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TITLE:

“HOW DO CHARACTERISTICS OF THE MUNICIPALITIES AFFECT THE ADOPTION OF ELECTRIC VEHICLES IN NORWAY?”

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Executive Summary

A future objective for the Norwegian government is to have a majority of electric vehicles (EVs) in the vehicle market. Compared to other countries, Norway has been successful in the adoption of EVs. However, it is important to note that there are large differences between counties and municipalities considering our data. For the further adoption of EVs, it is important to grasp the significant factors that drive the EV share growth forward, and maybe equally important to shed light on the factors that slow the development. This thesis therefore aims to answer the following research question: "How do municipality characteristics impact the adoption of electric vehicles?"

To study this we perform a multiple regression analysis with municipality-level data for several conducted variables related to these two factors. In addition, to gain information on how variables change with the inclusion of new variables, we perform two minor regressions containing variables related strictly to population characteristics, and to the structural characteristics of a municipality which are more related to macro variables. The paper contributes to existing literature by analysing many aspects of EV shares in a municipality with a regression of 30 variables. The regression results present that five variables have a significant and positive influence on EV shares; presence of a major city has the strongest impact, followed by private roads, toll roads, the highest income level group and men. The negative regression results indicate that people above the age of 80 are the largest hindrance towards EV share increase. This is followed closely by European highway roads, the age group between 25-34 and lastly people with primary school as their highest finished education.

The results imply that infrastructure plays a great role in the adoption of EVs and can present issues towards increasing the number of EVs in the rural areas of Norway. Ideally, we would have obtained more precise variables to empower our model, yet we conclude that income and infrastructure have been the two largest contributors to the EV shares increasing in a municipality so far. We note that in particular, infrastructure will be important for increasing future adoption of EVs. Most of our findings are in line with corresponding literature within EV adoption, but some differences occur given that Norway is different in some areas than other countries, and that some studies are performed on a regional or country-level. Other studies have neglected to discuss the importance of roads; however, this might be due to them capturing this effect in other ways.

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Due to certain circumstances, we were assigned a new supervisor at the end of January, and we appreciate how quickly and carefully he got an understanding of our work and plan for the thesis. Therefore, we want to thank our supervisor from the end of January, scholarship holder Maximilaan Willem Pierre Thijssen. By providing valuable suggestions and constructive feedback he has been helpful in guiding us through the process.
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Herman Håland Strømdal and Håkon Frivoll
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1. Introduction

The threat of climate change has forced numerous businesses, politicians and consumers to think in a new way, and ultimately the phenomenon has had a great impact on the economy and how consumers live their lives. Indeed, one of the markets that have been rapidly changed due to the environmental awareness of consumers is the transportation market. The result of this is the creation and adoption of Electric Vehicles, also named EVs. The implementation of EVs has varied in different parts of the world. In Norway, the adoption of EVs has seen a rapid development compared to the rest of the world in recent years. As much as 50% of the market share of vehicles sold in Norway in the past years has been electric vehicles, excluding plug-in hybrids (Norsk Elbilforening, 2020). The Norwegian capital, Oslo, has been heralded as the EV capital of the world as a result of all the electric vehicles driven in the city (Crosse, 2018).

While Norway is among the countries with a wide adoption of EVs, there is substantial variation within Norway between municipalities, presented by Figure 1. The figure illustrates the percentage of vehicles that are EVs in municipalities in Rogaland. The county was chosen as an example, and the big differences between the municipalities indicate that there likely are similar differences within other Norwegian counties.

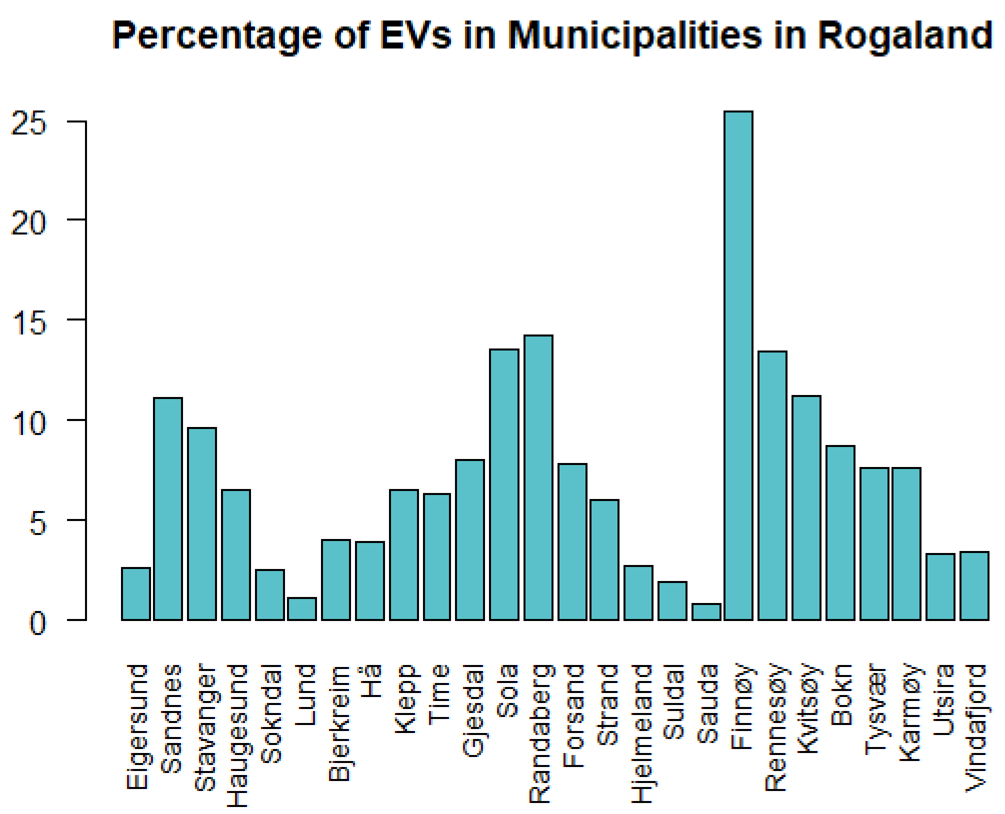

Figure 1.1: Visualization of the percentage of EVs for the municipalities in Rogaland in 2018. Data collected from SSB, 03.02.21. URL: https://www.ssb.no/statbank/table/07849/.

While the Norwegian government incentivizes the adoption of EVs across the country, the wide variation between the municipalities indicates that in some places the policies are not having an effect. The variation may reflect characteristics of people living in the different municipalities, but it may also reflect structural factors (for example number of charging stations) that complement the adoption of EVs. Evidence on such structural factors can usefully benefit the Norwegian government to boost the adoption of EVs in municipalities with low adoption rates. Our research question is therefore:

"How do municipality characteristics affect the adoption of electric vehicles in the municipalities".

