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THE MORE, THE BETTER? Charging stations and EVs across fylker and kommuner

A Look at The Norwegian EV Market From 2014 - 2021

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Master thesis in Economics & Economic Analysis

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

In this master thesis, we have shown that building more chargers in a given year in a fylke or kommune does not result in a significant increase in the amount of EVs bought in this year in this fylke or kommune after accounting for factors such as fast charging, accessibility, location of the chargers, size of the population and income. This result holds for both fylker and kommuner, even more so after accounting for heteroscedasticity and autocorrelation.

We have also considered the impact that chargers built in the past, for example one year earlier, may have on the adoption of EVs in the year after. Taking this into account generates an explanatory variable that is statistically significant which indicates that past charging stations may be a better predictor of EVs bought in the future than chargers being made currently available. This has also helped to deal with reverse causality.

This may to some extent help to alleviate the chicken and egg problem for policy makers wondering what comes first: The cars or the chargers. This result holds at both the kommune and fylke levels. However, after accounting for heteroscedasticity and autocorrelation, it only remains significant at the fylke level. This suggests that the fylke may be a better territorial unit to organize the charging network around in Norway than the kommune which makes sense given that the kommuner in Norway tend to be only sparsely populated in comparison to the fylker.

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1.0 Introduction

Norway has been at the forefront of the adoption of electric vehicles (hereafter EVs) and represents the global leader with the highest electrified car park which is estimated to be roughly 20 % in 2022 (Elbil, 2022). One likely explanation for the early adoption is the combined weight of the incentives which the Norwegian government has been pushing since the mid 1990's (Bjerkan, et al, 2016)

The purpose of this master is to attempt to investigate if charging stations are the main driver behind the adoption of electric vehicles (EVs) here in Norway. This analysis will be conducted at both the fylke and kommune levels to check if what holds for the fylke also holds for the kommune. In our attempt to investigate this relationship, we will make use of datasets provided by NOBIL, our supervisors and data about population and income at both the fylke and kommune levels downloaded from the SSB website.

Furthermore, an interesting question arises with this topic; what comes first, the EVs or the charging stations? One could argue that EVs need to come first before any player in the market dares to build the first charging stations. On the other hand, who would like to buy an EV if there exists no public charging infrastructure? From these arguments, the existence of the chicken and the egg conundrum with respect to this topic is clearly established and one cannot exclude the possibility of reverse causality (Schulz and Rode, 2021).

The Norwegian car market has been subject to several pull mechanisms to encourage an early adoption of electric vehicles (Bjerkan, et al, 2016). The incentives are both present during the initial face of buying an EV as well as in the daily use of the EV post purchase. The initial benefit of EVs can be found in exemption of both vehicle registration tax and value added tax (VAT) (Thomassen, 2017). Post-purchase, EVs benefit from no/reduced toll barriers, cheaper ferries, and parking fees. (Bjerkan, et al, 2016).

Although the Norwegian government were early in incentivizing the use of EVs, it took some time before the numbers were reflected in the car park. In 2010, Norway registered 394 newly purchased plug-in hybrids and EVs. Fast forward to 2021, the number of newly purchased EVs was roughly 110 000 (Statista, 2021).

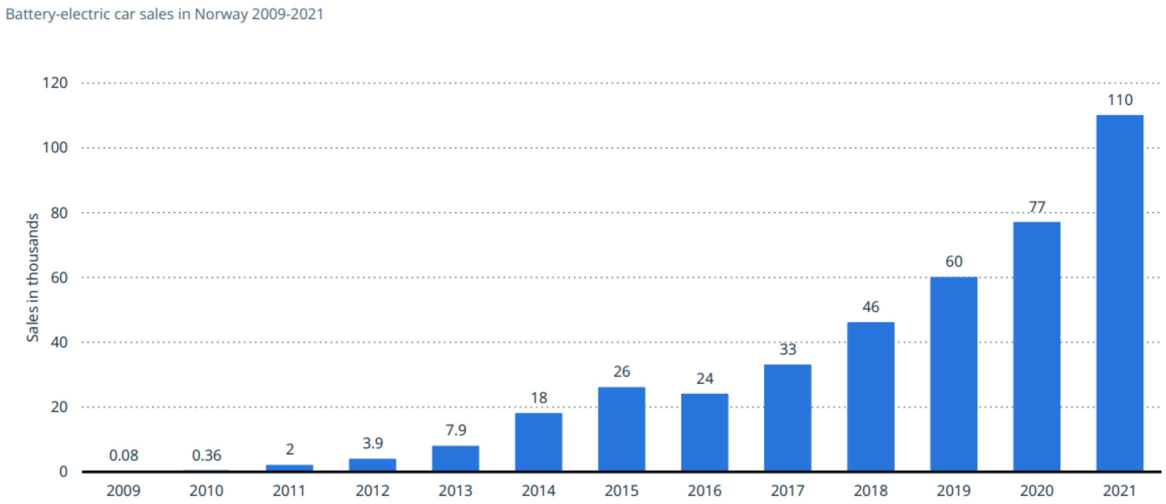

Figure 1. Battery-electric car sales in Norway from 2009 to 2021. (Source: Statista)

One possible explanation for the slow growth is the process of technology and innovation. Back in 2010, EV models such as Think and Buddy comprised 50 % of the EV car market (Bjerkan, et al. 2016). These car models were limited in both speed and range. One could argue that popular models such as Nissan Leaf and Tesla model S around 2013 were important as they provided both improved range and speed compared to Buddy and Think.

Norway has given its citizens strong incentives to buy battery electric vehicles (EV) since the mid 1990's (Bjerkan, et al, 2016). Pull incentives to motivate and encourage the adoption of EV's has been important for Norway to increase its EV market share in such a short period of time. Examples of pull mechanisms are the exemption of both vehicle registration tax and value added tax on EVs.

1.1 Climate change and sustainable development goals

As the paragraph above indicates, Norway has been at the forefront of promoting the adoption of EVs, but why? Well, roughly 17.7 % of Norway's CO2 emissions stems from road traffic (SSB, 2021). In order for Norway to meet their obligation after the Paris agreement (Mission of Norway to the EU, 2021), Norway has to cut the emissions wherever it is possible. Norway has agreed with the rest of the world to reduce its global emissions such that we can limit the global temperature to roughly 1.5 – 2 degrees Celsius.

As Norway is committed along with the rest of the world to keep the temperature increase down, new goals have to be made. The Norwegian government recently made a new goal to cut CO_2 emissions by 55 %, compared to the 1990-levels (Regjeringen, 2022). The goal was made clear just before the COP27 meeting in Egypt 2022. Along with the new reduction goal of CO_2 emissions, Norway has further strengthened its status on the international stage. A climate fund agreement for poorer countries has been delivered. The climate fund seeks to compensate poorer countries for loss and damages, as well as to promote the introduction of new and cleaner energy production (UNFCCC, 2022).

Climate change is and will drastically change our current and future world as we know it. The effect of climate change impacts us in different ways, both economically in terms of taxes on emissions of CO_2 (Lin & Li, 2011), and biologically with the effects of climate change on various habitats, on both land and the sea (Hijmans & Graham, 2006). The tax on CO_2 emissions could alter our behavior if the tax levels reach a sufficient and global level with rates at an appropriate level to reduce CO_2 emissions. (Lin & LI, 2011).

The reduction of emissions is just one of several points in which Norway has committed to with respect to the sustainable development goals by the UN. There are a total of 17 goals and several of them are directly addressing issues related to climate change such as nr. 13 – Stop global warming, and nr. 15 – Life on land (UN, 2022). Both goals are either directly or indirectly related to the issue of climate change. In order to stop global warming, every country must do their part and own up to their own emissions.

The social development goal nr. 13 - Stop global warming, is directly addressing the issue of global temperature change and emissions. The goal has several targets in which it seeks to reach over time. For instance, two of the goals from the UN database states as follows: "Integrate climate change measures into national policies, strategies and planning" (UN, 2022) and "Improve education, awareness-raising and human and institutional capacity on climate change mitigation, adaptation, impact reduction and early warning" (UN, 2022). Essentially, these targets are smaller and more quantifying "stepping stones" in order to achieve the major goal, which is to stop climate change.

