher effect than normal chargers.

From 2003 BEVs are granted access to bus lanes. Local authorities have been given the authority to infer restrictions if BEVs cause delays for buses. In Oslo, bus lane access now requires carpooling with another passenger during rush hours, following a decision in 2015 (Norwegian Electric Vehicle Association, 2018).

2.2.1 Free parking

In 1999 parking became free of charge for BEVs in all Norwegian municipalities. On March 18 2016 the Norwegian government developed a new regulation for parking: municipalities were allowed to determine whether electrical vehicles should park for free or pay partly/fully, made valid from January 1 2017. As a result, some municipalities kept offering free parking, some introduced a 50% rebate for parking (in relation to ICEVs) and others decided that EVs should pay the same fee as any other car for parking. Reasons for the decision to stop offering free parking include EVs taking up too many parking spaces and willingness to prioritize other means of transport (public, bikes, walking). Further, as the installed base of BEVs in Norway has increased, arguments have been brought forward that EVs now contribute to congestion and have a need for greater space compared to other means of transportation.

Figure 4 presents results from a survey made by the Norwegian Electric Vehicle Association on the top three most important incentives according to EV owners. Approximately 1 500 out of 12 000 EV owners – 13% – believed that free parking was among the three most important incentives.

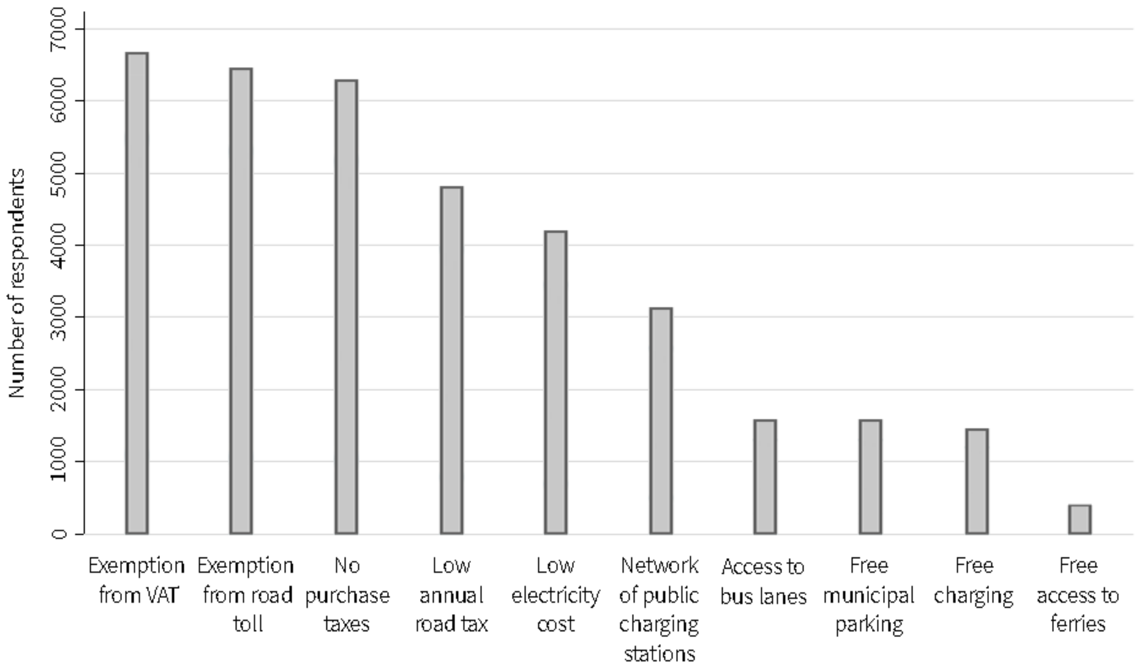
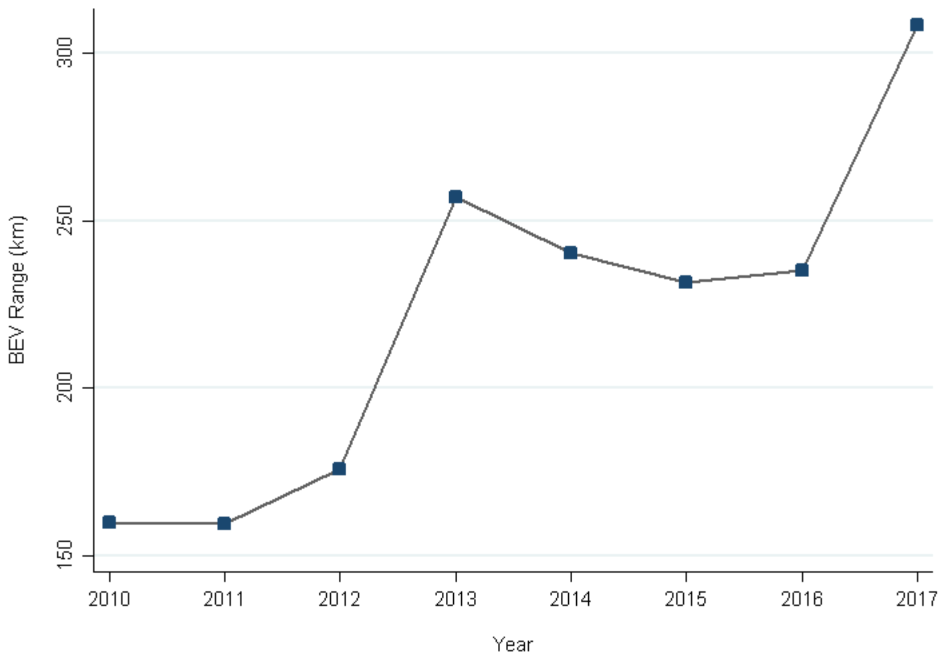


Figure 4: Most important EV incentives according to Norwegian EV owners, source: NEVA

In 2017, 38 out of 418 municipalities decided to start charging BEV owners for parking. A majority of the municipalities commenced on January 1 while some started later in 2017. The rest of the municipalities kept offering free parking in 2017.

2.4 Range

One evident difference between ICEVs and BEVs is range. On average, range is shorter for BEVs. Although recent technology has improved BEV ranges they are not yet in the likes of cars of other fuels. In 2016 small and mini vehicles had ranges of 150 – 230 km and compact vehicles of 160 – 280 km. Tesla cars had ranges of 400 – 550 km, but are also more expensive than most BEVs (Institute of Transport Economics, 2018). Figure 5 shows the average range of sold BEVs from 2010-2017. Average range increased from 160 km in 2010 to 308 km in 2017



. *Figure 5: Mean range of sold BEVs in Norway, 2010-2017, measured as NEDC, source: OFVAS*

Range is measured according to the New European Driving Cycle (NEDC) in Europe, which has been subject to criticism. The NEDC test is built on a theoretical driving profile, based on driving in the 1980's, when the test was designed. The weaknesses in the measure has been noted by the EU as it plans to switch to another measure called WLTP in 2018 (European Automobile Manufacturers Association, 2017). One particularly aggravating flaw of the NEDC is that the range resulting from the test is unrealistic, due to the very nature of the test. For instance, average speed of the test is 34 kilometer per hour, and the maximum speed is 120 km/h. WLTP will instead use an average speed of 46.5 km/h and a top speed of 131 km/h. Table 4 shows main differences between NEDC and WLTP test procedures. In general, the NEDC test fails to take into account factors important to range, namely driver habits and driving conditions.

	NEDC	**WLTP**
Test cycle	Single test cycle	Dynamic cycle more representative of real driving
Cycle time	20 minutes	30 minutes
Cycle distance	11 km	23.25 km
Driving phases	2 phases, 66% urban and 34% non-urban driving	4 more dynamic phases, 52% urban and 48% non-urban
Average speed	34 km/h	46.5 km/h

Table 4: Main differences between NEDC and WLTP test procedures, source: ACEA

Further, temperature has a large effect on BEV range. Cold temperatures decrease range significantly. For instance, a report from the American Chemical Society suggests that cold winters may decrease the range with 40% compared to the maximum range achievable with the same vehicles (American Chemical Society, 2015). Hence temperature is an important factor when driving a BEV.

2.5 Charging stations

In order to mediate range anxiety for BEV drivers, an extensive network of charging stations is important. Although most BEV owners charge their vehicles at home – according to a study made by the Institute of Transport Economics 94% of BEV owners do – charging infrastructure allows for longer travel distances and more flexibility (2018).

Charging stations have been subject to governmental support in Norway. In 2009, the first support scheme for public charging subsidized installation costs for normal chargers. From 2010-2014 a similar scheme supported installation costs for fast chargers. Figure 6 shows the monthly number of charging points from 2010 to 2017.

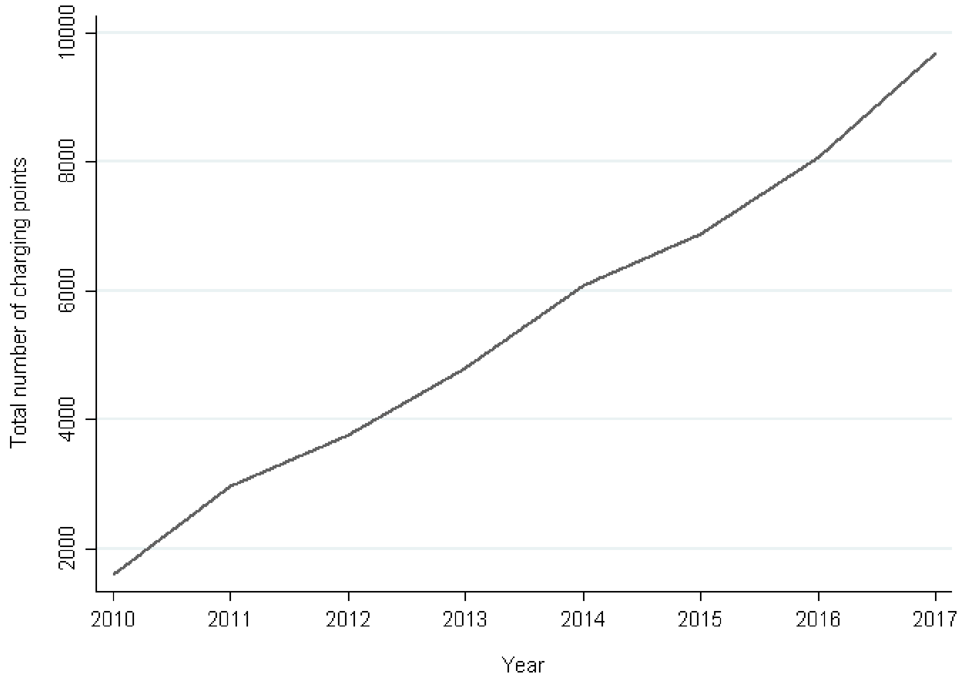


Figure 6: Development of charging network in Norway 2010-2017, source: Nobil

Figure 7 shows that the number of charging points and cumulative BEV sales are positively correlated. As of 31 December 2017, there were 9 246 publicly accessible charging points in Norway. Corresponding figures for Sweden and Iceland were 4 071 and 114 respectively. Norway has more than twice as many public charging points than Sweden, even though Sweden's total area is larger (17%) and population is almost twice as big (91 %).