We aim to characterize the municipalities that have seen a great adoption of EVs. We therefore seek to explore the differences in the municipalities, both on a structural level, such as infrastructure and distances, and on a populational level, such as income and age. Most of the data we use, which consists of demographic, financial, technological and geographical variables, is obtained from Statistisk Sentralbyrå (SSB). The website is the main provider of official statistics in Norway, but we also collect some data from other sources. By controlling for the differences between municipalities, and analysing through an OLS regression, we examine how the characteristics of populations in municipalities and how a municipality's structural factors increase the possibility to be able to adopt the use of EVs.

We find that the most impactful factors for EV adoption were two structural factors: presence of a major city and private road with estimates of 0.707 and 0.413 respectively. This is closely followed by toll roads in a municipality, with an estimate of 0.337. From the variables related to the population characteristics, the highest income level in our study was seen as the most impactful variable on EV adoption, with an estimate of 0.232. Other factors that turned out to have a negative influence on EV adoption were highways, ages between 25-34, ages 80+ and lastly a low education variable. These findings suggest that infrastructure plays a significant role in the purchasing decision together with high income. On the contrary, population variables play a significant role in the negative impact of EV share in a municipality. With current technology and prices, it is still a challenge to implement EVs in the rural areas where people generally earn less. Our model captured around 70% of the variation in the EV adoption. More detailed data on income and data on different policies in the municipalities could have improved our results, as they are both factors that likely would have had an impact on the EV adoption.

We contribute to the literature by finding the length of road type to be a major predictor of the number of EVs. Highway roads were seen as a significant explanatory variable for negative EV share in a municipality, while private roads were shown to be a significant predictor for positive EV share. These two variables appear to be a good measure for infrastructure, and capture the effects of distant areas. Previous literature we have looked at has not used this type of variable in their research on EV adoption, and in general, our research includes more variables in the regression and analysis than others have done. Unlike a similar study by Mersky et al. (2016) researching EV growth on a municipality level, we also find toll roads to affect EV shares on a municipality level. In addition, most of the studies performed in other countries find charging stations to be a significant factor for EV adoption. Our results indicate that charging stations are not a significant predictor for the number of EVs. A possible explanation for this is that other studies have researched larger areas, and their analyses were done on a regional level. The rest of our findings are in line with most of the previous literature.

2. How do People Decide to Spend Their Money?

The following section will be based on consumer theory and discrete choice theory from Dagsvik (1998) to structure our thoughts concerning the adoption of EVs. It is crucial to study the municipality's consumers in order to recognize factors they consider important in an EV. If the goal is to make the consumers choose an EV instead of other vehicles, then EVs need to provide the highest utility depending on variables such as range, price, safety and other important factors.

Consider a simplified economy in which consumers can buy one of two cars. Every consumer has a budget constraint. Assuming the consumer spends all his or her money, the budget constraint equation will be

$$P_1 x_1 + P_2 x_2 = M \tag{1}$$

Where M denotes income, P_1 denotes price of good x_1, and P_2 denotes price of good x_2

While the consumers face the same budget constraint, they have individual preferences. To capture these uniqe preferences, we use a utility funcion, which are specific for every consumer. We express the utility function as $U(x_1, x_2)$, indicating that the utility, U, is a function of the quantities of goods x_1 and x_2. Together with the prices of goods and the consumers purchasing power given by their income, this utility function gives us what is the optimal quantity for the consumer to purchase.

What utility a consumer obtains from a good depends on which attributes the good contains, and how the consumer values the different attributes. In many cases with vehicles in mind, consumers only need one good, and hence choose from a set of mutually exclusive alternatives. Every car provides the same main service, but each car also contains a unique bundle of attributes, which for a car may consist of factors like price, brand, engine size, fuel, safety and comfort.

To structure our thought concerning consumptions behaviour, we will introduce a stylized model using discrete choice theory. This model covers the attributes belonging to different goods. The model builds on the theory of the report from Dagsvik (1998) regarding the discrete choice models

We let $U = U_j(\mathbf{x}_j, \boldsymbol{\theta})$ denote the utility associated with product $j \in \{1, \dots, J\}$, where $\mathbf{x}_j$ denotes a $(1, m)$-dimensional vector of attributes associated with product j, and $\boldsymbol{\theta}$ is a $(1, m)$-dimensional parameter vector that quantifies the importance of each attribute. A consumer with 2/two* alternatives thus chooses from,

$$U_1 = U_1(x_{11}, x_{21}, \dots, x_{m1}, \boldsymbol{\theta})$$

(1) $$U_2 = U_2(x_{12}, x_{22}, \dots, x_{m2}, \boldsymbol{\theta})$$

A rational consumer will choose the alternative that gives highest utility and will therefore choose alternative U_1 if and only if $U_1 > U_2$ The attributes can typically be divided into monetary attribute, and non-monetary attributes. Therefore, a good y_J is represented by this equation:

$$y_j = \{monetary\ attribute(x_{1j}), nonmonetary\ attributes(x_{2j} \dots X_{nj})\}$$

Where $x_{1j} = (Income - price\ j) = (I - P_j), and\ we\ expect \frac{dU_j}{dX_{1j}} > 0,$

For non-monetary attributes, the maximizing utility is increasing in income available for other goods and services, all else equal. For the non-monetary attributes, the attribute is desirable if $\frac{dU}{dx} > 0$, and undesirable if $\frac{dU}{dx} < 0$

Consider a world in which there are three types of cars, $j \in \{fuel, hybrid, electric\}$, and where the attributes are given by:

$$y_j = \{I - p_j), Appearance\left(A_j\right), Pollution\left(P_j\right), Comfort(C_j)$$

This gives the following possible utilities

$$U_1 \ = \beta m \ (I - P_1) + \beta_A * A_1 + \beta_P * P_1 + \beta_C * C_1$$
$$U_2 \ = \beta m(I - P_2) + \beta_A * A_2 + \beta_P * P_2 + \beta_C * C_2$$
$$U_3 = \beta m \ (I - P_3) + \beta_A * A_3 + \beta_P * P_3 + \beta_C * C_3$$

where $\theta = (\beta_M, \beta_A, \beta_P, \beta_C)$, and the consumer will choose the alternative that gives the highest level of utility.

Even though this model describes a situation on a consumer level, it could also be useful to keep in mind when analysing the adoption of EVs on a municipality level. Information on the characteristics of EV buyers will tell us what type of consumers that value the attributes connected to EVs given that they have the purchasing power. If we view a municipality as a consumer, and let the characteristics of a municipality represent characteristics of a consumer, we are then able to tell what type of municipalities that value the attributes connected to EVs. A concern by doing this, however, is that we treat one aggregated group as if it would react like a group that is less aggregated. This problem is often referred to as the aggregation problem (Gordon, 1992), which may cause problems regarding the validity of the results. However, even if the estimates are less precise on a consumer level, the results will give us some indications on what the consumers value.