Data from Statista (2022) shows that there has been more or less a continuous growth in C02 levels the last 80 years with an exception in 2020 due to the Corona pandemic. The exception itself is just a temporary one due to the restrictions of the corona pandemic (UN, 2022). The UN has been fairly vocal about the short-term effects of the fall in C02 as being temporary and to some extent negligible (UN, 2022). In a table below we can observe the annual C02 emissions.

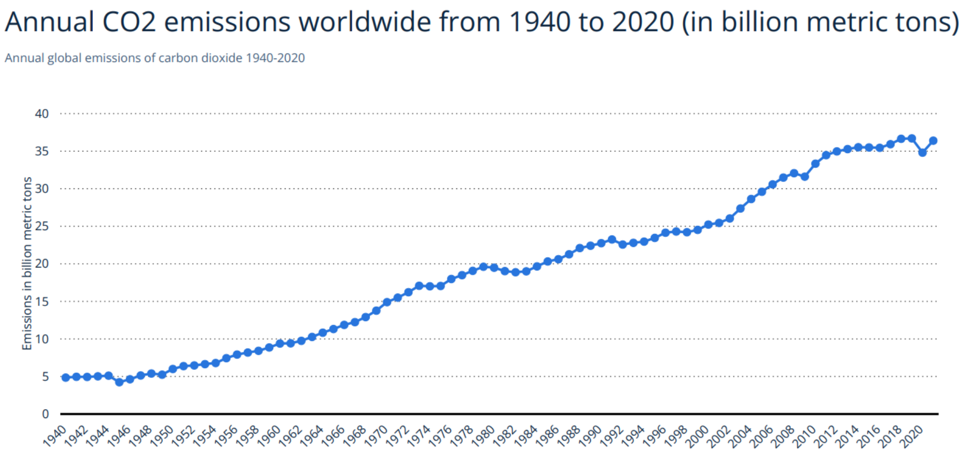

Figure 2. Annual CO2 emissions worldwide from 1940 to 2020. (Source: Statista)

Furthermore, one could argue that Norway has a great responsibility to reduce emissions. Firstly, Norway is a significant oil & gas producer which reaps high profits from its petroleum sector and should therefore do their part in the issue of climate change as they emit significant amounts of CO2 per capita (SSB, 2021). Secondly, Norway has a major role as being a role model for the rest of the world. Norway is after all one of the richest countries in the world with the highest score on the human development index (HDI), which is often used to measure quality of life (UN, 2022). If they cannot reduce their emissions, then how can the rest of the world be expected to do so?

1.2 A first glance at the Norwegian charging market

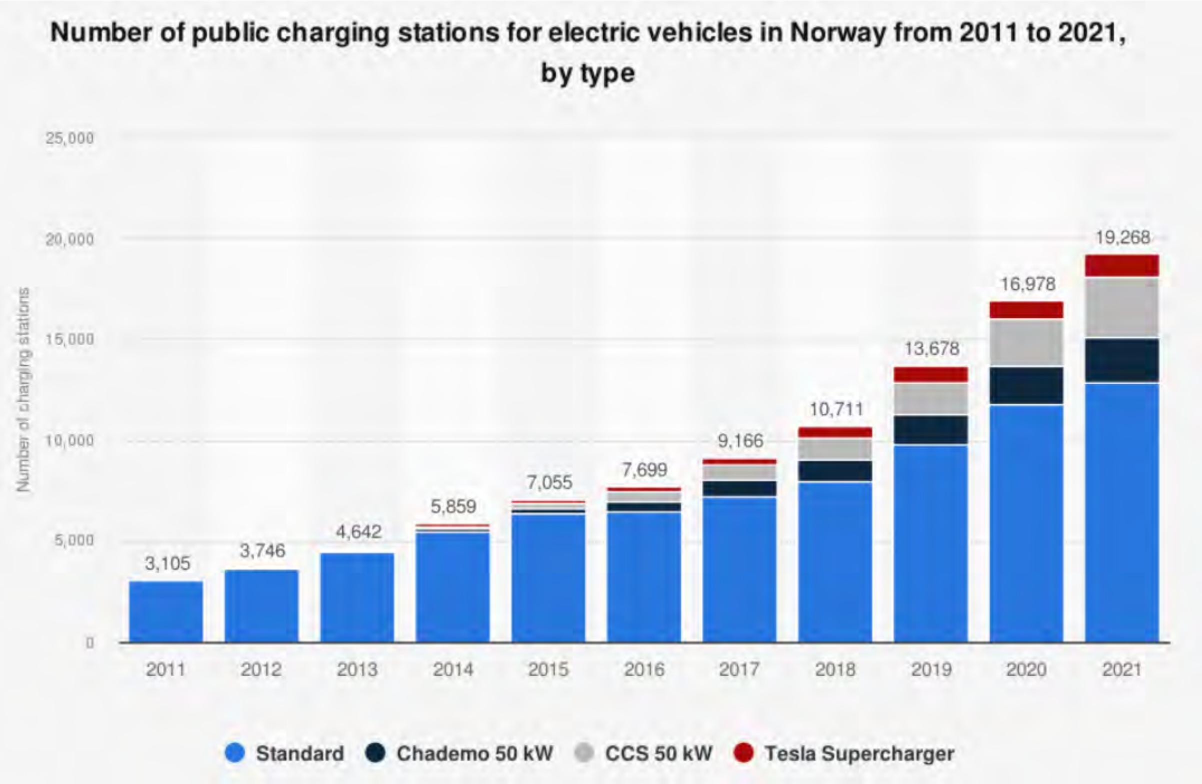

Figure 3. Number of public charging stations for electric vehicles in Norway from 2011 to 2021, by type. (Source: Statista)

The Norwegian charging network consists of primarily four types of charging outlets. The four outlet types are Schuko, Type 2, CHAdeMO and CCS. Schuko is of a type which is common in a Norwegian household. Type 2 is the standard outlet for charging in stations in Europe. Both can be classified as slow charging outlets. Combined charging system (CCS) and CHAdeMo are on the other hand related to the category of fast charging outlets, capable of recharging the EV in a lower amount of time.

The Norwegian EV charging infrastructure consists of both private and public players. The first charging stations were built by the Norwegian government back in 2010, in an attempt to kick-start the sales of EVs. Due to a lack of market opportunities for private investors, the public sector had to initiate the first charging stations as there were not enough EVs on the road (Lorentzen. Et al. 2017). These charging stations were made with the outlet type Schuko, which later was deemed as insufficient in the long run. (Lorentzen. Et al. 2017).

Over time the charging infrastructure technology was improved, which made way for fast charging stations. Since 2015 with support from state enterprise Enova, fast charging stations have been operating around the Norwegian main roads (Lorentzen. Et al. 2017). The fast-charging stations are operated by private competitors who compete between themselves to get public funding. Unlike the first public charging stations which were slow and only featured the Schuko outlet, the newer stations feature the type 2 outlet as well as a fast-charging possibility with CCS and/or CHAdeMO (Lorentzen. Et al. 2017).

Above we have discussed briefly about the main operators of charging stations. Another interesting question which has yet to be discussed is charging behavior. Although one can observe that both charging stations and EVs have increased over time, but exactly how many EV owners make use of the charging stations is another question. Lorentzen. Et al (2017), conducted a study about the charging behavior of 12 000 respondents who owns an EV. Interestingly, most of the respondents reported on average that the majority of charging took place at home (Lorentzen. Et al 2017). Depending on the housing situation (detached housing or apartment buildings), the study indicates that people who live in detached houses almost exclusively makes use of home charging (97 % charge at home, daily or weekly). For apartment buildings the numbers are not as “severe”, as 64 % charge at home, daily or weekly.

A likely explanation as to why the vast majority of EV owners charge at home is likely related to convenience. Home charging often takes place during the night, so EV owners wake up the next day with a charged EV. Thus, this reduces the necessity of EV owners to make use of public charging stations on a daily or weekly basis. Data from Lortenzen (2017) indicates that charging stations are most likely to be used during longer travel distances, or as a “safety net” if the EV is running low on electricity.