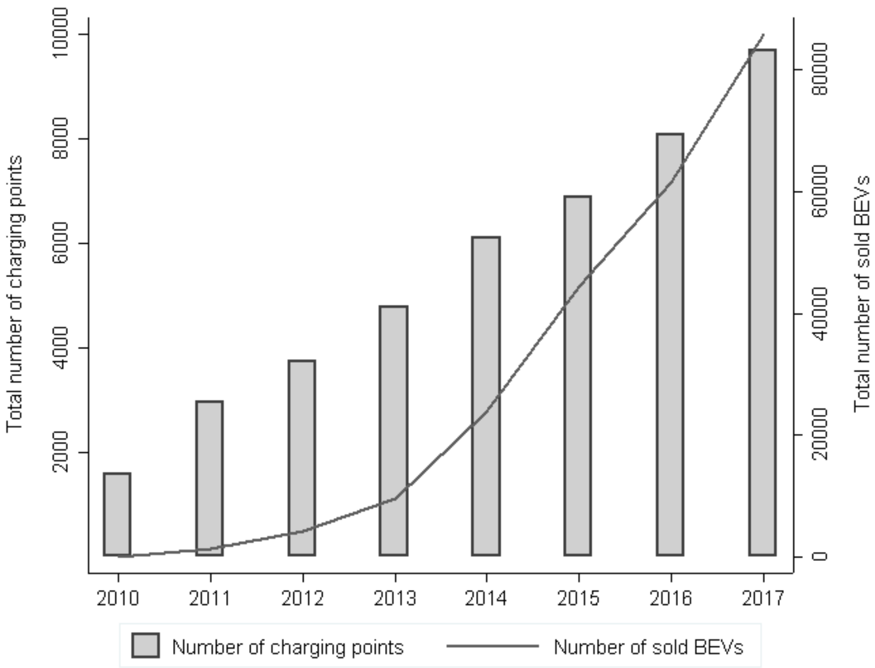


Figure 7: Number of Charging Points and Cumulative BEV Sales in Norway, source: OFVAS

Charging outlets are divided into three types: normal, semi-fast and fast. Normal outlets have effects from 0 to 21 kW, semi-fast chargers range from 22 to 40 kW and fast chargers have effects above 40 kW. Higher kW effect translates into faster charging per kilometer of range. Figure 8 shows the distribution between the three charging outlet types in 2017. Normal chargers account for the majority of outlets.

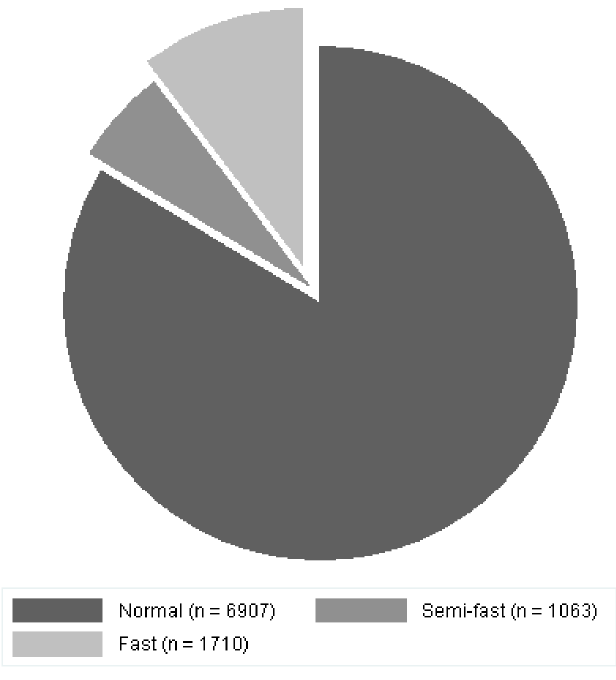


Figure 8: Charging outlets per type, 2017, source: OFVAS

3. PREVIOUS LITERATURE

Looking for a suitable econometric model to be able to estimate demand from vehicle sales and attributes data, we have encountered a rich set of literature. We find literature about vehicle demand and vehicle choice in various geographical locations. Further, we study papers about governmental initiatives and subsidies on different alternative fuel vehicles, and their effect on sales.

3.1 Vehicle choice

Train and Winston (2007) study vehicle choices of consumers in order to understand the decreasing market shares of American car producers. They use consumer level data on car sales, which includes vehicle attributes as well as consumer attributes. Train and Winston consider unobserved variation in tastes. They address that unobserved taste variation could affect more than what car a certain consumer chooses; it might also affect whether a consumer buys a new car at all. The writers criticize the approach taken by Berry (1994) and Berry, Levinsohn and Pakes (1995, from now on BLP). As we develop in section 5.2, BLP introduce an "outside good", representing all the alternatives a consumer has to buying a new car, namely buying a used car or not buying a car at all. Train and Winston (2007) believe that the modelling of other alternatives as an outside good, done by BLP (1995) is problematic as characteristics cannot be attributed to them, even though they are likely to affect the very choice. They argue that it is difficult to specify attributes to the outside good, and that unobserved consumer tastes will have an effect on assessments of the outside good, not only the "inside good". As a result, Train and Winston study vehicle choice of consumers that have chosen to buy a car. They do not account for the possibly changing market sizes, as they study the market shares of sold cars only. Instead, they examine the distributions of preferences on a sample of new vehicle consumers, with the help of a customized survey. The results show that the market share loss of American car manufacturers can be almost entirely explained by relative changes in basic characteristics, namely size, price, transmission type, body style, reliability, operating cost and power. Their findings indicate that common concerns about the effect of unobserved characteristics on vehicle demand and vehicle choice are overrated, as the effect on consumer vehicle choice is unimportant. We acknowledge the findings, but are not able to make a similar study as we do not have such detailed data.

3.2 Government initiatives and alternative fuel vehicles

Pavan (2015) studies the effectiveness of a subsidy to consumers for alternative fuel vehicles to that of a subsidy to gas stations installing pumps for the same fuels. She estimates a joint model of demand for green cars and supply of alternative fuels. The data used is from the Italian market and includes consumer new car sales at municipality level, car characteristics as well as locations and characteristics of filling stations. Pavan finds that price rebates are efficient in increasing adoption of alternative fuel cars. Yet, as it has an indirect effect on pump density, this implies that the effect would disappear if the subsidies were to expire. As a contrast, subsidies to alternative fuels filling stations show strong effects on both sides of the markets. The effect on the supply side suggests that its impact would be more persistent than that of consumer subsidies.

More closely related to our thesis, Springel (2016) aims to understand which governmental efforts are most efficient in increasing sales of electric vehicles. Springel (2016) models the BEV sector as a two-sided market with network externalities in order to show that subsidies are non-neutral, and to decide which side of the market should be subsidized, choosing the most efficient option. This depends, she argues, on vehicle demand and charging supply primitives. The data set contains new vehicle registry data from Norway – similar to what we have – from 2010-2015. Springel shows that BEV purchases are positively related to subsidies on both sides: price and charging stations. Using counterfactual simulation, she finds that every 100 million Norwegian kroner spent on station subsidies resulted in 835 additional BEV purchases, between 2010 and 2015, in comparison to a state of no subsidies on either market side. The same amount spent on consumer price subsidies resulted in 387 additional BEV sales. But, this relation inverts as spending increases; the impact of station subsidies on BEV sales declines faster than corresponding price subsidies.

Li et al (2016) study the U.S. market for plug-in electric vehicles. The data set consists of quarterly new EV sales and detailed information on public charging stations in 353 Metropolitan Statistical Areas, from 2011-2013. Two equations are estimated: (i) a demand equation that quantifies the effect of the availability of charging stations on EV sales and (ii) a charging station equation, which quantifies the effect of changes to the EV stock on charging station deployment. The authors demonstrate that positive indirect network effects in both EV demand and charging station distribution give rise to feedback loops, which amplify shocks to the system and have important policy implications. Indirect network effects on both sides of the market (cars and charging stations) imply that subsidies on either side will lead to an increase in both EV sales and the number of charging stations. However, Li et al (2016) find that the relative cost-effectiveness of different policies depends on consumer price sensitivity for electric vehicles as well as the relative magnitude of indirect network effects on both sides of the market. Li et al (2016) find that subsidizing charging station deployment is much more cost-effective than the current policy of EV purchase subsidies, given the low price sensitivity of early adopters (EV consumers) and the relative strength of indirect network effects on the EV demand side.

4. Data

We have compiled the data from several independent sources. The main data were collected from Opplysningsrådet for Veitrafikken, OFVAS, a Norwegian member organization working to help politicians and authorities build safer and more efficient roads in Norway.

4.1 Car sales

Market level car sales data were collected from OFVAS, where all new car registrations for consumers in Norway 2010-2017 make up the data. It only includes personally registered vehicles. The data contain number of cars registered of a specific brand, model and fuel type sold in a specific month and year, in a given municipality. With 418 municipalities and a period of 96 months, we end up with a total of 40 128 markets. Some details on product characteristics for the models are included in the data, e.g. engine displacement, fuel type and CO_2 emissions. These characteristics are useful in merging car sales data with price data. The sales data include solely new vehicle purchases, hence used vehicle sales are not included.

4.2 Car characteristics

Data on car characteristics were also obtained from OFVAS, together with the price data. The dataset includes information on fuel type, body style, number of doors, seats and cylinders, horse power, effect (kW), cylinder volume, number of gears, weight, length, CO_2 emissions, fuel economy and price for each car marketed in Norway in a given year and month. The data described is highly detailed, allowing us to match it to the sales data. A small number of models are sold but not included in the price data. The purchase price of a model is defined as the manufacturer's suggested retail price (MSRP) less related subsidies, namely purchase tax exemptions and other types of rebates discussed in section 2.2.

Data on range for electric vehicles has mainly been collected from OFVAS, and is specified per vehicle model and year. For the relatively small amount of BEV models in our data set that did not include range, we have manually collected the data from multiple sources: Gröna Bilister, a Swedish independent non-profit organization, Allt om Elbil, a meeting place for environmentally interested consumers and eGOtrip.se, a Swedish website for route planning with electric vehicles.

4.3 Charging stations

Data on charging stations was collected from the charging station database Nobil, and includes information on the number of charging stations (and outlets) in Norway, specified with the opening date of all stations and the corresponding coordinates. Characteristics for stations include location type, if the station was financially supported by the state or by a municipality, and the type of each outlet. From this data we are able to single out outlets with different effects: normal, semi-fast, and fast chargers. A small number of stations are marked as inactive in the data set. As the date and time of the closings are not specified, these stations are dropped.

4.4 Fuel and electricity prices

Fuel and electricity prices are collected from Statistics Norway and are specified by national monthly average prices.

4.5 Free parking

Data on parking fees for BEVs for 2017 has been collected from three different sources:

i) The Norwegian Electric Vehicle Association for 54 municipalities

ii) Directly from the municipalities for 82 municipalities

iii) Statistics Norway for 318 municipalities, where the number of paid parking spots are specified. These have only been used for municipalities where the number of paid parking spots equal zero in 2017, as this per definition means that BEV parking is free

Although a majority of the municipalities that chose to introduce payment set parking prices equally for BEVs and ICEVs, some introduced lower fees for BEVs. In this paper, we treat decisions to charge 50%, 100%, and other fees equally, as all options de facto remove free parking.

4.6 Demographic variables

Variables describing the demographic background of each market are collected from Statistics Norway and include population size, population density and income levels. We also obtain the number of households in each market, which is used to define market sizes.

4.7 Additional data

We collect weather data as the range of BEVs is affected by temperature. Data includes daily maximum, minimum and average temperatures. Besides, data on whether it snowed or not on a certain day is included. The data is collected from eKlima, a portal giving access to the climate database of the Norwegian Meteorological Institute. Consumer price index (CPI) is collected from Statistics Norway, and is used to deflate car, fuel and electricity prices.

4.8 Summary statistics

Table 5 shows descriptive statistics. We present means for the variables used in the empirical analysis. Drive train takes on the values 1 and 2 for two and four-wheel drive. Transmission does the same: the value 1 is for manual transmission, a '2' indicates automatic transmission.