3. Literature Review of Electric Vehicle Adoption

There are several extensive research papers in the field of battery electric vehicles (BEVs) and hybrids with focus on adoption into a country, along with variables or factors that make them more attractive to one city compared to another. Purchasing these environmental substitutes compared to gasoline and diesel vehicles could be influenced by factors such as vehicle price, total cost of ownership (Lévay et al., 2017; Palmer et al., 2018), the consumers experience driving BEVs (Skippon et al., 2013; Berkeley et al., 2018), availability of charging infrastructure (Sierzchula et al., 2014; Mersky et al., 2016; Berkeley et al., 2018), social preferences (Schuitema et al., 2013; Rezvani et al., 2018), environmental awareness (Onat et al., 2015; Casals et al., 2016; Milfont, 2012) and many other factors.

Norway has been the subject of many studies on the country's adoption of EVs. Reasons regarding how and why Norway has such a huge market share of EVs in the last 10 years compared to the rest of the world has been a focus for many studies. Some of the studies found variables like incentives, charging stations and other infrastructural factors to impact the adoption rates significantly (Gallagher & Muehlegger., 2011; Sierzchula et al., 2014; Mersky et al., 2016; Zhang et al., 2016). Demographic variables have also been tested to capture its influence on EV sales in a country (Sierzchula et al., 2014; Mersky et al., 2016; Zhang et al., 2016; Searle et al., 2016; Sovacool et al., 2018). In this section, we provide a set of sources that provide the academic foundation of this thesis.

3.1 Why Do Consumers Adopt Electric Vehicles?

A controversial topic and debate for the past 30 years has been the impact vehicles have on the environment. There have been alternatives from gas or diesel vehicles such as hydrogen vehicles, hybrid vehicles and of course electric vehicles. Hybrids were the alternatives consumers went for most often when it came to environmental alternatives to the gas or diesel vehicles, in large part due to the lacking technology for hydrogen vehicles and the battery range of the electric vehicles. In the past 15 years the electric vehicle has been an increasingly popular alternative to hybrid vehicles, and the battery range has been developed consistently during this time. The hybrid cars typically use two types of energy, diesel or gas together with electricity. The hybrid vehicle is similar to an EV, the only difference is that at high speeds the hybrid uses gas or diesel to maintain the high speed. Like with EVs, the hybrid vehicle needs to be charged routinely and has had incentives in many countries to garner interest from consumers. Gallagher & Muehlegger (2011) explored factors that made hybrid vehicles attractive to the public. Their tests resulted in only two significant variables that impacted hybrid sales positively between 2000-2006 in the US, tax incentives and rising gasoline prices. Carpool lanes are very useful in large cities with traffic; however, the variable was insignificant to hybrid sales in their study. While gasoline prices might have some influence on consumers, studies focusing on electric vehicles are a better way to disclose variables related to electric vehicle adoption. The data's recency is also a bit of a problem since consumers might have different priorities than the two predictors found in the study.

A more recent study by Sierzchula et al. (2014) researched 30 countries' adoption processes of EVs. Their findings revealed that financial incentives, the number of charging stations and the presence of local EV manufacturers were positive and significant to explain the EV adoption rates on a country level. The charging infrastructure was the greatest indicator of a country's EV market share according to the authors. Moreover, they found that socio-demographic factors such as income levels and education were insignificant predictors of adoption levels. It is, however, pointed out that this might be due to the relatively low automobile sales at the time. The study also reveals that incentives and presence of local EV manufacturers alone does not guarantee high EV adoption rates. Instead, it is mentioned that these two variables might be explained by other dynamics which in turn impacts EV rates. While Sierzchula et al. (2014) found results on a country level, Mersky et al. (2016) researched both regional and municipal predictors of EV growth. Furthermore, the study is strictly focusing on Norway's implementation of EVs. Mersky et al. (2016) supports that the best predictor for EV sales was charging stations. In particular, they found that the number of charging stations in a municipality has the largest indicative effect on EV adoption in Norway on a regional level. Income was also found to be significant in the growth of EV sales in the study. This contrasts the conclusion by Sierzchula et al. (2014), despite their claim of the data's weakness. The rest of the variables, such as exemption from toll roads and access to bus lanes, did not produce any significant results according to Mersky et al. (2016). Zhang et al. (2016) produced some similar results, presenting that charging stations were the best incentive for EV adoption. Contrary to the findings by Mersky et al. (2016), they found that exemption from toll roads was also a good predictor for EV growth. Mersky et al. (2016) also found that on a municipal level, EV sales were sensitive to the presence of major cities. The authors noted that this effect might stem from the charging station frequency along with the free tolls and exclusive bus lane access. The three studies mentioned in this paragraph have produced several interesting factors with different results on a country, regional and municipal level in relation to EV growth. In this study we would like to test all the variables they found to have a predictive power on EV adoption on a municipal level to see if their results differ from ours.

To increase the market share of EVs, Zhang et al. (2016) studied the EV variables that Norwegians value the most. Personal and business battery electric vehicle (BEV) sales were distinguished as two separate groups. The authors found that both groups desire technology improvement above all. This included new specifications that other gas or diesel vehicles were obtaining, together with increased battery range. They also found that consumers would like better prices together with improved incentives. The study's incentives in particular included exemption from toll roads, bus lane access and more charging stations. Of the two groups, business buyers are less influenced by these compared to personal buyers. The authors also found that demographic variables and municipal incentives might have less impact on BEV market shares compared to the BEV technology development. Hence, it may indicate that technology on BEVs is the most important factor for the consumer in Norway.

The studies presented thus far provided differing results towards income levels' impact on EV adoption, and education was found to be insignificant according to Sierzchula et al. (2014). The different results between the studies suggests that there might be some interesting demographic variables to test, and that the usage of the demographic variable is crucial in capturing an effect on EV adoption. In a study by Sovacool et al. (2018), men with higher levels of education in full time employment between ages 30-45 were found to be the most likely buyer of an EV. Similarly, Hidrue et al. (2011) found that younger people between 18-35, or middle-aged people between 36-55, were more likely to buy an EV than other age groups. However, contrary to the study by Sovacool et al. (2018), they could not produce significant results on gender. The research by Sovacool et al. (2018) was done using a prior survey of 5000 respondents in the Nordic countries to perform an analysis with focus on variables such as gender, education, age and household size. Using the stated preference method, the authors also found higher income females and retirees to have an increased interest in EVs in recent years. Moreover, the authors provided data on households between one to five members, and households with five or more members. The results showed that a household increase would also increase the chance of purchasing an EV. The study performed by Hidrue et al. (2011) used a choice experiment method on 3029 respondents in the US over 17 years of age. Age was found to be a significant predictor of EV growth, together with higher education, green lifestyle and the prospects of gasoline prices rising in the future. This supports Gallagher & Muehlegger's (2011) assessment of hybrid vehicle owners' tendencies towards green vehicle alternatives when gasoline prices are expected to rise in the future.