1.3 The Fylker and kommuner of Norway

In our attempt to understand the effect of charging stations on EV ownership we have decided to make use of two of Norway’s various geographical subdivisions. Firstly, we have the fylker which are used in our dataset. Fylker are large administrative counties similar to swiss cantons for example. There is a total of 11 fylker in Norway as of 2022, but the number is subject to change as the political debate with respect to fylke is ongoing.

Furthermore, each fylke is also divided into smaller municipalities. As of 2022, there are a total of 356 municipalities (kommuner) in Norway.

The geographical framework can help provide us with valuable information. It can help answer important questions such as: which geographical unit should be taken as a reference when designing a plan for the charging network for the country, the fylke or the kommune? The inadequate availability of charging can be one of the main barriers to the adoption of EVs and being able to answer questions such as the one mentioned above can go a long way in overcoming this barrier.

2.0 Literature review

The literature and data on how charging stations affect EV ownership (or the reverse for that matter) is not abundant. A paper, by Schulz and Rode (2021), attempts to find a relationship between charging stations and EV adoption. The data collection took place from 2009 – 2019, with a dataset from a total of 356 local administrative units (kommune). The paper also addresses two major disadvantages of EVs compared to ICEVs, discussed in a paper by Egbue & Long (2012). The disadvantages are range and charging time (Egbue & Long, 2012). Particularly the charging time factor is interesting given the context for this paper. Given the rate of technological progress, especially on range development in EVs, the latter problem of charging time might be of more focus for the future.

Based upon the results in the paper by Schulz and Rode (2021), the authors found that public charging infrastructure on average has a positive effect on EV ownership (Schulz and Rode, 2021). The authors conducted the study based upon treatment- and control groups. By the use of Panel data and OLS where they address municipality fixed effects, they found indeed a significant difference of 1.5 percentage points between treatment - and control group. Thus, the paper indicates that public charging stations could positively impact the ownership of EVs. The paper also discusses the possible reverse correlation between charging stations and EV ownership. Although the paper found no indication of a reverse relationship, they are still reluctant to dismiss the idea of its presence.

Another paper by Xiong et. Al (2015) seeks to find the optimal EV charging stations placement, given that EV owners are tactical in their decision-making, i.e., the drivers are strategic with respect to minimizing charging costs as well as long queue times which negatively affect the adoption of EVs Xiong et al. (2015). The authors used an algorithm called OCEAN, which is supposed to calculate the optimal charging station placement in Singapore. The core of the algorithm is to calculate the optimal charging station based upon a single-level optimization problem Xiong et al. (2015). The authors are defining the optimal charging station placement based upon the minimization of social costs.

In their experimental analysis they compare three baseline models which are: Baseline 1 – assigns charging stations in consideration of demand. Baseline 2 – a dynamic model which assigns charging stations based on the traffic conditions. Lastly, Baseline 3 – assigns charging stations averagely. Their results indicate that the algorithm OCEAN-(C) outperforms the baseline methods with respect to minimizing social costs (Xiong et al., 2015). Thus, the algorithm could be an effective tool to speed up an adoption of EVs and optimize charging stations placement.

Furthermore, a paper by Li, et. al (2017) found that there exists an indirect network effect in the relationship between EVs and amount of charging stations though their model. Indirect network effects can be defined as the increased utility that EV owners derived from a higher number of charging stations or vice versa (Clements, 2004). Based on quarterly EV sales and charging stations in 353 metro areas in the US between 2011 to 2013, they found indirect network effects on both sides of the market. It implies that the government can increase the amount of charging stations to increase the sales of EV and vice versa (Li, et al. 2017). The authors quantified the indirect network effects by estimating two demand functions: one for EV sales based upon availability of charging stations, and another one on charging stations that quantifies the stock of EVs based upon the available charging stations.

After estimating the two demand functions and addressing endogeneity problems due to simultaneity of the two equations, the authors found statistically significant results. For instance, the estimates of the first demand function found that a 10 % increase in the number of public available charging stations would increase EV sales by roughly 8 %. Vice versa, the authors found that a 10 % growth in EV would lead to a 6 % increase in new charging stations. (Li, et al. 2017). These results indicate that the government should perhaps increase the number of available charging stations first and foremost, as the indirect network effects appear to be greater in demand function one compared to the second one.

However, there are many factors which affect the likelihood of purchasing an EV as discussed previously in the paper. The study is over five years old and limited to a single, but although important country. Perhaps the driving habits of a country such as the US is not necessarily comparable to most European countries, and especially Norway which is our country of interest. Nevertheless, the paper indicates support for a relationship which is intuitive: an increased number of charging stations should increase the probability of purchasing an EV.

3.0 Factors affecting the adoption of EVs

The adoption of EVs is something which is on the mind of several countries. The main drivers for adoption of EVs seems to broadly fit in two categories: internal and external factors (Coffman, Bernstein & Wee, 2016). The internal category can be defined as factors which affect the ownership of EVs in a direct sense. The external category is the opposite, meaning factors which are indirectly affecting the ownership of EVs.

3.1 Internal factors

A paper review by Coffman, Bernstein & Wee (2016), discusses various internal factors which are critical to the adoption of EVs. They reviewed most of the research on this subject and found that there are primarily three of such factors which are: Vehicle ownership costs, driving range and charging time.

The vehicle ownership costs are one major disadvantage if the comparable price between an EV and ICEV is too large. A survey from the USA indicates that the cost of vehicles is critical for the adoption of EVs (Coffman, Bernstein & Wee, 2016). Through a survey in 21 large U.S cities, Carley et al. (2013) found that the price of EVs is the most dominant factor explaining consumer's choice between EV or ICE. 55 % of the responders considered the EV price as a "major disadvantage". Furthermore, 30 % of the responders conceived the EV price as "Somewhat of a disadvantage". Given the survey, it implies that the majority of potential buyers are sensitive to the relative price between EVs and ICEs. Although this argument is relatively intuitive, the price difference between an EV and an ICE should not be taken for granted if a country has ambitions to electrify their car fleet.

Additionally, the vehicle cost post-purchase should also be considered. A paper in the literature suggests that EVs tend to have greater lifetime costs compared to ICEVs (Coffman, Bernstein & Wee, 2016). However, the literature on this is somewhat unclear. For instance, Prud'homme and Konig (2012) found that the total cost of ownership for EVs is 15 000 Euros more expensive compared to ICEVs in France. This contrasts with a study by Hagman, Ritzen, Stier and Susilo (2016), which found that EVs can have a lower total cost of ownership compared to ICEVs in Sweden. Overall, the literature on post-purchase costs indicates some heterogeneity. The various studies are all based upon assumptions which tend to vary across time and location (Coffman, Bernstein & Wee, 2016). Given that most countries have different policies related to fuel prices and electricity prices, the various results are perhaps not as surprising after all.

Furthermore, driving range and charging network seems to be important factors in the adoption of EVs. A study in the USA by (Carley, et al 2016) found that about 70 % of the responders deemed driving range as a major disadvantage or somewhat of a disadvantage. The study was conducted in an urban area which implies a group of responders who are likely to drive shorter distances compared to the non-urban population. Furthermore, a U.S web-based survey by Hidrue et al. (2011) found that the willingness to pay for EVs increased to over $5 600 for the average respondent, given that the range increased from 75 - 150 miles. The study also found that if the driving range increased from 75 - 300 miles, the average respondent's willingness to pay increased to $12 700. Thus, the study suggests that the willingness to pay for driving range is increasing, but at a diminishing rate. Given the two studies by Carley et al (2016) and Hidrue et al (2011), driving range seems to be an explanatory factor for the likelihood of purchasing an EV, but only to a certain threshold.

Moreover, charging time is also addressed as an important factor in the adoption of EVs. A study by Graham-Rowe et al. (2012) found that charging time was seen as "dead time" in a survey among the UK consumers. Hackbarth and Madlener (2013) conducted a survey and found that the willingness to pay for EVs increased by an interval of 3150-6300 euros if the charging time were reduced from 6 hours to 10 minutes. Various studies mentioned in the paper by Coffman, Bernstein & Wee (2016) indicate a high willingness to pay for EVs if the charging time is severely reduced. Thus, it implies that slow charging stations will not be sufficient to impact the adoption of EVs. Policy makers should, based on the paper by Coffman, Bernstein & wee (2016), focus on fast charging stations as a measure to increase the adoption of EVs.