Year	Models	Price	Engine displacement	Length	Weight	Fuel economy	HP	Drivetrain (1-2)	Transmission (1-2)
2010	226	317 542	1742	440	1396	0.56	120	1.27	1.30
2011	223	317 618	1697	439	1393	0.53	120	1.26	1.32
2012	250	331 808	1690	440	1397	0.53	125	1.29	1.40
2013	265	332 647	1674	440	1390	0.52	129	1.35	1.49
2014	267	341 332	1580	441	1411	0.47	135	1.37	1.59
2015	274	350 412	1525	442	1433	0.44	142	1.41	1.70
2016	281	384 623	1553	446	1478	0.42	158	1.43	1.79
2017	301	404 506	1469	448	1520	0.38	166	1.42	1.87

Note: the table shows yearly descriptive statistics for main variables and product attributes. The models column shows the total number of distinct models sold per year. All other statistics are yearly sales weighted means.

Table 5: Summary statistics

From 2010 to 2017 number of models, price, length, weight and horse power have increased. Simultaneously, mean engine displacement and fuel economy have decreased. The trend is moving towards four-wheel drive and automatic transmission for the last eight years.

5. Method

5.1 Background

In order to measure the demand for vehicles, and specifically the effects of free parking on vehicle demand, we must define a suitable econometric model. There are particular attributes of the car market that need to be considered. A car is a differentiated product, meaning that demand could be determined by factors other than price. Besides, cars have unobserved characteristics that cannot be seen by the econometrician; e.g. style and reputation. Hence, we may not be able to capture all demand factors determining car market shares.

We will use a discrete-choice model since it is not possible to buy a fraction of a car. Usually, non-continuous models are modeled using the cumulative distribution function, the most common model being the logit model (Gujarati, 2003). Drawing on Berry (1994), we will use a standard instrumental variables regression that allows estimation of the logit although still allowing for unobserved characteristics.

5.2 Model definition

Our model consists of M regions and T time periods, which gives us M*T markets. Each market holds N_{mt} firms who sell one product each. The product, *j*, is a certain model of a certain brand with a certain fuel type (e.g. Volvo V40 Diesel), sold in market *mt*. In our model, the firms are assumed to be price-setting oligopolists. The implication is that firms will face a steeper demand curve than if the market would have been perfectly competitive. Observed characteristics, including price, are denoted x_{jmt}, for product *j* in market *mt*. The unobservable characteristics are denoted ξ_{jmt} and are assumed to be mean independent of the observed characteristics in a given market, as well as independent across markets.

Following Berry (1994), demand will be estimated using a utility function. In our model, each person in a given market will choose to purchase the car that maximizes that same person's utility. Both individual preferences and product characteristics affect the level of utility the consumer receives.

The consumer chooses between buying an inside good (*j* = 1,…, J) from one of the firms or the alternative outside good (*j* = 0). The outside good constitutes the option to buy a used car or not to buy a car at all. The price of the outside good is assumed to be uncorrelated with the price of the inside good. Insertion of the outside good guarantees that the total demand for cars is not perfectly inelastic.

The utility of consumer *i* from consuming product *j* in market *mt* is specified as

$$u_{ijmt} = \tilde{\beta}_{ijmt} x_{jmt} + \xi_{jmt} + \epsilon_{ijmt} \tag{1}$$

where the consumer specific taste parameters are $\tilde{\beta}_{ijmt}$ and ϵ_{ijmt}. The term ξ_{jmt} can be thought of as the mean of the consumers' valuations of an unobserved product characteristic, e.g. product quality and ϵ_{ijmt} represents the distribution of consumer preferences about this mean. Assuming the error term, $\epsilon_{ijmt,}$ to be mean-zero, we are given the mean utility level, δ, of product *j* in market *mt*[3]

$$\delta_j = \beta x_j + \xi_j \tag{2}$$

As we lack data on individuals and their respective preferences, we will use the market level data to estimate the market shares of the firms and products based on their respective mean utilities. Without individual data we cannot observe ξ. The unobserved product characteristics will constitute the error term alone. The market share function is defined with the multinomial logit formula, where market share of product *j* is given by

$$\xi_j(\delta) = e^{\delta j} / (\textstyle\sum_{k=0}^{N} e^{\delta j}) \tag{3}$$

With the mean utility of the outside good normalized to zero we can compute the mean utility of a product, based on observed market shares, as

$$\ln(s_j) - \ln(s_0) = \delta_j = \beta x_j + \xi_j \tag{4}$$

[3]The subscript *mt* will from here on be left out to facilitate the reading

where s_j is the market share of firm *j* and s_0 the market share of the outside good (*j* = 0). This can be re-written as

$$\ln(s_j / s_0) = \delta_j = \beta x_j + \xi_j \tag{5}$$

where $\ln(s_j / s_0)$ is an expression for consumer mean utility

5.3 Regression Equation

Our regression equation is formulated as

$$\ln(s_j / s_0) = \alpha + \beta_1 PF*BEV + \beta_2 \ln(CA*BEV) + \beta_3 x_j + y_j + \xi_j \tag{6}$$

where PF represents the parking fee dummy, taking on the value 1 for municipalities that inferred parking fee for BEVs in 2017, integrated with a BEV dummy, CA represents charging availability integrated with a BEV dummy in order to estimate the availability effect on BEVs specifically, x contains the price and a number of product characteristics and y contains various fixed effects. The effective purchase price of a product *j* is defined as the manufacturer's suggested retail price (MSRP) minus the subsidies affecting the product.

One considerable flaw of the regression equation (6) is that the price variable is likely to be correlated with the error term. Later, we address this using instrumental variables.

5.4 Variables

5.4.1 Charging stations

We apply four different measures of charging station availability. All measures are interacted with a BEV dummy, as we aim to understand the effect of charging station availability on BEV market shares. The following measures are used:

Measures for charging stations	Variable names
Number of charging points within 200 kilometers (~124 miles)	log_n_cp_200km_dBEV
Number of charging points within 100 kilometers (~62 miles)	log_n_cp_100km_dBEV
Number of charging points within 50 kilometers (~31 miles)	log_n_cp_50km_dBEV
Number of charging stations per municipality	log_n_cp_muni_dBEV

The effect of having a given amount of charging points within a municipality on BEV demand could depend on the municipality's size, among other things. Therefore, the amount of charging points within a certain radius could be more important to consumers. We believe that BEV owners care about charging stations within reachable distances. However, we are unsure of how such a reachable distance should be specified. We therefore compare the effect of the number of charging points within four different distances. First, we use 200 kilometers as a measure, as BEV ranges usually are between 150 and 280 kilometers. We then try the measure of 100 kilometers. Further, with similar logic, we add the measure of total number of charging points within 50 kilometers. We use the coordinates of the charging points and the mean coordinates of all zip codes in a certain municipality in order to create the three measures described. All three availability measures are logged and interacted with a BEV dummy, which allows the effect of charging station availability on BEV demand to be diminishing.

5.4.2 Fixed effects

We choose to include a combination of fixed effects. Time fixed effects are included in order to capture time specific events that possibly could affect the results. For instance, consumers could be less willing to purchase BEVs in colder months. We also include regional fixed effects to account for regional differences. Brand fixed effects capture unobservable preferences for specific brands not related to included exogenous car characteristics. Vehicle model fixed effects control for unobserved product characteristics, e.g. reputation and brand loyalty that affect consumer demand. Fuel fixed effects are included to capture differences between the different fuel types.

5.4.3 Car characteristics

Product characteristics believed to be relevant for vehicle choice are included in the regression. These are sales price, CO_2 emissions, number of doors, number of cylinders, kerb weight, engine displacement (cylinder volume), engine effect (HP) and (inverse) fuel economy. Fuel economy is measured as liters consumed per 10 km.

5.4.4 Population characteristics

Characteristics are: population, median income and population density. These are used to control for demographic differences across regions.

5.4.5 Parking fee for BEV's

The parking fee dummy is set to 0 for all municipalities that kept offering free parking for electric vehicles in 2017. Until January 1 2017 this dummy will be 0 for all observations. From the start of 2017, observations within municipalities that changed policy will take on the dummy value 1. The coefficient is integrated with a BEV dummy, as this paper focuses on the effect on the change in policy on BEVs.

5.5 The market

In order to go from observed quantities to observed market shares we must define the size of our market, M_{mt}. Following BLP (1995), we use the total number of households to constitute the potential market, which are potential buyers of a new car. It is, however, not likely that households buy a new car each month. We assume that households (consumers) buy a car every fifth year. This means that we will divide the number of households by 60 for all observations (12*5). The market share of the outside good for each market is calculated as the residual; one minus the sum of shares of all products sold in the specific market.

5.6 Instrumental variables

Unobserved product characteristics include everything that consumers can observe, but the econometrician cannot; quality, safety, style etc. If producers know these attributes prices are likely to be correlated with them (BLP 1995). In the vehicle demand literature it is well documented that failing to control for unobserved product characteristics could result in downward price coefficient estimates, for instance Berry et al. (1995). If prices are endogenous, the risk is unrealistically high own-price elasticities. This issue can be addressed using instrumental variables. By choosing a set of instrumental variables correlated with the endogenous variable – price – but uncorrelated with the error term (unobserved product characteristics), we should be able to alleviate the problem of endogeneity.

The method is divided into two regressions, called two-stage least squares (2SLS). In the first stage, the instrument is an independent variable and the endogenous variable – price – is the dependent variable

$$p_j = \pi_0 + \pi_1 z + \pi_2 PF*BEV + \pi_3 \ln(CA*BEV) + \pi_4 x^*_j + y_j + \xi_j \tag{7}$$

where p = price, z = instrument and x* are the controls as before, in (6), except for the price. The second stage regression is almost equal to the first one, the difference being that the price variable is replaced by the fitted values from the first stage regression

$$\ln(s_j / s_0) = \alpha + \hat{p_j} + \beta_1 PF*BEV + \beta_2 \ln(CA*BEV) + \beta_3 x^*_j + y_j + \xi_j \tag{8}$$

Following BLP (1995), we will use three instruments for each exogenous car characteristic:

i) The car characteristic itself
ii) The sum of the characteristic across all own-firm products
iii) The sum of the characteristic across competitors' products

We run the specifications above for the three instruments in search for optimal instruments. We then use the same algorithm to create instruments from the average of characteristics. We want the price elasticity to be negative as price and demand are negatively correlated. Similarly, the absolute value of elasticity should be above 1; the demand of a car should be elastic.

Although we include a rich set of control variables, the EV charging station variable is endogenous. Unobserved demand shocks could still affect charging station investment decisions and thus the number of charging stations. To deal with the endogeneity we need to find a suitable instrument correlated with the number of charging points in a municipality, but uncorrelated with the unobserved shocks to EV demand. As an instrument for number of charging points we follow Li et al (2016), using the interaction term between the number of restaurants in a municipality with the number of charging points in all municipalities except for the very municipality corresponding to a certain observation (lagged by one month). Li et al (2016) lag by quarters instead, as their data is specified per quarter. They also use grocery stores and superstores, not restaurants. As the number of restaurants is rather stable during our sample period it gets absorbed by the municipality fixed effects. In order to allow for temporal variation we multiply the amount of restaurants with the lagged number of charging points in other municipalities, capturing the national level trend in charging point investment due to aggregate shocks. As mentioned by Li et al (2016), the construction of the instrument variable is similar to the Bartik instrument used in the labor literature to isolate local labor demand changes (Bartik, 1991).

We argue that restaurants should be correlated with charging points as the latter often are located in the proximity of the former. For instance, 918 out of the 10 278 charging points in Norway are located by a restaurant/hotel. We also argue that instrumenting with restaurants should satisfy the exogeneity assumption as the number of restaurants is unlikely to directly affect BEV sales. Common unobservables might exist that influence both BEV sales and the number of restaurants. As our model controls for regional fixed effects the time-invariant unobservables should be captured.