For some consumers, the important value of driving electric vehicles is the feeling that they are polluting less than if they were driving a gas or diesel vehicle. This has created a positive perception towards purchasing electric vehicles for many individuals. Schuitema et al. (2013) revealed that people's intention to adopt plug-in hybrid vehicles (PHEVs) and Battery Electric Vehicles (BEVs) was stronger if they had a positive perception of their hedonic and symbolic attributes. The hedonic attribute defined is the pleasure of driving, while the symbolic attribute expresses self-identity and social identity. Driving an EV can promote the consumer as a person that wants to be environmentally focused. Consumers value the positive perception of driving sustainable vehicles, and supporting this, Rezvani et al. (2018) examined consumers with high social norms regarding reducing environmental impacts of car driving. Positive emotions and personal moral norms have a higher positive influence on the adoption rate of EVs compared to people who perceive low social norms, and a mindset towards polluting less is a strong factor in purchasing an EV.

Individual behavior towards climate change and perception towards global warming has been studied by Van Der Linden (2015). He used a sample of 808 respondents of the population of the UK, and performed multiple regression models on variables such as altruistic values, personal experience, affection. The author found that influence of cognitive, experiential and socio-cultural factors explain a large amount in terms of climate change risk perceptions, and the study suggests that risk perceptions of climate change are both complex and multidimensional. Education and climate awareness was found to have a positive relation to each other, and this phenomenon was also found in the study performed by Luís et al. (2015). Drawing data from 46 221 respondents in 33 countries, Luís et al. (2015) found individuals in countries with higher CO_2 emissions to have a lower societal risk perception towards climate change, since they had a higher awareness towards climate change causes. Those who were motivated to act in a more environmentally concerned way were more resilient to risk perception normalization. In a study with national data from New Zealand, Milfont (2012) performed regression models on three main variables, knowledge, personal efficacy and concern about global warming. The author found positive relations between the variables, and the study showed that concern mediates the influence of knowledge on personal efficacy. Knowledge about global warming and climate change increases concern about the risks these issues create towards our planet, and this turned out to increase the respondents perceived efficacy and responsibility to solve the issues. However, unlike Van Der Linden (2015) and Luís et al. (2015), the author did not find education post high school to have an effect on the climate risk perception, suggesting that education programs by themselves are unlikely to increase the knowledge about global warming and climate change.

3.2 Why Do Individuals Hesitate to Adopt Electric Vehicles?

An important aspect and widely researched subject regarding EVs are their limited range because of the inconsistent developments in battery technology. In the last 10 years batteries have taken a technological leap because of the needed capacity increase for appliances like phones and EVs. Today a number of EV models even have a larger range compared to regular internal combustion engine (ICE) vehicles such as gasoline and diesel vehicles, but there are still doubts towards the EVs range from consumers. A random trial, performed by Skippon et al. (2016), split up 393 consumers to see how half the testers would react to driving modern BEVs while the other half would drive a normal ICE vehicle. The BEV testers were positive to test the cars, however, their willingness to buy a BEV declined after the test due to the insecurities of the cars range. Despite some of these vehicles having a larger range than the ICEs, they still preferred the gasoline-fueled vehicle. One crucial factor was due to the charging itself and how long this took even at a local charging station. A similar study by Berkeley et al. (2018) asked 26 000 motorist drivers in the UK about their concerns regarding EVs. Several barriers were listed amongst the drivers related to purchasing EVs. The most substantial barriers were high purchase prices and the availability of public charging stations. Other barriers included: how long it would take to offset the more costly price of an EV through savings made in fuel and taxation, along with concerns over resale values. Battery performance was also listed as an issue together with the time it takes to charge the vehicle. Lastly, availability of infrastructure for maintenance, service and repair was brought up as a concern for the motorists. This is supported by the study performed by Hidrue et al. (2011), where range anxiety, long charging time and high purchase price was the main reason individuals had doubts towards EVs.

Concerns made by Zhang et al. (2016) regarding the technology development of EVs are largely related to the concerns made in the studies by Hidrue et al. (2011), Skippon et al. (2016) and Berkeley et al. (2018). One of the biggest issues for the participants was the battery and range, and Zhang pointed this out and even suggested that technology on BEVs impacts the consumers choice the most. Furthermore, in a study performed in the US, Yuksel & Michalek (2015) noted that temperature might be an important factor in the decision of purchasing electric vehicles. The EVs battery is impacted heavily by colder temperatures, and a Nissan Leaf's range could be reduced from 70 miles to as low as 45 between the coldest days according to the authors.

Berkeley et al. (2018) remarked in the former section that the biggest barriers against purchasing EVs were high purchase prices and availability of public charging stations. In a study focusing on the costs of EVs, Lévay et al. (2017) performed research in eight European countries where electric vehicles and internal combustion engines (ICE) were compared to find the difference in total cost of ownership (TCO) in the respective country. Norway had various fiscal incentives that made EVs cost competitive to ICE vehicles, which had a large impact on EV sales. The majority of EVs in the other seven countries were more expensive in comparison to the ICEs on a TCO basis. This also meant that the EV sales in the other countries was behind Norway's by a large margin, showing that fiscal incentives play a large role in the adoption of EVs together with the car prices.

Onat et al. (2015) researched the carbon and energy footprint analysis for conventional cars, hybrids and EVs in 50 states in the US. EVs were found to be the least carbon-intensive option in 24 states, while in comparison hybrid electric vehicles were found to be the most energy-efficient option in 45 states. These unclear results from EVs stems from where the energy powering source comes from. The energy that charges up the battery electric vehicle can be more damaging towards the environment due to the process used to generate this energy. However, the added energy consumption of charging up an EV at home was not as big of an increase as one would expect. A Norwegian study performed by Figenbaum (2017) revealed that the average household consumption of electricity was at 16 MWh and charging an EV at home only added about 15% more energy consumption per year. Furthermore, Casals et al. (2016) found that the usage of EVs will generally imply reductions in the net greenhouse gas (GHG) emissions in countries in Europe. The GHG emissions are all the sources of emission on the planet, and currently the transportation sector generates the largest share of GHG emissions. In addition, the authors note that countries like France or Norway, who have a high usage of renewables in their electricity generation, are more suitable for EV adoption.

3.3 Hypotheses

The Tesla business plan from 2006 illustrates that Tesla vehicles were expensive in their earlier models (Musk, 2006). Even though EVs have been discounted by the government and become increasingly popular to the point where almost every car manufacturer sells EVs, the green alternative to gas or diesel vehicles have not been affordable for many in the early stages of life. This is especially true in terms of the EVs with the desired battery range and model specifications that satisfy the cost (Skippon et al, 2016). Some of the academic foundation on EV adoption stated that income has had an insignificant effect, while other studies from Sovacool et al. (2018) and Hidrue et al. (2011) found income to be a significant factor for a consumer to purchase an EV.

Taking the prior studies into consideration with the fact that EVs have not been on the mainstream market for more than 10-15 years, it is reasonable to expect that other attributes than those affecting the environmental aspect will be valued by a large proportion of EV purchasers. These aspects might be comfort or appearance, and these attributes are often strengthened by a higher purchasing price for the car. Additionally, individuals with low levels of income may not have a budget constraint that allows them to purchase an EV despite their relatively low cost in the Norwegian market. We therefore expect the population’s income to have a significant effect on the share of EVs in a municipality, especially at the higher income levels.