3.2 External factors

Furthermore, the paper also touches upon the external factors at play. The main ones being cost of fuel, consumer characteristics and charging infrastructure. Research seems to indicate that a higher fuel price increases the likelihood of a consumer purchasing an EV (Coffman, Bernstein & Wee. 2016). A possible explanation for this relationship could be linked to the substitution effect, i.e., when the cost of two comparable goods becomes significant, consumers might want to switch to the cheaper and more affordable option.

In terms of consumer characteristics, research indicates that the consumers who purchase an EV share some similarities. For instance, the purchasers of EVs tend to be more educated, more environmentally friendly and love technology (Coffman, Bernstein & Wee. 2016). For Norway in particular it appears that people who live in urban areas are more likely to purchase an EV (Fevang, Et. Al 2020).

The effect of public charging stations on EV ownership in Norway in particular is somewhat different from any other country. For instance, a study from Figenbaum and Nordbakke, (2019) found that over 80 % of EV owners use their home as the main charging point. A possible explanation for the higher number could be traced to the high degree of private parking space with an available charging outlet. Another factor could be explained through the price mechanism of public charging stations vs home charging. The relative cost between the two options appears to be of sufficient magnitude. Data from Norsk Elbilforening (2020) indicates costs about three to four times greater for public charging compared to home charging (Schultz and Rode, 2022).

So, given that past research seems to indicate that a substantial proportion (over 80 %) of EV owners in Norway charge at home, how has the charging station location been determined so far? A paper from Lorentzen et. al (2017) previously mentioned in our paper, they mention that the first EV charging stations were introduced in 2009-2010. These charging points were spread all over the country. Although there seems to be a lack of papers on exactly how these charging locations were determined, we can somewhat extrapolate from the data that we have gotten from NOBIL that urban areas were more or less chosen. The document covers the development of charging stations in Norway from 2010 to 2022. This does not come as a huge shock given that urban habitants are more likely to buy EVs (Coffman, Bernstein & Wee. 2016).

Furthermore, in the paper by Lorentzen et. al (2017), they discussed the support scheme of ENOVA in 2015. The goal was to cover main Norwegian roads with fast charging stations every 50 km. The most likely explanation for the scheme was to provide EV owners with a possible charging location regardless of where you live as well as to be able to drive longer distances if necessary. Thus, the literature review seems to indicate that the first charging stations were determined by where the charging stations would be most beneficial, i.e., where the highest amount of EVs are present and where they are most likely to be bought.

Secondly, after the initial placement of charging stations, the focus seemed to shift in favor of covering the Norwegian main road network more broadly.

Moreover, charging infrastructure is pointed to as an important external factor in the adoption of EVs. Studies by Egbue & Long (2012) mention the presence of adequate charging infrastructure as critically important to the adoption of EVs due to limited driving range. Egbue & Long (2012) found in their study that 17 % of the responders identified lack of available charging stations as their main concern. Sierzchula et al. (2014) found that charging infrastructure relative to population is positive and significantly correlated to EV market share.

Lastly, the paper addresses charging infrastructure as being of great importance. A simulation analysis conducted by Tran et. al (2013) found that EVs are preferred to PHEV if the charging infrastructure is sufficient. The paper also indicates that more accessible charging stations better address range anxiety than extended driving range through technological innovation. Although the findings of the analysis are interesting, one should be aware that this analysis is roughly 10 years old and the rate of technological improvement of the range of EVs has greatly increased over the years. The newer car models on the market have an average of 331 km per charge (EV - Database, 2022). But nonetheless, it raises questions about how the charging infrastructure affects EV ownership.

4.0 Exploratory Data Analysis

In the context of this master thesis, we have made use of two datasets: the first dataset contains data about the sales of vehicles in Norway and we have looked at the period starting in 2014 and ending in 2021. The reason why we have done it this way is because the sales of electric cars did not really take off before 2014 in Norway. The second dataset contains data about the charging network in Norway and we have also looked at the same time period. This dataset is from NOBIL and it covers the period ranging from 2010 to 2022, but we have only made use of the period starting in 2014 and ending in 2021. We have also supplemented these two datasets with additional data for population and income at both the fylke and kommune level that we downloaded from the SSB website.

Based on the 2021 mobility report from Statista regarding the state of the electric vehicles market, Norway has the highest adoption rate for EVs in the world (Statista, 2021). For the following graphs, we will use our data to show where the charging stations are located, who have access to them and the distribution of the charging power of the stations.

4.1 Graphical Presentation of some of the data

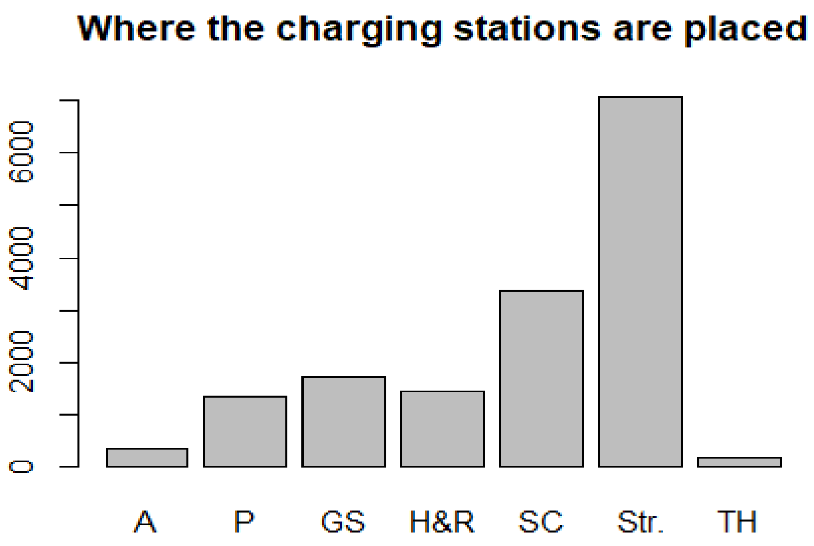

Figure 4. Location of the charging stations.
"A","P","GS","H&R","SC","Str.","TH" stand respectively for Airport, Car park, Gas station, Hotel & Restaurant, Shopping Center, Street and Transport hub.

Regarding the location of the charging stations, most of them are placed in either the streets or in shopping centers. The idea for why we see this may be due to the fact that streets and shopping centers have more space to accommodate a larger number of cars than the other places mentioned in the graph. We intend to use this variable as a control variable in the form of a ratio of the number of charging stations per kommune or fylke in a given year placed in the streets and in shopping centers over the total number of stations located in these two places per kommune or fylke in a given year.

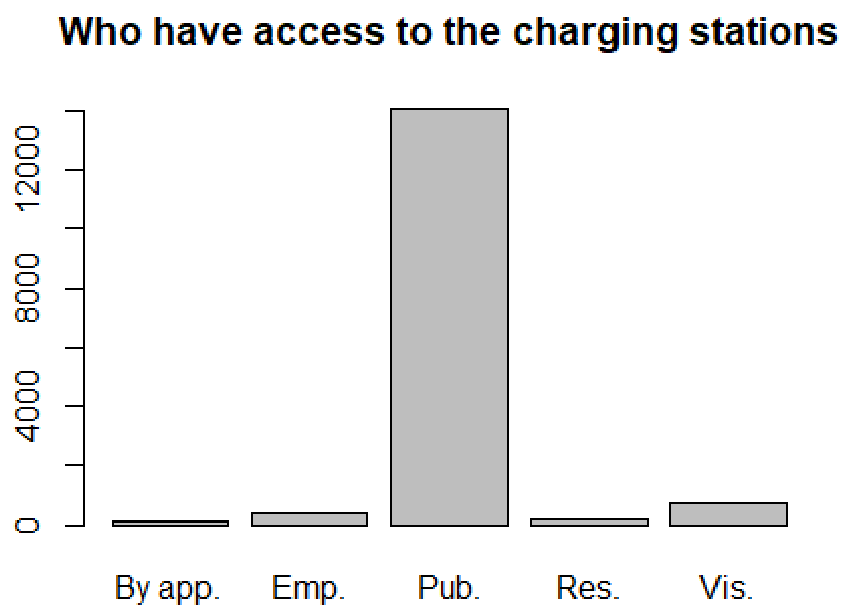

Figure 5. Who can charge here? "By app.","Emp.","Pub.","Res.","Vis." stand, respectively, for By appointment, Employees, Public, Residents and Visitors.