5.7 Nested logit

A shortcoming of the logit model is that it tends to produce unrealistic cross-price elasticities. This happens as it is unable to relate the cross-price elasticity between the two products to their difference in attributes. Two vehicles with identical market shares will be assumed to have identical substitution patterns in the logit, which is unrealistic. A common way of addressing this problem is the usage of a nested logit model. With the nested logit all cars are divided into different classes, or nests, and the market share of the cars within the own nest is added to the model as an explanatory variable. The nested logit model allows a consumer's preferences for a car j in market mt to be correlated with other cars from the same group. This creates aggregate demand functions with relatively reasonable substitution patterns – compared to the simple logit model - allowing for localized competition between cars from the same nest. In our aggregated nest model, we try different combinations of groups and subgroups, as well as non-aggregated group nests only. First, we define the group as car segment (defined as body style) and the subgroup as fuel type. Then, we define the group as fuel type and the subgroup as car segment. Lastly, we define the model as a single-level nested logit considering only cars within the same fuel type or segment closer substitutes than other cars. We add the nest shares as explanatory variables to the model. The estimating equation for the two-level nested logit is specified as

$$\ln(s_j / s_0) = \alpha + \beta_1 PF*BEV + \sigma_1 \ln(s_{j|hg}) + \sigma_2 \ln(s_{h|g}) + \beta_2 \ln(CA*BEV) + \beta_3 x^*_j + y_j + \xi_j \tag{9}$$

Where the variable s_j is the market share of a product *j* in the potential market, $s_{j|hg}$ is the market share of the product *j* in its subgroup *h* of group *g* and $s_{h|g}$ is the market share of subgroup *h* in group *g*. A prerequisite for the nested logit to be superior to the original logit, the nest coefficients, σ_1 and σ_2 need to take on values significantly different from both 0 and 1. Besides, the restriction $0 \leq \sigma_2 \leq \sigma_1 \leq 1$ needs to hold (McFadden, 1978).

Market shares may correlate with the unobserved attributes term, ξ_j. Hence we need to instrument the nests, as well. We follow Verboven (1996), adding sums of the other product characteristics by subgroup and group.

If σ_2 approaches σ_1, preferences are equally correlated across all cars belonging to the same group. In this case, we should turn to the single-level nested logit model. The estimating equation for the single-level nested logit is specified as

$$\ln(s_j / s_0) = \alpha + \beta_1 PF*BEV + \sigma \ln(s_{j|g}) + \beta_2 \ln(CA*BEV) + \beta_3 x^*_j + y_j + \xi_j \tag{10}$$

6. Empirical Results

6.1 Ordinary Least Squares logit regression

Table 6 presents the coefficients estimated from an OLS logit regression, using our four charging station measures described in section 5.4. Variables included are price, engine displacement, inverse fuel economy, power/weight, drive train, transmission, length, median income, parking fee integrated with a BEV dummy, range integrated with a BEV dummy, and the four measures for charging station availability. BEV dummies have been integrated with variables where we are interested in seeing a certain effect on BEV demand. The rest of the attributes in the data set have been excluded as they either have been insignificant or correlated with the mentioned attributes.

Table 6: OLS logit regression results

VARIABLES	OLS logit (a) meanutility	OLS logit (b) meanutility	OLS logit (c) meanutility	OLS logit (d) meanutility
vehicle price	-0.000833***	-0.000835***	-0.000839***	-0.000844***
	(2.32e-05)	(2.32e-05)	(2.31e-05)	(2.29e-05)
displacement	2.32e-05***	2.38e-05***	2.29e-05***	2.16e-05***
	(5.20e-06)	(5.20e-06)	(5.18e-06)	(5.13e-06)
inversefuelecon	0.170***	0.168***	0.172***	0.176***
	(0.00837)	(0.00837)	(0.00834)	(0.00825)
power_over_weight	-0.343***	-0.365***	-0.304***	-0.292***
	(0.0709)	(0.0708)	(0.0706)	(0.0698)
2.n_drivetrain	-0.0426***	-0.0423***	-0.0434***	-0.0445***
	(0.00318)	(0.00318)	(0.00317)	(0.00314)
2.n_transmission	-0.0725***	-0.0727***	-0.0718***	-0.0730***
	(0.00206)	(0.00206)	(0.00205)	(0.00203)
length	-7.15e-05	-7.87e-05	-5.30e-05	-9.52e-05
	(0.000138)	(0.000138)	(0.000138)	(0.000136)
medianincome	1.45e-06***	1.42e-06***	1.49e-06***	1.04e-06***
	(1.06e-07)	(1.06e-07)	(1.06e-07)	(1.05e-07)
1.parkingfee_dBEV	0.0820***	0.0770***	0.0985***	-0.0497***
	(0.0110)	(0.0110)	(0.0110)	(0.0109)
range_dBEV	0.000245***	0.000288***	0.000235***	0.000447***
	(8.31e-05)	(8.29e-05)	(8.26e-05)	(8.17e-05)
log_n_cp_200km_dBEV	0.0496***			
	(0.00268)			
log_n_cp_100km_dBEV		0.0200***		
		(0.000868)		
log_n_cp_50km_dBEV			0.0998***	
			(0.00177)	
log_n_cp_muni_dBEV				0.180***
				(0.00166)
Observations	390,337	390,337	390,337	390,337
R-squared	0.873	0.873	0.874	0.876
Mean elasticity	-.2882368	-.2889125	-.2904324	-.2920345
Year-month fixed effects	Yes	Yes	Yes	Yes
Brand fixed effects	Yes	Yes	Yes	Yes
Vehicle model fixed effects	Yes	Yes	Yes	Yes
Fuel fixed effects	Yes	Yes	Yes	Yes
Region fixed effects (muni)	Yes	Yes	Yes	Yes

Note: Dependent variable is meanutility. In column (a) the charging point variable includes all charging points within 200 kilometers from the municipality where a certain car was sold. In column (b) we measure availability as the number of charging points within 100 km. In column (c) the variable includes all charging stations within 50 km. In (d) the variable includes all charging points within the same municipality where a certain car was sold. Standard errors in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Columns (a), (b), (c) and (d) have different specifications. In (a), charging point availability is measured as the total charging points within 200 kilometers from the municipality where a certain car was sold. In column (b) the specification is different: the variable is narrowed down to 100 kilometers. In column (c), charging points are within 50 km. Finally, in column (d) charging availability is measured as the number of charging points per municipality. Regressions in (a) to (d) include a rich number of fixed effects. Year-month fixed effects control for time-varying common unobservables across municipalities. Brand fixed effects capture unobservable preferences for specific brands not related to included exogenous car characteristics. Model fixed effects control for unobserved product characteristics, e.g. style and brand loyalty that affect consumer demand. Fuel type fixed effects are included to capture differences between the different fuel types, for instance their market shares. Regional fixed effects consider regional differences; e.g. differences in preferences for unobservable attributes. The described fixed effects are also present in the coming regressions.

Given the log-log specification, the logged coefficients can be interpreted as elasticities; when regressing the log of one variable on the log of another, the estimate of the coefficient becomes an estimate of the elasticity. Many of the estimated coefficients are intuitive and statistically significant: vehicle demand increases with higher engine displacement, higher inverse fuel economy, higher median income and a lower vehicle price. Yet, vehicle demand decreases with four-wheel drive, automatic transmission and higher power/weight. All estimated coefficients are significant on 1% level except for length. BEV demand increases with longer range. It also increases with an increased amount of charging points for all four measures. As the charging point coefficient is the highest in column (d), we will continue using charging points on municipality level as our availability measure. The charging point coefficient becomes increasingly influential the closer it is narrowed down to where a certain car was sold. OLS results in (d) indicate that a 10% increase in the number of charging stations in a municipality increases BEV demand with 1.80%.

Price elasticities are negative but small, ranging from -0.288 to -0.292. As expected, the OLS logit returns unrealistic price elasticities. When studying the European vehicle market, Goldberg and Verboven (2001) find average own-price elasticities between -3.63 and -6.45. We note, however, that these estimates are from 1990 and acknowledge that the vehicle market and customer preferences may have changed since then. Nevertheless, price elasticities < -1 should be discarded as improbable. To achieve more realistic price elasticities, we try different sets of instruments, suggested by BLP (1995), in an instrumental variables logit regression.

6.2 Instrumental variables logit

Keeping the charging point availability measure in (d) we add instruments to address the endogeneity of vehicle prices in our model. Price is believed to correlate with unobserved product characteristics. We do this as specified in equations (7) and (8). In search for suitable instruments we follow the algorithm suggested by BLP (1995). We try two different styles: in (b) we use the standard BLP instruments, taking the sum of a series of characteristics across the same firm and other firms. In (a) we use the same characteristics but calculate the averages instead. We find the best performing instruments to be the standard BLP instruments – using sum instead of averages - considering the price elasticities. The estimated coefficients are presented in table 7.

Table 7: IV logit regression results

VARIABLES	IV logit (a) meanutility	IV logit (b) meanutility
Instrumented:	vehicle price	vehicle price
Instruments:	AVG BLP	BLP
vehicle price	-0.00158***	-0.0109***
	(8.33e-05)	(0.000132)
displacement	6.01e-05***	0.000550***
	(6.64e-06)	(9.22e-06)
inversefuelecon	0.143***	-0.272***
	(0.00900)	(0.0116)
power_over_weight	0.862***	15.54***
	(0.144)	(0.220)
2.n_drivetrain	-0.00522	0.495***
	(0.00532)	(0.00790)
2.n_transmission	-0.0574***	0.141***
	(0.00265)	(0.00370)
length	0.000332**	0.00576***
	(0.000144)	(0.000183)
medianincome	1.04e-06***	1.04e-06***
	(1.05e-07)	(1.28e-07)
1.parkingfee_dBEV	-0.0475***	-0.0194
	(0.0109)	(0.0134)
range_dBEV	0.000662***	0.00339***
	(8.51e-05)	(0.000107)
log_n_cp_muni_dBEV	0.180***	0.183***
	(0.00166)	(0.00203)
Observations	390,337	390,337
R-squared	0.876	0.815
Mean elasticity	-.5455523	-3.770438
Year-month fixed effects	Yes	Yes
Brand fixed effects	Yes	Yes
Vehicle model fixed effects	Yes	Yes
Fuel fixed effects	Yes	Yes
Region fixed effects (muni)	Yes	Yes

Note: In both columns price is instrumented. The instrumental variables are the average/sum of attributes of cars produced by the own firm and by other firms. In (a) average is used, in (b) sum is used. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Going from column (a) to (b), the coefficient for power/weight increases greatly. Transmission and drivetrain change signs, from having negative effect on mean utility to positive. In IV logit (b) most coefficients are intuitive: car demand increases with higher engine displacement, more power/weight, higher median income and lower price. Now, in contrast to in the OLS regressions, transmission, length and drive train have positive estimates, all on 1% level. Parking fee decreases demand for BEVs, however the coefficient estimate is not statistically significant when instrumenting price with the standard BLP instruments. Charging point availability increases utility for BEV consumers. In IV (b), the price elasticity is considerably lower than in OLS regressions. The price elasticity of -3.77 is in line with previous literature on vehicle demand for the European market. Hence, from OLS regressions to IV regressions car demand has gone from being inelastic to elastic, which is the expected and desired outcome of instrumenting for price endogeneity.