Hypothesis 1: Income has a positive effect on the adoption of electric vehicles.

One of the main reasons why there is a market for EVs is their sustainability. Climate change has been named the biggest challenge in recent times by many scientists, and it is important to not ignore the environmental aspect when performing a study on EVs. A lot of people have a desire to act environmentally sound due to the climate crisis, and these people value the attributes the car create by being sustainable. Some people might buy an EV since they see where the future is heading, regardless of their thoughts on the environment. For some of the people that bought an EV in the early stages, a desire to pollute less has likely been a driving force in the purchasing decision. As the vehicles get closer and closer in their attributes towards regular gas or diesel vehicles, the regular consumer will garner more interest for the EV. Prior research has shown that people with higher education tend to be more aware of climate change according to Luís et al. (2015) and Van Der Linden (2018). Furthermore, populations consisting of a large proportion of highly educated people will probably have a higher adoption of EVs. Contrary to their findings, Milfont (2012) studied the interplay between knowledge and climate change and found that higher education had little or no effect on climate risk perception. The different findings might indicate that not all forms of education will play a role in the EV adoption, but the higher educational levels might have some effect. In addition, because purchasing EVs in early stages of life is quite expensive for many people, we think that the effect of higher education will be lower than the effect from the highest income group.

Hypothesis 2: Education has a positive effect on the adoption of electric vehicles.

Hypothesis 3: Income has a larger impact on the adoption of electric vehicles than education.

Additionally, factors related to characteristics of the population are suggested by literature as a good predictor for EV adoption, particularly age groups between 25-44 years. One could argue that younger people will be more open to modern solutions and technology, and they will likely also have a bigger concern for the future and their sustainable use than the older generations.

The Norwegian municipalities differ in many other areas than just their populations. One of the main issues with EVs is the battery capacity which creates range anxiety among potential buyers. Factors related to the structure of the municipality may be a decisive factor in the purchasing decision, since this might include the expansion of more charging stations. When we include more relevant variables, we also reduce the risk of omitted variable bias, and our aim is therefore to capture as much of the variation in the EV adoption as possible. Findings presented in the literature section investigated access to charging stations and presence of a major city. Lastly, other infrastructural variables such as the type of roads in the municipality could be a factor because of their range. Driving on private roads and municipal roads is often related to their own municipality or maybe one close by, but driving on a highway is more often associated with long distance driving.

Negative attributes associated with an EV such as range limitations, mentioned by Zhang et al. (2016), Skippon et al. (2016) and Hidrue et al. (2011) will arguably be more negative for people living in smaller rural areas. As an example, there have been political discussions on EVs because the people in smaller municipalities and villages feel that they are forced to pay more for driving a gas or diesel car, meanwhile they have no choice to purchase hybrids or EVs because of where they live (Krekling & Sølhusvik, 2020). A government solution to this would be to expand the number of charging stations in these areas, or maybe lower the prices of fuel. Structural factors may affect non-monetary attributes and monetary attributes that make consumers living in those areas to prefer an EV. These structural macro factors could therefore be important for the consumer's budget constraint related to the purchase of a car.

Considering this, we think that variables related to structure in a municipality will almost certainly have a large impact on the adoption of EVs. If we manage to capture the most important factors, we believe that access to charging stations, presence of a major city and road types will have significant influence on the amount of EVs in the municipality. The findings made by Mersky et al. (2016) and the similar study they performed makes us think that presence of a major city will be the most impactful variable related to structure, resulting in the following four hypotheses:

Hypothesis 4: Presence of a major city will have a positive effect on the adoption of electric vehicles

Hypothesis 5: Type of road will have a positive effect on the adoption of electric vehicles

Hypothesis 6: Access to charging stations will have a positive effect on the adoption of electric vehicles

Hypothesis 7: Presence of a major city will have a bigger impact on the adoption of electric vehicles than infrastructure and charging stations.

Some municipalities offer bigger advantages for driving an EV than others because of policies that have been adopted by both national and local authorities. In some places, EV drivers are allowed to use the bus lanes with less traffic, they have access to discounted or free parking and even have a free pass through toll roads. These examples give the consumers more utility through monetary attributes that will make EVs a preference regardless of the pollution aspect. We have not been able to analyse all the different government incentives, but we have been able to obtain data on toll roads in the municipalities. As mentioned in the literature section, toll roads were found to have a significant impact on the EV adoption (Zhang et al, 2016). However, Mersky et al. (2016) did not find this to have a significant effect in Norway. Nevertheless, the discussion regarding toll roads has gotten a lot of attention in Norway the past years, resulting in the creation of a new political party, Bompengepartiet. The party got a relatively decent election turnout in several of the major cities. Taking this information into account, we think that toll roads will be a positive predictor on EV shares in a municipality.

Hypothesis 8: Toll roads will have a positive effect on the adoption of electric vehicles.

4. Data

SSB is the main provider of official statistics in Norway, and the company works closely with the Norwegian government. As a result, the institution has great credibility on their data samples. This means that a large number of the variables collected are reliable and credible, and all the demographic variables collected were through SSB. Other variables we collected came from various sources. Nobil, a website that collects various types of data on electric vehicles, provided spreadsheets on charging stations in Norway. For the toll road variable, the website Bomstasjon was used to gather data. In this section we present the variables we want to produce with the data we collect, and assess their validity together with their respective sources.

4.1 Issues with Norway's New Regions and Municipalities

In 2017, the government decided that a large set of regions and municipalities were going to be merged by the end of 2019 (Regjeringen, 2020). This meant that the original 428 municipalities in Norway would be reduced to 356, and the 19 counties would become 11 as seen in figure 4.1. As most of our data was collected from SSB, this created a problem since some of the data we were interested in were not published by SSB from recent years, while others were collected to the new reform that would be established in 2019. These differences produced issues in regard to aligning data with each municipality. In light of this subject we decided to go further back, to data from 2018-2019, where every data set on SSB was aligned to the same standard 423 municipalities and none of the data tables were missing. This meant that we could gather complete data of all variables we deemed important to the analysis.