Who has access to a charging station is also an important factor as it may have an impact on the buying behavior of EVs in a certain area. Most charging stations in our dataset are available to the general public with only a small share of the total being available to visitors, employees and so on. We will also include this variable in our analysis as a control variable in the form of a ratio of the number of public stations in a given kommune or fylke in a given year over the total number of charging stations in this kommune or fylke in that year. It may help to account for the fact that not all chargers are available to everyone.

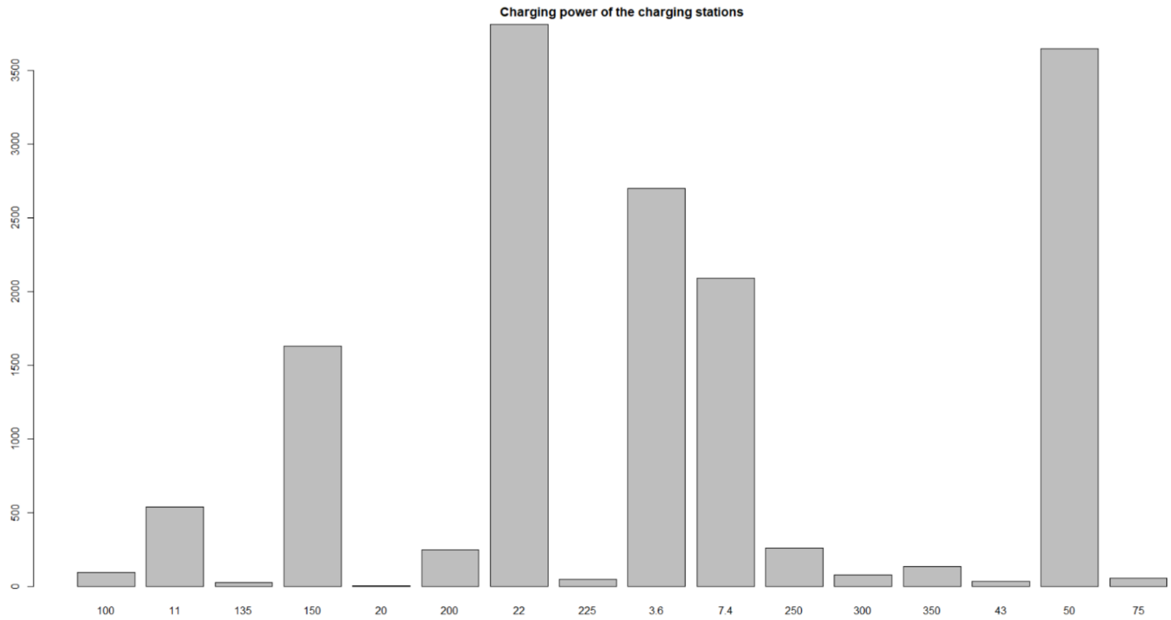

Figure 6. The numbers on the x-axis stand for the amount of charging power expressed in Kilowatts that the charging stations in this bar have. For example, "100" means all of the charging stations in the first bar have 100 KWs of charging power.

Where fast charging is available, it may serve as an extra incentive to buy an electric car, given that less time is needed there to charge an electric vehicle. Using multiple regression analysis, a paper published in 2017 (Neaimeh et al., 2017) has examined the relationship between daily driving distance and standard and fast charging and demonstrated that fast chargers are more influential. If this holds in reality, people living in fylker or kommuner with more fast charging will buy more EVs than people living in areas with less fast charging availability. We have included a variable in our analysis in the form of a ratio of the number of fast chargers available in a kommune or fylke in a given year over the total number of chargers available in that kommune or fylke in that given year to capture this effect in order to minimize the risk of misspecification of our models.

4.2 Summary Statistics

chargers_flyke	E	pop	fast_charg_ratio	public_ratio	main_ratio	avg_income
Min. : 10.00	Min. : 0.0	Min. : 237257	Min. : 0.00	Min. : 0.00	Min. : 0.00	Min. :440563
1st Qu.: 71.25	1st Qu.: 922.2	1st Qu.: 265367	1st Qu.:26.94	1st Qu.: 86.67	1st Qu.: 53.22	1st Qu.:492810
Median :135.00	Median : 1751.0	Median : 414145	Median :44.52	Median : 95.28	Median : 68.92	Median :528632
Mean :178.96	Mean : 4056.5	Mean : 513370	Mean :42.72	Mean : 90.32	Mean : 64.82	Mean :531048
3rd Qu.:211.00	3rd Qu.: 3677.2	3rd Qu.: 630864	3rd Qu.:60.05	3rd Qu.: 99.63	3rd Qu.: 79.75	3rd Qu.:562110
Max. :878.00	Max. :45344.0	Max. :1602646	Max. :77.78	Max. :100.00	Max. :100.00	Max. :692520

Table 1. Summary statistics for the variables used in our analysis for the fylke dataset.

The summary statistics for the data at the fylke level indicate that the number of chargers ranges from 10 to 878 with an average of almost 179 per fylke for the years used in this analysis. There is at least one year when there were no electric vehicles bought in one of the fykler and there was a year during which 45344 EVs were bought in one fylke. The three ratio independent variables are expressed in percentages and the yearly average income and population range from 440,563 NOK to 692,520 NOK and 237,257 people to 1,602,646 people respectively for the years used in this analysis.

chargers_kommune	E	pop	avg_income	fast_charg_ratio	public_ratio	main_ratio
Min. : 1.00	Min. : 0.0	Min. : 0	Min. : 0	Min. : 0.00	Min. : 0.00	Min. : 0.00
1st Qu.: 4.00	1st Qu.: 0.0	1st Qu.: 4526	1st Qu.:470482	1st Qu.: 0.00	1st Qu.:100.00	1st Qu.: 21.11
Median : 8.00	Median : 6.0	Median : 11666	Median :505680	Median : 50.00	Median :100.00	Median :100.00
Mean : 13.71	Mean : 186.7	Mean : 25532	Mean :497953	Mean : 44.31	Mean : 88.43	Mean : 67.34
3rd Qu.: 14.00	3rd Qu.: 142.0	3rd Qu.: 27190	3rd Qu.:537600	3rd Qu.: 66.67	3rd Qu.:100.00	3rd Qu.:100.00
Max. :190.00	Max. :14470.0	Max. :285601	Max. :738960	Max. :100.00	Max. :100.00	Max. :100.00

Table 2. Summary statistics for the variables used in our analysis for the kommune dataset.

The kommune is a smaller territorial unit than the fylke in Norway in terms of both area and people and the summary statistics show this clearly. The number of chargers per kommune for the time period covered in this master thesis ranges from 1 to 190, with an average of 13.71 chargers per kommune. There is at least one kommune with no EVs and the kommune with the highest amount of EVs has 14470 EVs. The yearly average income range and population range from 0 NOK to 738960 NOK and 0 people to 285601 people. The three ratio independent variables are expressed in percentages and they account for the percentage of fast charging available, the percentage of charging publicly accessible and where most of the chargers are located.

5.0 Econometric Theory[1]

Panel data, also called longitudinal data, is a type of data where the same units are measured in at least two periods. It encompasses a cross-sectional dimension and a time dimension. Having several observations for the same unit allows to say something about the slope of the coefficients which is assumed to be the same across all units. The cross-sectional dimension in our datasets is the fylker and kommuner and the time dimension is the years ranging from 2014 to 2021.

Using panel data comes with quite some advantages. This increases the sample size and given the structure of the data, it is easier to build dynamic models. This also reduces multi-collinearity problems due to the variation between cross-sections and the variation over time. Panel data are able to control for unobserved effects better than in cross-sections or time-series.