As Li et al (2016) argue, we also need to instrument for charging stations, which are assumed to be endogenous. A suitable instrument should be correlated with the number of charging points in a municipality, but uncorrelated with the municipality and time specific market shares of BEVs. We take advantage of a rich data set of charging stations, which includes information on where stations are located. Out of 10 179 charging points, 1 797 are located by car parks, 548 by gas stations, 1 620 by shopping centers, 4 734 by streets and 918 by hotels/restaurants. We choose to use the number of restaurants as an instrument, as charging points are significantly correlated with number of restaurants at the 1% level. Further, it is highly unlikely that BEV market shares are decided by the number of restaurants in a municipality. We use the total number of restaurants multiplied by the month-lagged number of charging points in Norway as an instrument for number of charging stations.

Table 8 presents the estimated coefficient from the IV regression using the instrument for charging station availability. The regression is almost identical to IV (b), with the only difference being the addition of the instrument for charging points.

Table 8: IV logit regression results 2

VARIABLES	IV logit (c) meanutility
Instrumented:	vehicle price log_n_cp_muni_dBEV
Instruments:	BLP Restaurants
vehicle price	-0.0212*** (0.000274)
displacement	0.00142*** (2.14e-05)
inversefuelecon	-0.797*** (0.0196)
power_over_weight	20.11*** (0.330)
2.n_drivetrain	1.068*** (0.0158)
2.n_transmission	0.389*** (0.00714)
length	0.0122*** (0.000292)
medianincome	1.16e-06*** (1.86e-07)
1.parkingfee_dBEV	-0.216*** (0.0198)
range_dBEV	0.00804*** (0.000178)
log_n_cp_muni_dBEV	0.233*** (0.00487)
Observations	390,337
R-squared	0.611
Mean elasticity	-7.351581
Year-month fixed effects	Yes
Brand fixed effects	Yes
Vehicle model fixed effects	Yes
Fuel fixed effects	Yes
Region fixed effects (muni)	Yes

Note: both price and number of charging points are endogenous. For price, the "classical" BLP instruments are used. For charging stations restaurants are used as instrument. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

When instrumenting for both price and number of charging points all estimates are significant at the 1% level. The estimated parking fee coefficient is now negative, in line with our expectations. Price elasticity is higher than in IV logit (b) and still within reasonable range. However, the coefficient is slightly larger than expected. The physical dimensions of the vehicles have a positive and significant effect on mean utility.

6.3 IV Nested Logit

To further increase the predictive ability of our model and to deal with unrealistic cross-price elasticities, we introduce a nested logit. With the nested logit all cars are divided into different classes, or nests, and the market shares of the cars within the own nest are added to the model as an explanatory variable. In Table 9 we present results from using two nests: segment (body style) and fuel.

Table 9: IV Nested logit regression results

VARIABLES	Nested IV logit (a) meanutility	Nested IV logit (b) meanutility	Nested IV logit (c) meanutility	Nested IV logit (d) meanutility
Instrumented	vehicle price log_n_cp_muni_dBEV nest share	vehicle price log_n_cp_muni_dBEV nest share	vehicle price log_n_cp_muni_dBEV nest share	vehicle price log_n_cp_muni_dBEV nest share
Instruments	BLP Restaurants BLP within nest	BLP Restaurants BLP within nest	BLP Restaurants BLP within nest	BLP Restaurants BLP within nest
vehicle price	-0.0119***	-0.0173***	-0.00749***	-0.00855***
	(0.000171)	(0.000248)	(9.15e-05)	(0.000103)
sigma_1_bsg	0.0271***			
	(0.00352)			
sigma_2_bsg	-0.0185***			
	(0.00447)			
sigma_bsg		-0.0410***		
		(0.00443)		
sigma_1_ftg			0.155***	
			(0.00302)	
sigma_2_ftg			0.183***	
			(0.00336)	
sigma_ftg				0.169***
				(0.00298)
displacement	0.000785***	0.00115***	0.000470***	0.000546***
	(1.39e-05)	(1.93e-05)	(8.33e-06)	(9.10e-06)
inversefuelecon	-0.370***	-0.598***	-0.198***	-0.257***
	(0.0133)	(0.0172)	(0.00955)	(0.0101)
power_over_weight	10.73***	16.11***	7.027***	7.905***
	(0.215)	(0.296)	(0.146)	(0.156)
2.n_drivetrain	0.561***	0.847***	0.311***	0.377***
	(0.00991)	(0.0141)	(0.00579)	(0.00639)
2.n_transmission	0.176***	0.297***	0.0771***	0.101***
	(0.00450)	(0.00632)	(0.00289)	(0.00312)
length	0.00662***	0.0102***	0.00441***	0.00493***
	(0.000215)	(0.000278)	(0.000150)	(0.000156)
medianincome	1.04e-06***	1.07e-06***	1.05e-06***	1.05e-06***
	(1.33e-07)	(1.64e-07)	(1.07e-07)	(1.11e-07)
1.parkingfee_dBEV	-0.145***	-0.191***	-0.102***	-0.109***
	(0.0142)	(0.0175)	(0.0114)	(0.0118)
range_dBEV	0.00463***	0.00657***	0.00324***	0.00365***
	(0.000123)	(0.000159)	(9.09e-05)	(9.52e-05)
log_n_cp_muni_dBEV	0.221***	0.235***	0.213***	0.213***
	(0.00351)	(0.00433)	(0.00280)	(0.00290)
Observations	390,337	390,337	390,337	390,337
R-squared	0.800	0.698	0.871	0.862

Mean elasticity	-4.128777	-5.976053	-2.593459	-2.95886
Year-month fixed e.	Yes	Yes	Yes	Yes
Brand fixed effects	Yes	Yes	Yes	Yes
Model fixed effects	Yes	Yes	Yes	Yes
Fuel fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes

Note: In all regressions price, charging station availability and nest shares are instrumented. Fuel types are gasoline, diesel, BEV, hybrid diesel, hybrid gasoline, PHEV diesel, PHEV gasoline, natural gas and hydrogen. Segments are defined as body styles: coupe, sedan, SUV, cab, station wagon, multi-purpose vehicle, pickup and executive.
Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The four specifications return different estimations. In (a) the group is defined as body style and the subgroup fuel type. The second nest coefficient is negative. To be regarded as an improvement over the logit, the nest coefficients must fall between 0 and 1. In (b) the single-nest coefficient based on body style is negative as well. In (c) the group is defined as fuel type and the subgroup body style. Both nest coefficients are positive, but σ_2 is larger than σ_1, which violates the condition for random utility maximization as presented by McFadden (1978). However, since both regressions where aggregated nests are included show the same pattern of σ_2 approaching σ_1 there is a clear indication that preferences are actually equally correlated across all cars that belong to one of the groups (Verboven, 1996). Comparing (b) to (d), it becomes evident that the only valid assertion we can make is that localized competition arises between cars within the same fuel type but not between those of the same body style. We therefore choose to use the single-nested logit (d) going forward.

In (d) the price elasticity is in line with previous literature: -2.96. The parking fee dummy is still negative and significant. The single nest coefficient – sigma_ftg – falls between 0 and 1 and is significant at the 1% level. It is also significantly different from 0. The relatively small nesting parameter of 0.17 indicates that cars within the same fuel type are not perfect substitutes, but it adds explanatory value to the model while allowing for substitution patterns across fuels. The nested logit (d) is considered an improvement compared to our previous specifications, IV (b) and (c).

6.5 Results from counterfactuals

Using the estimated coefficients from the preferred nested logit version (d), we calculate fitted values for our dependent variable. We then set the parking fee variable to zero for all observations in 2017 and predict the dependent variable again. We assume that the shares of the outside good are not changed by the parking fee. The zero-fee values are subtracted from the fitted values and translated into the change in total numbers sold using the formula:

$$\text{Change in total number of cars sold} = e^{(\text{meanutility+Ufitted1-Ufitted2})} * S_0 * \text{market size} \quad (11)$$

In table 10 we present monthly actual and counterfactual sales, setting the parking fee to zero for all observations in 2017. In total, we estimate that 697 more BEVs would have been sold had the policy remained unchanged.

Table 10: Actual and counterfactual sales, 2017

	Actual BEV sales	Counterfactual sales	Δ%
January	1646	1698	3.14%
February	1359	1400	3.04%
March	2110	2171	2.90%
April	1093	1127	3.10%
May	1582	1628	2.94%
June	2953	3041	2.97%
July	1366	1409	3.13%
August	1981	2039	2.95%
September	2978	3060	2.76%
October	1814	1868	2.97%
November	2014	2067	2.64%
December	3553	3637	2.37%
	24449	**25146**	**2.85%**

In table 11 we set the parking fee dummy to 1 for all observations. In a state where all municipalities had chosen to introduce parking fees, 1 908 fewer BEVs would have been sold.

Table 11: Actual and counterfactual sales, 2017

	Actual BEV sales	Counterfactual sales	Δ%
January	1646	1522	-7.54%
February	1359	1255	-7.64%
March	2110	1946	-7.76%
April	1093	1010	-7.58%
May	1582	1460	-7.73%
June	2953	2726	-7.70%
July	1366	1263	-7.55%
August	1981	1828	-7.72%
September	2978	2743	-7.88%
October	1814	1674	-7.70%
November	2014	1853	-7.99%
December	3553	3261	-8.23%
	24449	**22541**	**-7.80%**

In figures 9 and 10 we show the effects from setting the parking fee variable to 0 and 1 respectively for all municipalities in 2017.

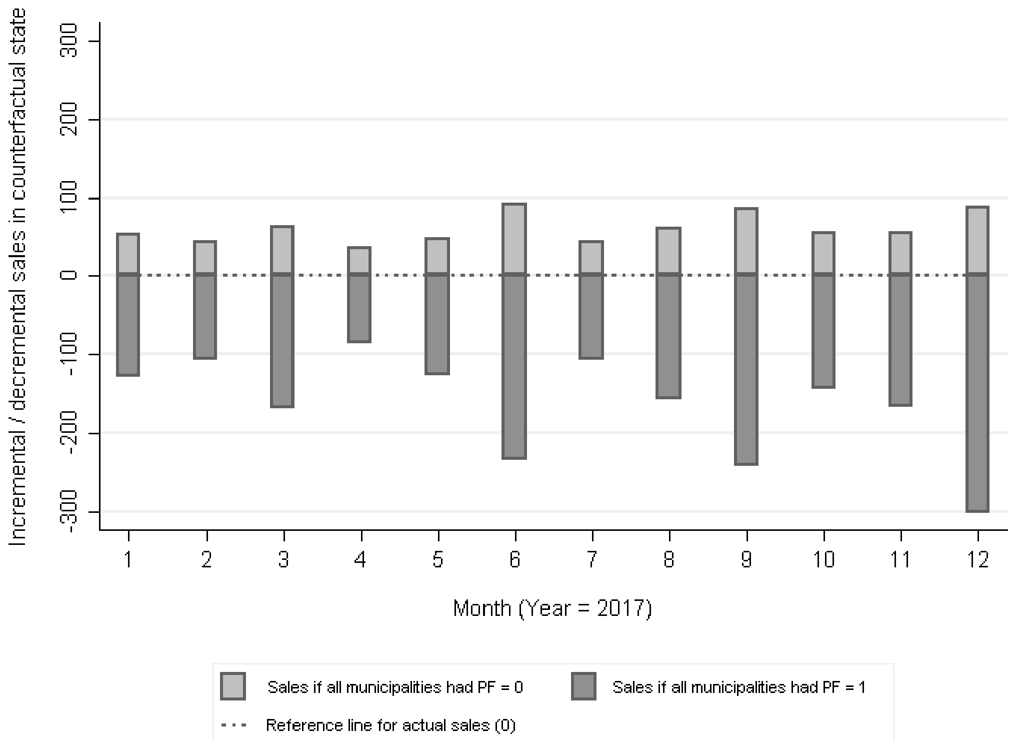


Figure 9: Counterfactual monthly sales with parking fee variable set to 1 and 0 for all municipalities