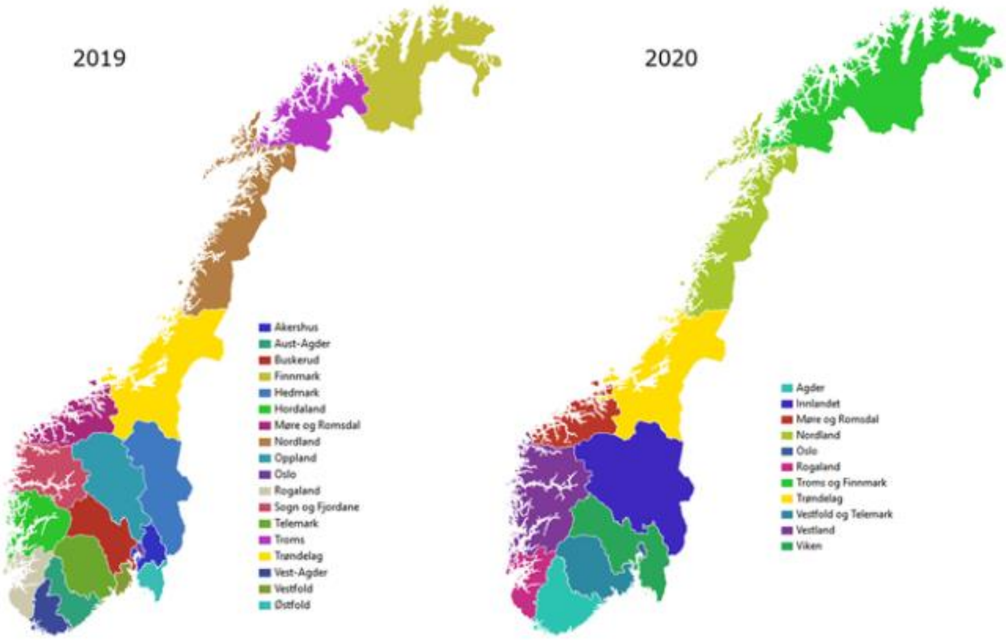

Figure 4.1: The Norwegian counties change in regions after 2019. Collected from Trondelagfylke on 23.03.2021. URL: https://www.trondelagfylke.no/vare-tjenester/plan-og-areal/kart-statistikk-og-analyse/nyhetsarkiv-kart-og-statistikk/faktafredag---norske-fylker-2019-og-2020/.

4.2 Variables

In this section we will describe our variables and some of their sources, dividing the variables into different categories. Table 4.1 presents an overview of all the variables afterwards for illustration purposes, followed by Table 4.2 which reveals the descriptive statistics of our data set.

4.2.1 Vehicle Shares in Norway

Capturing EV adoption in the analysis requires an independent variable that is able to capture the electric vehicle share in a municipality. A dataset from SSB was collected and provided information on all the vehicle types in Norway, with the municipality they were registered in

(2018-f, SSB). They were collected in numbers of the total amounts, and we created a variable from this data that would capture the share of electric vehicles in Norway in percentage of all vehicle types. This meant that our dependent variable would present the share of electric vehicles in a municipality.

4.2.2 Demographics

To capture effects of income, education, age and gender, we collected data splitting up the population to different groups within each category. Our variables within the categories were therefore a percentage of the population belonging to the respective income, education, age or gender-group. Since the variables added together will be 100% of the population, we needed to exclude some of the variables due to multicollinearity. Considering theory and findings from literature, we chose the variables that were most likely to have an impact on the EV adoption.

The income variables were separated by the individual's post-tax income level, and the data table originally contained seven income levels (2018-a, SSB). We decided to include the income levels of <150 000 NOK, 250 000-349 999 NOK, 550 000 – 749 999 NOk, and > 750 000 NOK, denoted as Lowest Income, Second Lowest Income, Second Highest Income and Highest Income in our study respectively. Both Mersky et al. (2016) and Sovacool et al. (2018) found income levels to be a predictor for positive growth of EV adoption and finding the results of the extremes < 150 000 NOK and > 750 000 NOK is of interest to our study.

Educational variables were captured in percentage of individuals' highest finished educational level, ranging from primary school all the way up to doctorate degrees (2018-b, SSB). Sovacool et al. (2018) showed that higher education had an impact on the attraction of EVs for both men and women. For many adults today, the need for a higher education was lower when they graduated high school. Education from a vocational school is also a relatively new trend. Therefore, we chose to include the variable for primary school, along with Higher Education Short, which is any higher education for a duration of 1-4 years that typically results in a Bachelor's degree, while the longer education represents 5+ years and more often than not a Master's degree or even a PhD.

Both age and gender was shown by Sovacool et al. (2018) to be a positive predictor in affecting EV sales. Tables from SSB were gathered, and they presented the percentage of the genders and six different age groups in each municipality (2018-c, SSB). In the end we only included the variable representing Male because of correlation to the variable Female. We also included age ranges 25-69 and +80 in our data, split up in age groups ranging between 25-34, 35-44, 45-69 and 80+ in our regression. These variables were considered the most interesting for our research in relation to prior literature.

We want to capture as much of the variation in EV shares as possible, and will therefore include variables that possibly could have an effect on the number of EVs in a municipality. Because range anxiety is a common worry for potential EV buyers, it could be interesting to investigate whether the numbers of cars a household has could affect the adoption of EVs. Therefore, we collected a dataset representing the percentage of the population in the municipality with 0, 1 or 2+ vehicles, and included the variables representing 1 and 2+ vehicles in our regression (2011-a, SSB). Additionally, there has been a lot of political discussion regarding EVs and other environmental policies in the past few years. We therefore chose to look at individuals' choice in politics and draw this to EV adoption. A table with the election turnout for all the political parties in Norway from the 2015 municipal election were collected (2015-a, SSB). Eventually, we included the parties Venstre (V) and Miljøpartiet De Grønne (MDG) to our dataset as these parties mainly have a focus on pro-environmental changes, while Senterpartiet (Sp) have a stronger interest in the rural areas. Sp is considered as one of the big parties opposing the adoption of EVs, and was therefore also interesting to study further. All parties may have voters that care much or little about EV and environmental politics. Because of all the political discussion on green politics, we also wanted to see if a municipality interested in politics, represented by voting participation, could have an effect on the EV adoption. The variable representing participation for each municipality in the 2015 election was therefore collected (2015-b, SSB).

4.2.3 Technological / Infrastructure

Even though SSB has a variety of data in their database, a section of the variables we wanted to test were not obtainable. Charging stations has been a significant predictor to positive EV growth in many studies (Mersky et al. 2016; Sierchula et al. 2016; Skippon et al. 2016; Berkely et al. 2018). To capture this variable, we received several spreadsheets from the Norwegian charging stations website Nobil (Nobil, n.d.). They have a database with variables that focus on EVs, and the data they sent us contained public charging stations by municipality for the years 2016 and 2020. We decided to use the charging stations data for 2020 since the data was more recent. Using the 2020 data also includes more charging stations per municipality, as the number of charging stations has been steadily increasing in Norway over the last 10 years, presented by Table 4.2. The data was not arranged to our standard in municipalities, so the municipalities were rearranged to fit our dataset. Further we divided the charging stations by the number of vehicles in each municipality.