Panel data is more than a sequence of cross-sections over time. In a sequence of cross-sections, we do not necessarily observe the same units over time. For the fylke dataset, we have balanced panels because there is a unit available for each of the years in the dataset. However, it is different for the kommune dataset because there are some kommuner which do not have data for some of the years and that leaves us with an unbalanced panel for the kommune dataset.

5.1 Assumptions for fixed and random effects

There is a set of assumptions at the core of the econometric methodology used to estimate the fixed effects regressions and the random effects regressions. For the fixed effects regressions, there are as follows:

a) For each *i*, the model is
$Y_{it} = \beta_1 x_{it1} + \ldots + \beta_k x_{itk} + a_i + u_{it}$, $t = 1,\ldots, T$, where the β_j are the parameters to estimate and a_i is the unobserved effect.
b) We have a random sample from the cross section.
c) Each explanatory variable changes over time (for at least some i), and no perfect linear relationships exist among the explanatory variables.

[1] This part draws heavily from the lecture notes used in the introductory econometrics course at NHH, ECN402 and the textbook used in this class, Introductory Econometrics by Woolridge.

d) For each t, the expected value of the idiosyncratic error given the explanatory variables in all time periods and the unobserved effect is zero: $E(u_{it}| X_i , a_i) = 0$. Under these first four assumptions, the fixed effects estimator is unbiased. Again, the key is the strict exogeneity assumption, $E(u_{it}| X_i , a_i) = 0$. Under these same assumptions, the FE estimator is consistent with a fixed T as N becomes bigger and bigger.

e) $Var(u_{it}|X_i , a_i) = Var(u_{it}) = \sigma^2_u$ for all t = 1,...,T.

f) For any $t \neq s$, the idiosyncratic errors are uncorrelated (conditional on all explanatory variables and the unobserved effect, $a_{i.}$) : $Cov(u_{it} , u_{is}|X_i , a_i) = 0$. If all these assumptions hold, the fixed effects estimator of the β_j is the best linear unbiased estimator.

g) Conditional on X_i and a_i , the u_{it} are independent and identically distributed as $Normal(0,\sigma^2_u)$.

For the random effects regressions, there are as follows:

a) There are no perfect linear relationships among the explanatory variables. The cost of allowing time-constant regressors is that we must add assumptions about how the unobserved effect, a_i, is related to the explanatory variables.

b) In addition to $E(u_{it}| X_i , a_i) = 0$, the expected value of a_i given all explanatory variables is constant: $E(a_i|X_i) = \beta_0$. This is the assumption that rules out correlation between the unobserved effect and the explanatory variables, and it is the key distinction between fixed effects and random effects. Because we are assuming a_i is uncorrelated with all elements of x_{it}, we can include time-constant explanatory variables. We allow for a nonzero expectation for a_i in stating $E(a_i|X_i) = \beta_0$ so that the model under the random effects assumptions contains an intercept, β_0.

c) In addition to $Var(u_{it}|X_i , a_i) = Var(u_{it}) = \sigma^2_u$ for all t = 1,...,T , the variance of a_i given all explanatory variables is constant: $Var(a_i|X_i) = \sigma^2_a$.

5.2 Random effects or fixed effects?

Because fixed effects allows arbitrary correlation between a_i and the x_{itj}, while random effects does not, FE is widely thought to be a more convincing tool for estimating ceteris paribus effects. Still, random effects is still applied in certain situations. Most obviously, if the key explanatory variable is constant over time, we cannot use FE to estimate its effect on y. If we are interested in a time-varying explanatory variable, we can only use the random effects methodology instead of the fixed effects methodology when $Cov(x_{itj},a_i) = 0$.

In our analysis, our goal is to determine whether the amount of charging available in a fylke or kommune in a given year has an impact on the number of EVs bought in this fylke or kommune in this year. The unobserved effect term; a_i, can contain information about the reliability of the charging network in a fylke or kommune or people’s attitude in a fylke or kommune towards EVs or charging stations. Even though, this may vary across fylker or kommuner, we assume in this thesis that it stays constant in a fylke or kommune over the years covered in the thesis. The explanatory variables that we have about the charging network such as the number of chargers or their accessibility are likely to be correlated with the unobserved effect term, a_i. This is the reason why we have decided to use fixed effects in our analysis instead of random effects. The fixed effects transformation will make sure that the unobserved error term is cancelled out.

To make sure that the strict exogeneity assumption holds; $E(u_{it}|X_i, a_i) = 0$, additional variables regarding the population and income levels will be added to account for the fact that places with more people are likely to have more chargers which may lead to people living there buying more EVs. Places with high income may also have more EVs which may lead to more chargers being built in these areas.

6.0 Empirical Analysis

In this part, we will use the econometric framework outlined above to run regressions on our data. The questions that we will try to answer is the following: **Does the number of charging stations in a kommune or fylke in a given year drive the adoption of EVs in this kommune or fylke in this year?** In order to do so, the same analysis will be conducted at both the kommune and fylke level. The analysis mainly focuses on the charging infrastruture as a driver of the adoption of EVs, the charging infrastructure is part of the external factors mentioned above as part of the factors affecting the adoption of EVs.

6.1 Names of the variables used in the regressions and what they mean.

Chargers_fylke or chargers_kommune which are the variables of interest here are respectively the number of chargers in a specific fylke or kommune in a given year.

Fast_charg_ratio is a variable set equal to the number of fast charging stations in a given fylke or kommune for a given year over the the total number of charging stations in this given fylke or kommune for this given year. In the context of this master study, a fast charger is any charger whose charging power exceeds or is is equal to 50 KWs. It is expressed in percentages.

Public_ratio is a variable set equal to the number of public charging stations in a given fylke or kommune for a given year over the total number of charging stations in this given fylke or kommune for this given year. Public charging stations are defined here as charging stations where anyone can charge. It is expressed in percentages.

Main_ratio is a variable set equal to the number of charging stations in a given fylke or kommune for a given year that are located in the street or a shopping center over the total number of charging stations in this given fylke or kommune for this given year. The reason why we have this variable is because it may be able to capture differences across fylker or kommuner when it comes to how convenient it is to charge the car. It is expressed in percentages.

Pop is a variable set equal to the number of people living in a kommune or fylke in a given year. It is intuitively true that an increase in people may also lead to an increase in the adoption of EVs, even if everything else stays constant.

Avg_income is a variable set equal to the average yearly income in a kommune or fylke in a given year. We expect kommuner or fylker with higher income to also have more EVs, even if everything else stays constant.

6.2 The analysis at the fylke level: Results and Discussion

Fixed Effects Regressions Results at the fylke level

	Dependent variable:			
	E			
	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
chargers_flyke	13.137**	12.220**	2.747	7.477
	t = 2.346	t = 2.100	t = 0.474	t = 1.208
lag(chargers_flyke)				16.929**
				t = 2.417
fast_charg_ratio		42.926	50.593	51.965
		t = 0.905	t = 1.165	t = 1.158
public_ratio		28.745	-65.022	21.507
		t = 0.510	t = -1.138	t = 0.201
main_ratio		46.152	-0.015	34.759
		t = 1.366	t = -0.0004	t = 0.925
I(pop/1000)			-19.264	-3.024
			t = -1.329	t = -0.191
I(avg_income/1000)			84.666***	38.577
			t = 3.824	t = 1.287
Observations	80	80	80	70
R^2	0.074	0.125	0.303	0.380
Adjusted R^2	-0.060	-0.047	0.140	0.193
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 3. Regression results for the fixed effects models at the fylke level.

The fixed effects model, at the fylke level, generates the results above. In the first model, the regression of number of electric vehicles on the number of chargers produces a coefficient that is significant at both the 10% and 5% levels. If this model is true, an increase of 1 unit in chargers in a fylke will lead to an increase of 13.137 EVs bought in this fylke. It is not difficult to see that this model may actually suffer from the omitted variable bias curse, given the amount of other variables that also affect sales of EVs that are not included in the regression. Therefore, the explanatory variable here is clearly correlated with the error term which violates the strict exogeneity assumption. To deal with this, we have run the second model with variables that account for differences in the distribution of fast charging, the accessibility of charging stations and their location across the fylker.