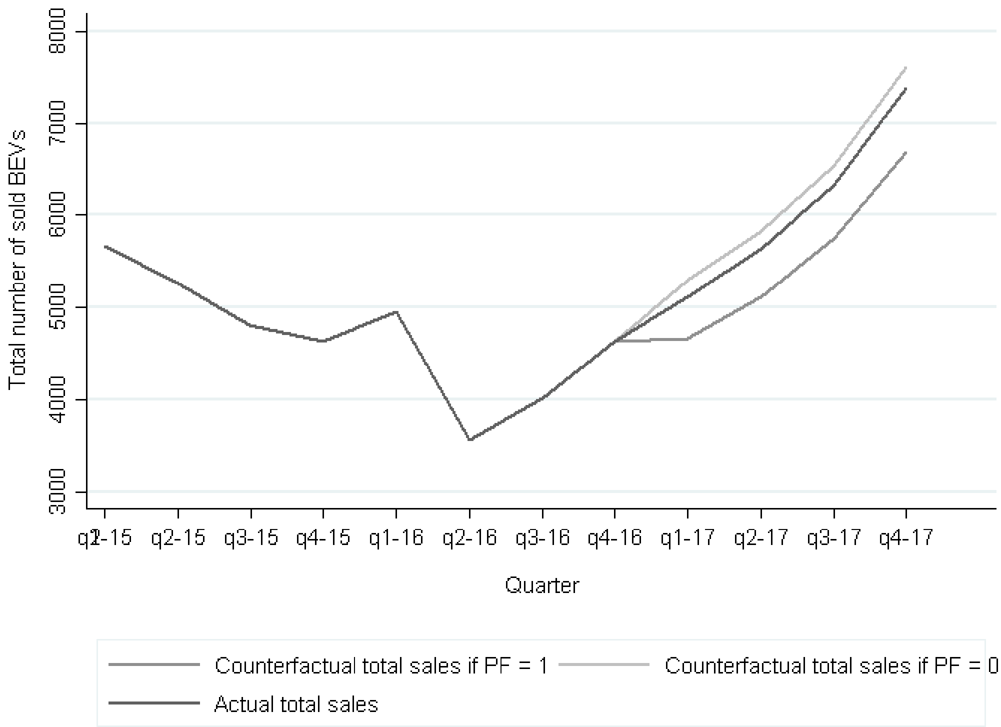


Figure 10: Counterfactual total sales with parking fee variable set to 1 and 0 for all municipalities

7. Interpretation & implications

Our results show that the introduction of parking fee in certain municipalities has had a negative effect on battery electric vehicles sales. The negative relationship is significant at the 1% level. All but one of the coefficients in the nested logit model (d) we present correspond with our prior notion in terms of both direction and size. A puzzling finding of our study is that increased fuel efficiency has a significantly negative effect on demand. This is something we are unable to explain. However, it is line with previous findings, for instance by Pavan (2015).

Using counterfactual simulations we estimate that the change in policy led to 697 fewer BEV sales in 2017 compared to a state of free parking in all municipalities. Even though the impact is relatively small in percentage terms, 2.85%, it is a considerable amount of BEVs seeing the immaturity of the global BEV market. Albeit a far-fetched comparison, a loss of 697 BEVs sold would have translated into a 16% loss of Sweden's BEV sales in 2017.

When simulating a state where all municipalities charged for parking in 2017 we estimate that the lost sales would be 1 908 BEVs, compared to the actual 2017 levels. This translates into a loss of 7.80%. The relative large impact on BEV sales from introducing parking fees for BEVs in all Norwegian municipalities should be put into perspective. It is not realistic that all 418 Norwegian municipalities would change their policy on parking. Some municipalities do not charge for parking at all, and the ones that do might be uninterested in changing policy for multiple reasons: environmental concerns, administrative issues relating to policy changes and resistance to pay for BEV parking by local population, to mention a few. Although we argue that free parking is an important factor when choosing to buy a BEV, the results from the counterfactual simulations are larger than we expected. This suggests that there might be unobserved factors that are included in but distinguished from the *actual* change in parking policy itself that contribute to the total loss in BEV sales. We argue that political signals is an important aspect and that consumers' interpretations of those signals could have a large effect on BEV sales. Consumers in municipalities that chose to act on the opportunity to remove the free parking incentive for BEVs have good reason to question the perseverance of other BEV incentives in that municipality going forward, such as the exemption from road tolls and bus lane access, which might make these consumers less inclined to purchase a BEV.

This is particularly interesting as it is well known that incentives are used in Norway to increase BEV adoption in a limited time period; they will not last forever. For instance, VAT and purchase tax exemption will continue until 2020. What happens after that is uncertain. Changes in price related policies are of a different nature than non-price related policies. They only affect the vehicle price. Non-price related policies affect the lifetime value and the relative advantage of owning a certain vehicle. Hence, changes in non-price related policies might have a larger effect on consumers' long term attitude toward BEVs.

Furthermore, it is possible that the Norwegian government were aware of the risks in terms of reducing BEV sales, when introducing the parking fee option. The reasons behind the choice are unknown to us, and we can only speculate, but there might be reasons behind the choice that we unaware of. Municipalities we have been in contact with have explained the choice of charging BEVs for parking as being related to lack of parking space. In municipalities with a high share of BEVs, available parking spaces could possibly be short in supply as BEVs can park freely. Hence, the policy change in parking fee could possibly have been introduced as the government felt compelled to help municipalities with the mentioned issues. In extension, this might make our simulation of BEV sales in case of parking fee in all municipalities somewhat extreme. The government might have known that it would only be implemented in a relatively small amount of municipalities.

In the OLS regressions we test four different measures for charging station availability. Going from (a), with the measure of charging points within 200 km to (d) with charging points on municipality, we notice two patterns. The R-squared value increases slightly and the availability coefficients increase in size, except for in (b). This indicates that BEV owners have a preference for charging points situated within a relatively short radius from their respective bases. One interpretation of this result is that people generally prefer to travel shorter distances with their BEVs and that consumers that often travel longer distances prefer ICEVs or hybrid cars. This is interesting, as it is a common pattern among BEV owners to own two cars; one for longer travels – usually an ICEV – and a BEV for shorter travels (Institute of Transport Economics, 2018). In extension, this means that the marginal utility of charging points would decrease with the distance from a certain consumer's base, which is also what our findings tell us.

Adding to this, we are able to show that range is an important factor in describing BEV demand. Drawing on both these results and our interpretation of the former, one hypothesis is that these two might be negatively correlated. Accordingly, as ranges increase and BEVs become closer substitutes to fuel cars in terms of range, the relative importance of charging point availability between point a and point b, where the distance between a and b is larger than 100 km, would decrease. Combining this analysis with the findings regarding consumers' preferences for charging station availability, this implies that increasing the number of charging points in densely populated areas could have a larger effect on BEV sales than the establishment of charging stations along highways, for instance. If this holds, Government funding should focus on clustered and local charging point availability, rather than sparse but nationwide availability.

Somewhat surprisingly our temperature variables proved insignificant and were dropped. One reason for the small impact could simply be that consumers do not take temperature into consideration when purchasing a BEV. Another explanation could be that the relative range is not as affected as the total range; ICEV range is also negatively correlated with cold temperatures.

Additionally, electricity, diesel and gasoline prices proved insignificant when explaining BEV demand. This could be as electricity costs for BEVs are trivial in relation to fuel costs for ICEVs; the changes in electricity prices might be irrelevant to consumers as they are not believed to ever reach corresponding fuel prices. The insignificance of diesel and gasoline prices on BEV demand is more surprising. One explanation could be that both prices have been quite stable during the sample period. Another could be that consumers' views of BEVs being cheap in terms of fuel and ICEVs being expensive are constant and does not change much in response to changes in diesel and gas prices.

8. Limitations

The model used in this thesis has some shortcomings. As variation in consumer tastes only enters the model through ϵ_{ij}, which is assumed to be identically and independently distributed across consumers and choices, the estimated model brings restrictions on the pattern of cross-price elasticities. In the model, nothing but the mean utility levels will differentiate two products. As mean utility levels are decided by market shares, two different products with the same market shares will have identical substitution patterns. This occurs as all properties of market demand, e.g. elasticities, are determined by the mean utility level, only. As a result, any pair of products with equal market shares will have identical cross-price elasticities with any given third product. For instance, sales of a BMW and a Fiat with the same market shares would be equally affected by a price change of an Audi. This is highly unrealistic as cross-price elasticities should be lower between cars within the same segment. To be precise, we would expect a BMW owner to be more willing to change to an Audi than a Fiat owner would be, if Audi prices were to change. As noted by BLP (1995), the cross-price elasticity problem also results in questionable own-price elasticities, as these will be linked solely to market shares. We address this issue with nested logit regressions. One deficiency of the nested logit model (d) we present is that the nests could have been more narrowly defined, thereby allowing for more accurate cross-price elasticities. We expected the combination of body style and fuel type to be decisive in the purchase of a car. However, as our regressions clearly illustrate, body style does not seem to be critical to consumers. We find that fuel type is a more appropriate nest, but there are surely many other ways to classify cars; some of which may very well be more adequate and accurate than fuel type.

One factor that could possibly be important in describing BEV demand is local environmental engagement and awareness. It is possible that we could have used some sort of proxy – e.g. number of votes for green parties from national elections – to control for this. In practice, this could however be difficult as (i) environmental attitudes are hard to quantify and (ii) if we could, we would need to collect monthly observations on municipality level to match our dataset. Furthermore, the Norwegian Electric Vehicle Association report that only 26 per cent of consumers choose an electric vehicle for environmental reasons, which casts doubt on the relevance of consumers' environmental concern when it comes to BEV demand.

As our dataset includes MSRPs as prices, and not the actual prices paid, our model does not take price reductions into account. Our model will not capture changes in sales related to price reductions correctly, but will relate the changes to other factors than price. The risk is thus that the estimation of the price coefficient might be incorrect.

The parking fee variable might also be flawed, as we do not have information on when the news regarding a certain municipality's choice on BEV parking policy was made public. The decision to change the policy was announced nationwide by the Norwegian government on March 18 2016. However, if a certain municipality made a decision and communicated that decision in April, it could have had a different implication than if it had been communicated in December. Making the case that political signals are of importance in relation to BEV demand, the timing of communication should not be underestimated and could be an important factor that we were not able to catch due to lack of available data.

We use the number of restaurants in a municipality integrated with the month-lagged number of charging points in Norway to instrument for the endogenous charging points variable. Our instrument is different from the instrument used by Li et al (2016).We chose to construct our instrument in such a manor since our data suggest that the correlation between restaurants and charging stations is stronger than that between grocery stores and charging stations. However, this finding might not hold since the data we used for grocery stores not only include grocery stores, but all retailers in that specific municipality. If we had had cleaner data on the number of grocery stores, the results might have been different.

Lastly, free parking availability and the number of charging stations could potentially be correlated. If so, this would however only decrease the precision of our estimates.