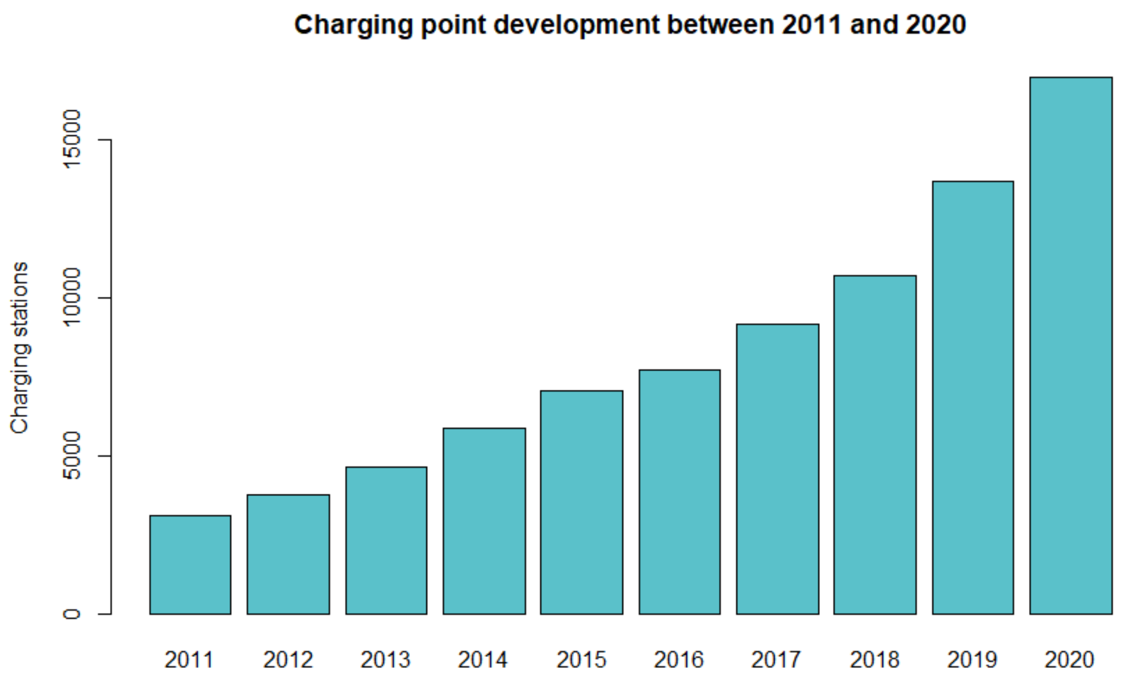

Figure 4.2: Charging station growth in Norway over the last 10 years. Data collected from Nobil 03.05.2021. URL: https://elbil.no/elbilstatistikk/ladestasjoner/.

University can be a measure of both technology and infrastructure in a city. We therefore made a dummy variable collected manually by obtaining a map of all the universities in Norway, giving a value of 1 if the municipality had a university, and 0 if no university existed in the area. Another variable that could be an indicator of a city's technology and infrastructure is the number of businesses in it. This data we were able to collect from SSB, which gave us the exact amount of businesses in each municipality in 2018 (2018-e, SSB). We adjusted this for the residents in the respective municipalities in the same year. Zhang et al. (2016) predicts that technological variables impact EV sales more than demographic. The study mentions that EV specification technology is the most important factor towards the increase of EVs, and that technological macro factors are not as good.

A variable related to infrastructure that we wanted to test was the length of different types of roads a municipality contained, because this factor may, among others, say something about the general distances in the area. These were also gathered from SSB and contained the total of specific roads in kilometres in each municipality (2018-d, SSB). The three specific road types were European Highway roads, municipal roads and private roads. All three types were divided by the area of the municipality in square kilometers. Range anxiety has widely been known as a major deterrence for EV purchasers, and municipalities with more private roads might be more interesting for EV drivers compared to highways. SSB provides statistics on the average length a car drives in each municipality every year, and we collect this data for 2018 to our dataset (2019-a, SSB).

4.2.4 Geography

The Norwegian climate is very different between the southern parts of Norway and the north. Yuksel & Michalek (2015) studied the impact cold temperatures had on consumers' decision to purchase electric vehicles. Data for average temperatures in each municipality was not available from Yr, which is one of Europe’s largest weather websites. We then decided to add a variable to find if electricity prices could be a factor to people’s perception of EVs. When you charge your car instead of using diesel or fuel, this might be an important factor for how cheap an EV is compared to other vehicles. This variable was collected from a report made by SSB and the data is from 2011 (Samfunnsspeilet, SSB, p.31). In an attempt to make variables that captured the temperature effect to some extent, we created two dummy variables, North and No Coast. For the North variable, we gave a municipality 1 if it belonged to the northern part of Norway, with the cut-off being in the county named Trøndelag. This was the cut-off because cities above this county usually have longer winters and lower average temperatures compared to the southern part of Norway. By doing this we tried to capture the coldest part, as we think there is little difference in effect between the places with warmer and milder climates. This can be shown in Figure 4.1, where the municipalities above the yellow area are denoted as the northern part of Norway in our variable. The second variable, No Coast, was made by giving municipalities without coastline the value of 1. Ideally, we would have been able to distinguish the municipalities with no coastline perfectly, but the lack of a clear definition created issues with this. In addition, we keep in mind that these variables might not capture the temperature effect in the most efficient way.

Presence of a major city has been recognized in previous literature as a strong indicator for EV adoption (Mersky et al, 2016). In 2002, the Norwegian government implemented a rule stating that cities with a population larger than 50 000 should be considered a "major city" through "Storbymeldingen" (Kommunal og regionaldepartementet, 2003). Since 2002, there has been an overall growth in the population, especially in urban areas. In the period 2002-2019 the urban population in Norway increased from just under 3 500 000 to about 4 400 000 (Mactrotrends, n.d.). This means that a number of cities has hit the threshold of 50 000 inhabitants during this time, and as of 2021 the number of cities has hit 19. We do not find it likely that all the cities with more than 50 000 inhabitants should be considered major cities, as Norway is a country with a relatively small population, and many countries have significantly larger cut-offs to be considered a major city.

To be sure we did not include municipalities that only were relatively larger in population than its surrounding municipalities**,** we found it reasonable to consider municipalities that in 2018 have more than 100 000 inhabitants to be considered as major cities. Even though this threshold is arguable and arbitrary, the cutoff seems reasonable for Norway and its population. We are still confident that our result will not change particularly much with different thresholds. The variable representing the presence of a major city was then created as a dummy variable, giving a value of 1 to municipalities that were in close proximity to a city with more than 100 000 inhabitants. In order to decide which municipalities that should be considered, we used the regional definitions from the government in "Storbymeldingen" (Kommunal or regionaldepartementet, 2003). For the largest region, Oslo, we used "Hovedstatsmeldingen" from 2007 (Kommunal og regionaldepartementet, 2007). An example is that Bærum had more than 100 000 inhabitants by itself, but the area is included in the Oslo region and has no clearly defined regional definition so the municipality was instead merged with Oslo for the variable.