Even when accounting for these factors, we still get a statistically significant coefficient on the number of chargers. It is significant at both the 10% and 5% levels. Holding the other variables constant, an increase of 1 unit in the number of chargers in a fylke will lead to an increase of 12.22 EVs bought in this fylke. The sheer amount of chargers available seems to be what matters the most, not the charging power of the chargers available, their accessibility nor their location. However, the sheer number of chargers may be highly correlated with population. Areas with more people may have more chargers and even if everything else stays the same, an increase in population can cause an increase in the number of EVs bought in a fylke.

To account for this effect, we have also included population in the third model. We have also added income to this model to account for the fact that fylker with high income will have more EVs than fylker with low income. After accounting for these two variables, the main variable we are interested in; the number of chargers, is no longer significant. This means that the sales of EVs across fylker is not driven by the number of chargers there are if this model is true. The income variable is significant at all the levels of significance considered here which means that places with higher income have, on average, more EVs. When the average income in a fylke increases by 1000 NOK, 84.66 new EVs are bought based on this model.

One concern to account for is the fact that chargers built in the recent past, for example one year earlier, may be the factor affecting the sale of EVs one year later instead of chargers built in the same year. Failing to account for this will mean that we will not be able to detect reverse causality if it is present. This is an example of the chicken and egg problem outlined in the introduction. To introduce the notion of reverse causality in our model, we have included a lag variable in the fourth model on top of all the other variables that we have already use in the third model.

The number of chargers is still insignificant at all the significance levels considered here but the lag variable which accounts for the idea that chargers built last year might have an impact on the sale of EVs in the current year is significant at all the significance levels considered. Its interpretation is as follows: Increasing the sheer amount of chargers at the fylke level by one unit the year before increases the number of EVs bought by almost 17 units in the year after, holding everything else constant. This is evidence that chargers built in the past may be a better predictor of the sale of EVs in a fylke in the current year than chargers being built in the current year.

6.3 The analysis at the kommune level: Results and Discussion.

Fixed Effects Regressions Results at the kommune level

	Dependent variable:			
	E			
	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
chargers_kommune	3.154^{**}	2.920^{**}	1.181	1.678
	t = 2.317	t = 2.135	t = 0.875	t = 0.706
lag(chargers_kommune)				9.387^{***}
				t = 3.906
fast_charg_ratio		-0.075	-0.251	0.544
		t = -0.099	t = -0.343	t = 0.295
public_ratio		1.459	0.558	0.302
		t = 1.568	t = 0.609	t = 0.126
main_ratio		0.917	0.611	1.535
		t = 1.511	t = 1.037	t = 0.967
I(pop/1000)			99.106^{***}	71.759^{**}
			t = 6.106	t = 2.345
I(avg_income/1000)			0.312	1.101
			t = 0.864	t = 0.969
Observations	847	847	847	358
R^2	0.009	0.018	0.084	0.147
Adjusted R^2	-0.421	-0.416	-0.325	-0.470
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Table 4. Regression results for the fixed effects models at the kommune level.

At the kommune level, the fixed effects methodology produces the results in the table above. The results for the first model mean that the number of chargers is a strong predictor of the adoption of electric vehicles across kommuner given its high level of statistical significance. However, the model most likely suffers from the omitted variable bias by having only the number of chargers as explanatory variable.

In the second model, we have tried to account for factors such the accessibility, charging power and the location of the charging stations that can also have an impact on the buying behavior of electric vehicles. The reason why we have decided these variables is because as mentioned in the literature review, fast charging has been shown to be a factor that can drive the adoption of EVs. A kommune with more fast charging available may have a greater number of EVs than a kommune with less fast charging, even if they had the same amount of charging stations. The same logic applies to the other two factors considered. Our main variable of interest is still very significant and none of the other factors seem to be statistically relevant in predicting buying behavior of electric vehicles across kommuner. If this model is a true representation of the state of the EVs market at the kommune level, then an increase in charging stations by one unit will lead to an increase of almost 3 new EVs bought.

The size of the population can also be a driver for the amount of EVs bought in a kommune, more people automatically implies a higher potential demand for EVs. Therefore, a model that accounts the size of the population into account helps to minimize the risk of omitted variable bias. Income is also another such factor that can drive the adoption of EVs because it implies a higher potential demand for EVs. Therefore, in the third model, we have included these as new control variables. Our main variable of interest is no longer significant and only the population variable is significant among the control variables. An increase in population by a thousand will lead to an increase of 99.106 new EVs bought on average, ceteris paribus. Even though this is surprising given the smaller number of people living in kommuner compared to fylker, an increase of a thousand in population in a most kommuner in a given year is also very unlikely.

To account for the fact that past chargers may be a better predictor of new cars bought than the number of chargers that are added to the charging network in the year the cars are bought, we have also included a lag variable in the analysis at the kommune level. In the fourth model, the coefficient on the lag variable is statistically significant at all the levels considered here and this may be an indication that past chargers, especially these made available one earlier, are a better predictor of EVs in the current year than chargers made available in the current year.

6.4 Robustness Checks

Due to the structure of the data, the common issues with heteroskedasticity and autocorrelation may also arise here. Therefore, we will try to account for this by running robustness checks and see how the new t-values compared to the ones that were computed earlier in the analysis without taking these issues into account.

6.4.1 At the fylke level

Results from the fixed effects models accounting for heteroskedasticity and autocorrelation

	Dependent variable:			
	Model 1	Model 2	Model 3	
	(1)	(2)	(3)	(4)
chargers_flyke	13.137***	12.220***	2.747	7.477
	t = 4.100	t = 3.663	t = 0.821	t = 0.977
lag(chargers_flyke)				16.929**
				t = 2.161
fast_charg_ratio		42.926	50.593	51.965
		t = 1.310	t = 1.085	t = 1.149
public_ratio		28.745	-65.022	21.507
		t = 0.858	t = -1.102	t = 0.318
main_ratio		46.152	-0.015	34.759
		t = 1.345	t = -0.001	t = 0.978
I(pop/1000)			-19.264	-3.024
			t = -0.906	t = -0.109
I(avg_income/1000)			84.666	38.577
			t = 1.577	t = 1.189
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5. Regression results at the fylke level adjusted for heteroskedasticity and autocorrelation.

The table above shows the coefficients of the model adjusted for heteroscedasticity and autocorrelation due to the structure of the data. For the first two models, the coefficients on the main variable of interest; the number of chargers, are even more significant as they have stayed the same but with an increase in the t-values. For the third model, the variable of interest is still not statistically significant but the population variable which was statistically significant when not accounting for heteroscedasticity and autocorrelation no longer is. This may be due to the fact that population tends to be highly correlated through time and not accounting for that can generated standard errors that are biased due to autocorrelation.

The results for the fourth model are still more or less the same, the variable of interest in this thesis is still not significant but the variable that we have added to account for the reverse causality phenomenon still is, even though the t-value has gone down a bit. This analysis shows that failing to account for heteroscedasticity and autocorrelation when dealing with panel data can be somewhat misleading.

6.4.2 At the kommune level

Results from the fixed effects models accounting for heteroskedasticity and autocorrelation

	Dependent variable:			
	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
chargers_kommune	3.154	2.920	1.181	1.678
	t = 1.137	t = 1.124	t = 0.746	t = 0.932
lag(chargers_kommune)				9.387
				t = 1.491
fast_charg_ratio		-0.075	-0.251	0.544
		t = -0.124	t = -0.382	t = 0.490
public_ratio		1.459	0.558	0.302
		t = 1.408	t = 1.038	t = 0.330
main_ratio		0.917*	0.611*	1.535
		t = 1.766	t = 1.900	t = 1.605
I(pop/1000)			99.106	71.759
			t = 1.578	t = 1.488
I(avg_income/1000)			0.312	1.101
			t = 1.486	t = 1.217
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6. Regression results at the kommune level adjusted for heteroskedasticity and autocorrelation.

Accounting for heteroscedasticity and autocorrelation at the kommune leved has made all the coefficients that were statistically significant when not accounting for these no longer significant. Norway is sparsely populated and that could be the reason why these issues; heteroscedasticity and autocorrelation, are magnified at the kommune level. Only the variable that accounts for the influence of location; main_ratio, has managed to become significant but we do not really know why or how.