9. Conclusion

In this thesis we have studied the effect of the change in free parking policy on the Norwegian sales of battery electric vehicles. In 2016, the Norwegian government revised the parking fee exemption for BEVs that was originally introduced in 1999. From January 1 2017 municipalities were allowed to charge BEVs for parking. To estimate the effect of the policy change, which was implemented by 38 municipalities, we use market level car sales data from 2010-2017. We argue that changes in the free parking policy should lead to a decrease in BEV sales as (i) it is an important policy for choosing a BEV according to owners, (ii) the change reduces the relative advantage of owning a BEV and (iii) it sends negative signals to consumers regarding the future political efforts to stimulate BEV demand. We find that the policy change had a negative effect on BEV sales in Norway. We also find that charging point availability is an important factor for BEV demand; in our preferred specification, nested logit (d) we estimate that a 10% increase in number of charging points on municipality level increases the demand for BEVs by 2.13 %. Using counterfactual simulations we estimate that the change in parking policy led to a 2.85% reduction in total BEV sales in 2017 compared to a state of no change in the same policy. The 2.85% reduction in sales stems from the 38 municipalities that chose to start charging BEVs for parking. Had all 418 municipalities chosen to charge BEVs for parking we estimate that the sales would have decreased by 7.80%, compared to the actual sales in 2017. It is however highly unlikely that all municipalities would act on the opportunity to remove the free parking incentive.

We argue that the relatively large estimated effect of the free parking policy on BEV sales could be attributed to more than the *actual* change in policy. Changes in political incentives send signals to consumers that could have a large effects on BEV sales. Consumers in municipalities that chose to act on the opportunity to remove the free parking incentive have reasons to question the perseverance of other BEV incentives in that municipality going forward, such as the exemption from road tolls and bus lane access. This could make consumers less inclined to purchase a BEV.

9.1 Suggestions for further research

In late 2017 the Norwegian government announced that the BEV parking policy would be changed again. It was decided that, starting in 2018, the tariff for tolls, ferries and parking for zero-emission vehicles must not exceed 50% of the conventional vehicle tariff (Stortinget, 2017). As this could be seen as an attempt to regain BEV demand lost as a result of the first parking policy change it would be highly interesting to investigate the effect of the second policy change.

Further, the effect of other non-price related incentives would be interesting to study. Both road toll exemption and bus lane access are mentioned as the most important factors for choosing a BEV. Road tolls would be interesting to investigate considering the possibility to monetize the subsidy and its effect on BEV sales. In a survey from 2016 by the Institute of Transport Economics the average user stated that local incentives have a value of EUR 1 500 per year and vehicle, where toll roads accounts for 50% and time savings from using bus lanes 30%. Estimating how much these incentives affect BEV demand and sales and comparing them to the free parking incentive would be fascinating, in our opinion. Another area of interest for such studies would be to isolate which, if any, of these non-price related incentives are sustainable in the long run. For example, free parking and bus lane access for BEVs has its evident limitations; as the installed base of BEVs grows beyond a certain number relative to the total number of cars in a country, the policy will overcrowd parking spots and clog bus lanes for BEV owners as well.

Finally, if we would have had access to individual sales data rather than market level data, it is possible that the effects studied in this report could have been investigated more exhaustively. With more detailed data, we could have included demographic variables on individual level, e.g. consumer income, which could help explain vehicle choice without having to make many of the general assumptions required by the method applied in this paper.

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Gröna Bilister, contact: http://www.gronabilister.se/

Norwegian Electric Vehicle Association, contact: https://elbil.no/

10.4 Other

Interview with managing editor at Vi Bilägare on April 4th 2018

Interview with board member at Gröna Bilister on April 6th 2018

A. Appendix

A.1 Data adjustments

A.1.1 Car characteristics and price

We received the information on the number of cars sold and MSRPs from OFVAS in two different files. These files were merged on year, month, brand, model and a few overlapping characteristics between the two files. In those cases where a match was not found, one condition at a time was relieved in order to find a better match. In those cases, the most conservative matching technique was used, i. e. treating the observed car as a base model and merging it with the lowest price among duplicates dropped. Using this technique, we were able to match all but approx. 5,800 observations (of approx. 450,000 observations). These observations were dropped. In order to specify adequate nests, we also had to treat a model of a car as unique based on brand, model name, fuel type and market (time and municipality). In order to do this, we had to sum the numbers sold of some 60,000 observations and treat those cars as the same, leading to our final 390 337 observations.

A.1.2 Parking fee

As complete information of parking fee decisions on municipality levels is incomplete, we have collected the data from three different sources, described in section 4.5. Having collected data for 404 municipalities, we were unable collect data for the remaining 14. We have unsuccessfully tried to contact these municipalities on multiple occasions. As the majority of the Norwegian municipalities kept offering free parking for BEVs in 2017, we assume that the 14 missing municipalities also kept offering free parking.

A.1.3 Income

As official income data for 2017 is unavailable due to tax reasons, we use the income for 2016 for both years.

A.2 Estimation results

Here we present more detailed results from the estimations.

Table A1: OLS regression (a)

VARIABLES	OLS $\ln(s_j/s_0)$
price	-0.000833***
	(2.32e-05)
displacement	2.32e-05***
	(5.20e-06)
inversefuelecon	0.170***
	(0.00837)
power_over_weight	-0.343***
	(0.0709)
2.n_drivetrain	-0.0426***
	(0.00318)
2.n_transmission	-0.0725***
	(0.00206)
length	-7.15e-05
	(0.000138)
medianincome	1.45e-06***
	(1.06e-07)
1.parkingfee_dBEV	0.0820***
	(0.0110)
range_dBEV	0.000245***
	(8.31e-05)
log_n_cp_200km_dBEV	0.0496***
	(0.00268)
Observations	390,337
R-squared	0.873

dy/ex	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
-.2882368	.0080353	-35.87	0.000	-.3039858	-.2724878

Table A2: OLS regression (b)

VARIABLES	OLS $\ln(s_j/s_0)$
price	-0.000835***
	(2.32e-05)
displacement	2.38e-05***
	(5.20e-06)
inversefuelecon	0.168***
	(0.00837)
power_over_weight	-0.365***
	(0.0708)
2.n_drivetrain	-0.0423***
	(0.00318)
2.n_transmission	-0.0727***
	(0.00206)
length	-7.87e-05
	(0.000138)
medianincome	1.42e-06***
	(1.06e-07)
1.parkingfee_dBEV	0.0770***
	(0.0110)
range_dBEV	0.000288***
	(8.29e-05)
log_n_cp_100km_dBEV	0.0200***
	(0.000868)
Observations	390,337
R-squared	0.873

dy/ex	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
-.2889125	.0080332	-35.96	0.000	-.3046574	-.2731677

Table A3: OLS regression (c)

VARIABLES	OLS $\ln(s_j/s_0)$
price	-0.000839***
	(2.31e-05)
displacement	2.29e-05***
	(5.18e-06)
inversefuelecon	0.172***
	(0.00834)
power_over_weight	-0.304***
	(0.0706)
2.n_drivetrain	-0.0434***
	(0.00317)
2.n_transmission	-0.0718***
	(0.00205)
length	-5.30e-05
	(0.000138)
medianincome	1.49e-06***
	(1.06e-07)
1.parkingfee_dBEV	0.0985***
	(0.0110)
range_dBEV	0.000235***
	(8.26e-05)
log_n_cp_50km_dBEV	0.0998***
	(0.00177)
Observations	390,337
R-squared	0.874

dy/ex	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
-.2904324	.0080063	-36.28	0.000	-.3061245	-.2747404

Table A4: OLS regression (d)

VARIABLES	OLS $\ln(s_j/s_0)$
price	-0.000844***
	(2.29e-05)
displacement	2.16e-05***
	(5.13e-06)
inversefuelecon	0.176***
	(0.00825)
power_over_weight	-0.292***
	(0.0698)
2.n_drivetrain	-0.0445***
	(0.00314)
2.n_transmission	-0.0730***
	(0.00203)
length	-9.52e-05
	(0.000136)
medianincome	1.04e-06***
	(1.05e-07)
1.parkingfee_dBEV	-0.0497***
	(0.0109)
range_dBEV	0.000447***
	(8.17e-05)
log_n_cp_muni_dBEV	0.180***
	(0.00166)
Observations	390,337
R-squared	0.876

	Delta-method				
dy/ex	Std. Err.	z	P>|z|	[95% Conf. Interval]	
-.2920345	.0079199	-36.87	0.000	-.3075572	-.2765118

Table A5: IV logit regression (a)

VARIABLES	IV $\ln(s_j/s_0)$
price	-0.00158***
	(8.33e-05)
displacement	6.01e-05***
	(6.64e-06)
inversefuelecon	0.143***
	(0.00900)
power_over_weight	0.862***
	(0.144)
2.n_drivetrain	-0.00522
	(0.00532)
2.n_transmission	-0.0574***
	(0.00265)
length	0.000332**
	(0.000144)
medianincome	1.04e-06***
	(1.05e-07)
1.parkingfee_dBEV	-0.0475***
	(0.0109)
range_dBEV	0.000662***
	(8.51e-05)
log_n_cp_muni_dBEV	0.180***
	(0.00166)
Observations	390,337
R-squared	0.876

First stage

Variable | F(9,389357) P-val | SW Chi-sq(9) P-val | SW F(9,389357)

Second stage

F(11,389365) = 1888.10 Prob > F = 0.0000
Total (centered) SS = 77657.86722 Centered R2 = 0.8760
Total (uncentered) SS = 77657.86722 Uncentered R2 = .
Residual SS = 73722.59212 Root MSE = .4352

Sargan statistic: 3018.816
Chi-sq(8) P-val = 0.0000

Instrumented: price
Instruments: numberofdoors n_fuel instr_inversefuel_avg instr_inversefuel_avg_o instr_pow_avg instr_pow_avg_o instr_length_avg instr_length_avg_o n_bodystyle

Delta-method

dy/ex	Std. Err.	z	P>|z|	[95% Conf. Interval]	
-.5455523	.0288222	-18.93	0.000	-.6020428	-.4890619

Table A6: IV logit regression (b)

VARIABLES	IV ln(s_j/s_0)
price	-0.0109***
	(0.000132)
displacement	0.000550***
	(9.22e-06)
inversefuelecon	-0.272***
	(0.0116)
power_over_weight	15.54***
	(0.220)
2.n_drivetrain	0.495***
	(0.00790)
2.n_transmission	0.141***
	(0.00370)
length	0.00576***
	(0.000183)
medianincome	1.04e-06***
	(1.28e-07)
1.parkingfee_dBEV	-0.0194
	(0.0134)
range_dBEV	0.00339***
	(0.000107)
log_n_cp_muni_dBEV	0.183***
	(0.00203)
Observations	390,337
R-squared	0.815

First stage

Variable | F(9,389357) P-val | SW Chi-sq(9) P-val | SW F(9,389357)

Second stage

F(11,389365) = 1864.47 Prob > F = 0.0000

Total (centered) SS = 77657.86722 Centered R2 = 0.8151

Total (uncentered) SS = 77657.86722 Uncentered R2 = .