6.4.3 Alternative analysis

Fixed Effects Regressions Results at the fylke level

	Dependent variable:			
	E_per_capita			
	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
chargers_flyke_per_capita	0.190	2.217	2.685	5.800
	t = 0.037	t = 0.401	t = 0.464	t = 0.944
fast_charg_ratio		0.068		0.086
		t = 0.951		t = 1.124
public_ratio		-0.020		0.109
		t = -0.208		t = 0.650
main_ratio		0.034		0.067
		t = 0.649		t = 1.086
factor(year)2015	1.099	0.056		
	t = 0.300	t = 0.013		
lag(chargers_flyke_per_capita)			5.908	7.530
			t = 0.952	t = 1.190
factor(year)2016	0.757	-0.081	0.053	0.616
	t = 0.208	t = -0.019	t = 0.014	t = 0.161
factor(year)2017	1.450	-0.136	0.251	-0.894
	t = 0.397	t = -0.030	t = 0.065	t = -0.229
factor(year)2018	3.163	1.976	1.403	0.411
	t = 0.867	t = 0.425	t = 0.363	t = 0.102
factor(year)2019	4.760	4.210	2.791	2.288
	t = 1.279	t = 0.884	t = 0.693	t = 0.535
factor(year)2020	7.193*	5.096	4.267	1.119
	t = 1.829	t = 0.954	t = 0.940	t = 0.224
factor(year)2021	11.310***	9.699*	7.894*	5.288
	t = 3.033	t = 1.931	t = 1.745	t = 1.086
Observations	80	80	70	70
R^2	0.206	0.222	0.210	0.254
Adjusted R^2	-0.012	-0.042	-0.048	-0.051
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 7. Regression results at the fylke level for the alternative analysis

We have assumed in the main analysis that variables[2] such as attitudes towards EVs or the reliability of the charging remain constant over the years covered by our analysis in a given fylke or kommune. Here, we are assuming that the effect of these variables of the sale of EVs in a given fylke or kommune are probably captured by the time dimension in our data, the year variable. Therefore, we have decided to include year in an alternative analysis as control variables and see what effect it has on our main variable of interest here which is the number of chargers.

Before running the regression, we have transformed both the variable accounting for the number of EVs and the variable accounting for the number of chargers in a given fylke or kommune. Both variables have been divided by the population variable which was itself divided by 1000 in order to facilitate the interpretation of the results obtained. This transformation also helps to deal with the fact that population is not evenly distributed across the fylker or kommuner in Norway. **Here, the "per capita" expression stands for a unit of one thousand (1000).**

In the table above, we can see that the number of chargers per capita variable is not statistically significant in the first model. The time effect slowly increases over the years and it becomes significant in 2020. In 2021, the number of EVs bought at the fylke level has increased to 11.31 more EVs per capita in comparison to the baseyear, 2014. This result suggests that other factors not accounted for in our data but that do change over time may be driving the sale of EVs per capita instead of the number of chargers available per capita. Similar results have been obtained for the other models considered, and this further strengthens our claim that other factors not included in our data such as people's attitudes towards EVs or the reliability of the charging network may be the ones driving the adoption of EVs in Norway. These models have accounted for the possibility that fast charging, accessibility and location could also have impacted the sale of EVs. The possibility of charging stations built in the past affecting the current sale of EVs has also been taken into account through the lag variable used in some of the models.

In the next table, we will present the same analysis at the kommune level to see if the same dynamics hold. The same results seem to hold here as for the analysis at the fylke level. For

[2] See the discussion of fixed effects or random effects in the econometric theory part for more information.

example, in the fourth model, our main variable of interest is not statistically significant and the lag variable introduced to account for reverse causality is not statistically significant either. The time effect increases and decreases to finally reach statistical significance in 2020. In 2021, the number of EVs bought per capita a the kommune level has increased to 8.15 EVs more in comparison with the baseyear, 2015 here because of the lag variable.

Fixed Effects Regressions Results at the kommune level

	Dependent variable:			
	E_per_capita			
	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
chargers_kommune_per_capita	0.010	0.011	-0.385	-0.487
	t = 0.092	t = 0.101	t = -0.549	t = -0.683
fast_charg_ratio		-0.001		-0.010
		t = -0.139		t = -0.565
public_ratio		-0.007		0.013
		t = -0.620		t = 0.572
main_ratio		0.005		0.013
		t = 0.688		t = 0.849
factor(year)2015	1.524	1.604		
	t = 1.367	t = 1.420		
lag(chargers_kommune_per_capita)			-0.013	-0.022
			t = -0.020	t = -0.033
factor(year)2016	1.190	1.302	0.560	0.546
	t = 1.102	t = 1.192	t = 0.284	t = 0.276
factor(year)2017	1.820^{*}	1.895^{*}	2.890	2.940
	t = 1.740	t = 1.771	t = 1.391	t = 1.402
factor(year)2018	2.694^{**}	2.747^{**}	1.737	1.549
	t = 2.438	t = 2.427	t = 0.845	t = 0.745
factor(year)2019	3.069^{***}	3.231^{***}	3.018	2.984
	t = 2.880	t = 2.958	t = 1.478	t = 1.427
factor(year)2020	3.527^{***}	3.680^{***}	5.002^{***}	4.971^{**}
	t = 3.431	t = 3.433	t = 2.660	t = 2.563
factor(year)2021	5.814^{***}	5.942^{***}	8.256^{***}	8.151^{***}
	t = 5.780	t = 5.667	t = 4.439	t = 4.268
Observations	839	839	353	353
R^2	0.073	0.075	0.121	0.128
Adjusted R^2	-0.351	-0.356	-0.524	-0.535
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 8. Regression results at the kommune level for the alternative analysis.

Conclusion

Our analysis has shown that the number of chargers made available in the current is not a good predictor of sale of EVs in the current year after accounting for the omitted variable bias and making sure that the strict exogeneity assumption holds both across fylker and kommuner. What this means is that increasing the number of chargers in a fylke or kommune in a given will not lead to an increase in the number of EVs bought in this fylke or kommune in this year, everything else staying the same. From this, someone may ask if the new chargers added this year will not impact sales of EVs in the future which may shed some light on what comes first: the chargers or the cars. To take this aspect into account in our analysis, a new variable; the lag variable, has been added to reflect the fact that past charging may have a greater influence on the adoption of EVs in the current year than chargers added to the charging network in the current year.

This new variable is statistically significant across both fylker and kommuner and this is even after accounting for differences in the charging network such as accessibility, charging power, location of the chargers and other differences between fylker and kommuner such as population and income. After accounting for heteroscedasticity and autocorrelation due to the structure of the data, this new variable is still significant at the fylke level but not at the kommune level. This result highlights two facts: future adoption of EVs can be incentivized by building new stations now and the fylke may be the better territorial unit to use to design a charging network that optimally serves the Norwegian population.

As outlined in the alternative analysis, there could be potentially useful information not included in our analysis. Information about people’s attitudes towards EVs or the perception that they have on the reliability of the charging network are important factors. These factors are probably captured by the time dimension; the year variable, but we cannot say anything about them due to lack of data.

Limitations and further research

In the literature review, we mentioned that more 80% the EVs owners in Norway have access to home charging. The fact that we were not able to include data into our analysis that reflect this fact limits the usefulness of our analysis for policy decisions. Further research can try to incorporate such data into an analysis that goes along the same lines as ours to see if and how home charging actually affects EVs adoption in Norway.

We also mentioned in the literature that people that are better educated seem to buy more EVs on average. A study that also takes into account differences in education levels across fylker and kommuner may produce more reliable results than ours due to the fact that not having included education levels in our analysis may be a case of omitted variable bias.

Past research has also shown that people living in urban areas are more likely to buy EVs than people living in non-urban areas. We did not account for that in this master thesis and incorporating this information into future research on this topic can further strengthen the understanding of the impact of charging stations on EVs.

Access to information about the perception of the charging network by people across fylker or kommuner or how people's attitudes towards EVs have evolved over the years will have helped us better understand the dynamics of the EVs market in Norway and that is something that future master theses can try to look into if such data become available.

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