Residual SS = 109972.445 Root MSE = .5315

Sargan statistic : 8743.749

Chi-sq(8) P-val = 0.0000

Instrumented: price

Instruments: numberofdoors n_fuel instr_pow_sum instr_pow_sum_other instr_length_sum instr_length_sum_other instr_inversefuel_sum instr_inversefuel_sum_other n_bodystyle

Delta-method

dy/ex	Std. Err.	z	P>|z|	[95% Conf. Interval]	
-3.770438	.0455925	-82.70	0.000	-3.859797	-3.681078

Table A7: IV logit regression (c)

VARIABLES	IV $\ln(s_j/s_0)$
price	-0.0212***
	(0.000274)
log_n_cp_muni_dBEV	0.233***
	(0.00487)
displacement	0.00142***
	(2.14e-05)
inversefuelecon	-0.797***
	(0.0196)
power_over_weight	20.11***
	(0.330)
2.n_drivetrain	1.068***
	(0.0158)
2.n_transmission	0.389***
	(0.00714)
length	0.0122***
	(0.000292)
medianincome	1.16e-06***
	(1.86e-07)
1.parkingfee_dBEV	-0.216***
	(0.0198)
range_dBEV	0.00804***
	(0.000178)
Observations	390,337
R-squared	0.611

First stage
Variable | F(10,389357) P-val | SW Chi-sq(9) P-val | SW F(9,389357)

Second stage
F(11,389365) = 987.09 Prob > F = 0.0000
Total (centered) SS = 77657.86722 Centered R2 = 0.6074
Total (uncentered) SS = 77657.86722 Uncentered R2 = .
Residual SS = 231056.1857 Root MSE = .7703

Sargan statistic: 1542.815
Chi-sq(8) P-val = 0.0000

Instrumented: price log_n_cp_muni_dBEV
Instruments: numberofdoors n_fuel instr_pow_sum instr_pow_sum_other
instr_length_sum instr_length_sum_other
instr_inversefuel_sum instr_inversefuel_sum_other
n_bodystyle instr_cp_dBEV

Delta-method

dy/ex	Std. Err.	z	P>|z|	[95% Conf. Interval]	
-7.351581	.0949261	-77.45	0.000	-7.537633	-7.16553

Table A8: Nested IV logit regression (a)

VARIABLES	Nested IV $\ln(s_j/s_0)$
price	-0.0119***
	(0.000171)
sigma_1_bsg	0.0271***
	(0.00352)
sigma_2_bsg	-0.0185***
	(0.00447)
log_n_cp_muni_dBEV	0.221***
	(0.00351)
displacement	0.000785***
	(1.39e-05)
medianincome	1.04e-06***
	(1.33e-07)
inversefuelecon	-0.370***
	(0.0133)
power_over_weight	10.73***
	(0.215)
length	0.00662***
	(0.000215)
2.n_drivetrain	0.561***
	(0.00991)
2.n_transmission	0.176***
	(0.00450)
1.parkingfee_dBEV	-0.145***
	(0.0142)
range_dBEV	0.00463***
	(0.000123)
Observations	390,337
R-squared	0.800

First stage

Variable | F(22,389345) P-val | SW Chi-sq(19) P-val | SW F(19,389345)

Second stage

F(13,389363) = 1224.24 Prob > F = 0.0000

Total (centered) SS = 77657.86722 Centered R2 = 0.8005

Total (uncentered) SS = 77657.86722 Uncentered R2 = .

Residual SS = 118648.8551 Root MSE = .552

Sargan statistic: 8750.452

Chi-sq(18) P-val = 0.0000

Instrumented: price sigma_1_bsg sigma_2_bsg log_n_cp_muni_dBEV

Instruments: numberofdoors n_fuel instr_inversefuel_sum instr_inversefuel_sum_other instr_pow_sum instr_pow_sum_other instr_length_sum instr_length_sum_other instr_sigma_1_vb_1 instr_sigma_1_vb_2 instr_sigma_1_vb_3 instr_sigma_1_vb_4 instr_sigma_1_vb_5 instr_sigma_1_vb_6 instr_sigma_2_vb_1 instr_sigma_2_vb_2 instr_sigma_2_vb_3 instr_sigma_2_vb_4 instr_sigma_2_vb_5 instr_sigma_2_vb_6 n_bodystyle instr_cp_dBEV

	Delta-method				
dy/ex	Std. Err.	z	P>|z|	[95% Conf.	Interval]
-4.128777	.0591399	-69.81	0.000	-4.244689	-4.012865

Table A9: Nested IV logit regression (b)

VARIABLES	Nested IV $\ln(s_j/s_0)$
price	-0.0173***
	(0.000248)
sigma_bsg	-0.0410***
	(0.00443)
log_n_cp_muni_dBEV	0.235***
	(0.00433)
displacement	0.00115***
	(1.93e-05)
medianincome	1.07e-06***
	(1.64e-07)
inversefuelecon	-0.598***
	(0.0172)
power_over_weight	16.11***
	(0.296)
length	0.0102***
	(0.000278)
2.n_drivetrain	0.847***
	(0.0141)
2.n_transmission	0.297***
	(0.00632)
1.parkingfee_dBEV	-0.191***
	(0.0175)
range_dBEV	0.00657***
	(0.000159)
Observations	390,337
R-squared	0.698

First stage

Variable | F(16,389351) P-val | SW Chi-sq(14) P-val | SW F(14,389351)

Second stage

F(12,389364) = 1013.54 Prob > F = 0.0000

Total (centered) SS = 77657.86722 Centered R2 = 0.6929

Total (uncentered) SS = 77657.86722 Uncentered R2 = .

Residual SS = 179767.8889 Root MSE = .6795

Sargan statistic: 3834.538

Chi-sq(13) P-val = 0.0000

Instrumented: price sigma_bsg log_n_cp_muni_dBEV

Instruments: numberofdoors n_fuel instr_inversefuel_sum instr_inversefuel_sum_other instr_pow_sum instr_pow_sum_other instr_length_sum instr_length_sum_other instr_sigma_2_vb_1 instr_sigma_2_vb_2 instr_sigma_2_vb_3 instr_sigma_2_vb_4 instr_sigma_2_vb_5 instr_sigma_2_vb_6 n_bodystyle instr_cp_dBEV

Delta-method

dy/ex	Std. Err.	z	P>|z|	[95% Conf. Interval]	
-5.976053	.0860042	-69.49	0.000	-6.144618	-5.807488

Table A10: Nested IV logit regression (c)

VARIABLES	Nested IV ln(s_j/s_0)
price	-0.00749***
	(9.15e-05)
sigma_1_ftg	0.155***
	(0.00302)
sigma_2_ftg	0.183***
	(0.00336)
log_n_cp_muni_dBEV	0.213***
	(0.00280)
displacement	0.000470***
	(8.34e-06)
inversefuelecon	-0.198***
	(0.00955)
power_over_weight	7.027***
	(0.146)
2.n_drivetrain	0.317***
	(0.00579)
2.n_transmission	0.0771***
	(0.00289)
length	0.00441***
	(0.000150)
medianincome	1.05e-06***
	(1.07e-07)
1.parkingfee_dBEV	-0.102***
	(0.0114)
range_dBEV	0.00324***
	(9.09e-05)
Observations	390,337
R-squared	0.871

First stage

Variable | F(22,389345) P-val | SW Chi-sq(19) P-val | SW F(19,389345)

Second stage

F(13,389363) = 1822.05 Prob > F = 0.0000

Total (centered) SS = 77657.86722 Centered R2 = 0.8706
Total (uncentered) SS = 77657.86722 Uncentered R2 = .
Residual SS = 76928.5069 Root MSE = .4445

Sargan statistic: 1.4e+04
Chi-sq(18) P-val = 0.0000

Instrumented: price sigma_1_ftg sigma_2_ftg log_n_cp_muni_dBEV
Instruments: numberofdoors n_fuel instr_inversefuel_sum instr_inversefuel_sum_other instr_pow_sum instr_pow_sum_other instr_length_sum instr_length_sum_other instr_sigma_1_ft_vb_1 instr_sigma_1_ft_vb_2 instr_sigma_1_ft_vb_3 instr_sigma_1_ft_vb_4 instr_sigma_1_ft_vb_5 instr_sigma_1_ft_vb_6 instr_sigma_2_ft_vb_1 instr_sigma_2_ft_vb_2 instr_sigma_2_ft_vb_3 instr_sigma_2_ft_vb_4 instr_sigma_2_ft_vb_5 instr_sigma_2_ft_vb_6 n_bodystyle instr_cp_dBEV

Delta-method

dy/ex	Std. Err.	z	P>|z|	[95% Conf. Interval]	
-2.593459	.0316865	-81.85	0.000	-2.655564	-2.531355

Table A11: Nested IV logit regression (d)

VARIABLES	Nested IV $\ln(s_j/s_0)$
price	-0.00855***
	(0.000103)
sigma_ftg	0.169***
	(0.00298)
log_n_cp_muni_dBEV	0.213***
	(0.00290)
displacement	0.000546***
	(9.10e-06)
inversefuelecon	-0.257***
	(0.0101)
power_over_weight	7.905***
	(0.156)
2.n_drivetrain	0.377***
	(0.00639)
2.n_transmission	0.101***
	(0.00312)
length	0.00493***
	(0.000156)
medianincome	1.05e-06***
	(1.11e-07)
1.parkingfee_dBEV	-0.109***
	(0.0118)
range_dBEV	0.00365***
	(9.52e-05)
Observations	390,337
R-squared	0.862

First stage

Variable | F(16,389351) P-val | SW Chi-sq(14) P-val | SW F(14,389351)

Second stage

F(12,389364) = 1897.65 Prob > F = 0.0000

Total (centered) SS = 77657.86722 Centered R2 = 0.8619
Total (uncentered) SS = 77657.86722 Uncentered R2 = .
Residual SS = 82130.13116 Root MSE = .4593

Sargan statistic: 1.2e+04
Chi-sq(13) P-val = 0.0000

Instrumented: price sigma_ftg log_n_cp_muni_dBEV
Instruments: numberofdoors n_fuel instr_inversefuel_sum instr_inversefuel_sum_other instr_pow_sum instr_pow_sum_other instr_length_sum instr_length_sum_other instr_sigma_2_ft_vb_1 instr_sigma_2_ft_vb_2 instr_sigma_2_ft_vb_3 instr_sigma_2_ft_vb_4 instr_sigma_2_ft_vb_5 instr_sigma_2_ft_vb_6 n_bodystyle instr_cp_dBEV

Delta-method

dy/ex	Std. Err.	z	P>|z|	[95% Conf. Interval]	
-2.95886	.0356043	-83.10	0.000	-3.028643	-2.889076

A.3 NOK/USD Monthly exchange rates

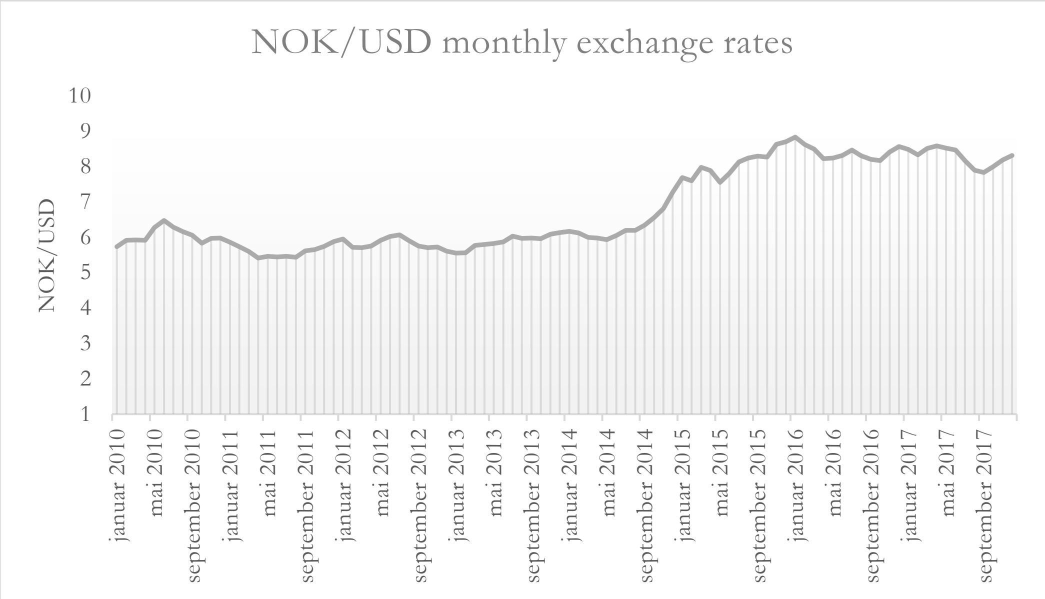

Figure A12: NOK/USD exchange rates, 2010-2017, source: Norges Bank