4.2.5 Financial

From previous literature, subsidies have long been discussed as a key contributor to the adoption of electric vehicles (Sierzchula et al., 2014; Zhang et al., 2016). Norway's government has been supporting the electric vehicle market with incentives including bus lane access, free toll roads, free or discounted parking with designated parking spots and reduced taxes compared to ICE vehicles. Due to lack of data, we decided to include only toll roads in our analysis. This variable was created as a dummy variable, where a value of 1 meant that the municipality had at least one or more toll roads. Even though a toll road usually represents a cost to the driver, for EVs it has been free in most parts of Norway. The dummy variable captures the fact that EVs will benefit from driving past every toll road in the country, either free or discounted, because if they had a regular fuelled vehicle they would be paying full price. To obtain the data, we used the website Bomstasjon.no where you can navigate through all the toll roads in Norway on a map (Bomstasjon, n.d.). Since there were no available spreadsheets with this information the variable was collected manually. For toll roads in municipalities that have been merged later than 2018, we needed to investigate when and exactly where the toll roads were located, in order to properly fit the data to our dataset.

Table 4.1: Short description of every variable

Variable name	Description	Year
Lowest Income	Percentage of households that has a yearly income less than 150 000 NOK	2018
Second Lowest Income	Percentage of households that has a yearly income between 250 000 NOK – 349 999 NOK	2018
Second Highest Income	Percentage of households that has a yearly income between 550 000 NOK – 749 999 NOK	2018

Highest Income	Percentage of households that has a yearly income above 750 000 NOK	2018
Primary School	Percentage of the population that has primary school as their highest form of education	2018
High Education Short	Percentage of the population that has finished 2-4 years of higher education	2018
High Education Long	Percentage of the population having finished more than 4 years of higher education	2018
Age 25-34	Percentage of the population being between the age of 25-34	2018
Age 35-44	Percentage of the population being between the age of 35-44	2018
Age 45-69	Percentage of the population being between the age of 45-69	2018
Age +80	Percentage of the population being more than 80 years old	2018
Male	Percentage of the population being male	2018
University	Presence of a university in the municipality	2018
One Car	Percentage of households having 1 car in the municipality	2018
Two Or More Cars	Percentage of households having 2 or more car in the municipality	2018

Toll Road	Presence of toll road in the municipality	2018
Electricity Price	Average electricity price in the county for the belonging municipality	2011
European Highway	Km of highways in municipality compared to in the municipality	2018
Private Road	Km of private roads in municipality compared to in the municipality	2018
Municipal Road	Km of municipal roads in municipality compared to in the municipality	2018
Business	Amount of businesses in area, adjusted by population	2018
V	Percentage of the population that voted 'Venstre' in the 2015 local election	2015
Sp	Percentage of the population that voted 'Senterpartiet' in the 2015 local election	2015
MDG	Percentage of the population that voted 'Miljøpartiet De Grønne' in the 2015 local election	2015
Participation	Percentage of the population that voted in the 2015 local election	2015
North	Municipalities that are located north for the county Trøndelag	2018
No Coast	Municipalities that has no coastline	2018

Charging Station	Public charging stations in the municipality, adjusted by the number of vehicles in the municipality	2020
Total Driving	Average driving length in the municipality per inhabitant	2018

4.3 Descriptive Statistics

We present a table of descriptive statistics of the non-standardized data set in Table 4.2 to summarize the data section. This table contains data about the observations (Obs), average values (Mean), standard deviations (Std.Dev), minimum values (Min) and maximum values (Max). The number of observations between each variable is roughly between 420-423 except for the Lowest Income variable, where only 379 observations are picked up.

From Table 4.2, we notice that the Charging Station variable has a standard deviation of 25.59. There is a large variation in the data, and the minimum and maximum values show the high discrepancy of between 0 – 474 charging stations in a municipality in Norway. In other words, there are cities in Norway where charging stations have not been implemented yet despite the high EV market share country wide. We note that the standard deviation of Two Or More Cars is twice that of the standard deviation of One Car, and that between 8.13% - 48.67% is the min and max values for Two Or More Cars. This shows that some municipalities have a low share of households with two or more vehicles at 8.13%, while other municipalities have close to half their households with more than one vehicle.

For the party variables, Sp has a standard deviation of 14.98 which shows a large discrepancy between the voters in the municipalities. This indicates that most of the votes originate from the same regions while other regions do not vote for them. Both the party V variable and the Participation variable have a standard deviation above 5. This suggests that the party variable has to some degree the same effect on voters as Sp, and the Participation variable gives a range between 50.20% - 84.30%.

The mean value of 2.45% for the Lowest Income variable and 28.33% for the Highest Income variable shows a large disparity between the two income levels. In the municipality with the highest share of low-income workers, the mean value is at 9%. This shows that the worst low-income city in Norway will have 9% of its workers below 150 000 NOK earned each year post tax. Conversely, at its peak, 44% of the inhabitants in a municipality will be earning more than 750 000 NOK each year post tax. For the educational variables, Primary School has the largest share of students at 29.57% in Norway. This is for students between the ages of 6-13 years. This is followed by High Education Short at 19.78% and High Education Long at 5.16%.

The age group between 45-69 is largely dominating the other three age variables by its mean value of 33.24%, but this is the largest age group in this study so this is not surprising. The road variables produce some clear differences in road lengths in Norway. European Highway has a mean value of 0.09 compared to Private road with 0.74 and Municipal Road at 0.39. This suggests that private roads is the most prevalent road type in Norway, while the least prevalent road type is the European highways. The three variables have been adjusted for the area of the municipality they are placed in.

Table 4.2: Descriptive statistics

	Obs	**Mean**	**Std.Dev**	**Min**	**Max**
Lowest Income	379	2.45	1.05	0	9.00
Second Lowest Income	422	14.52	2.13	0	22.00
Second Highest Income	422	18.45	2.03	0	26.00
Highest Income	423	28.33	5.13	0	44.00
Primary School	422	29.57	5.45	16.30	52.70
High Education Short	422	19.78	3.64	11.80	31.80

High Education Long	422	5.16	2.74	1.70	21.30
Age 25-34	422	11.22	1.87	5.88	21.23
Age 35-44	422	11.76	1.61	7.22	16.12
Age 45-69	422	33.24	2.65	26.04	41.83
Age +80	422	5.29	1.43	2.28	9.35
Men	422	51.02	1.07	48.15	56.46
One Car	421	43.08	3.40	31.41	52.97
Two Or More Cars	421	35.25	7.14	8.13	48.67
V	423	4.94	5.36	0	30.68
Sp	423	18.40	14.98	0	66.97
MDG	423	1.84	2.38	0	13.09
Participation	420	62.89	6.10	50.20	84.30
Presence Of A Major City	423	0.18	0.39	0	1.00
University	423	0.09	0.29	0	1.00
Toll Road	423	0.10	0.30	0	1.00
Electricity Price	423	95.26	9.19	72.10	107.60
European Highway	422	0.09	0.36	0	6.47

Private Road	422	0.74	0.96	0	11.89
Municipal Road	421	0.39	0.72	0	8.82
Business	423	0.13	0.04	0	0.28
North	423	0.32	0.47	0	1.00
No Coast	423	0.37	0.48	0	1.00
Charging Station	423	6.99	25.59	0	474.00
Total Driving	422	12 418.37	995.87	8259.00	15 546.00
El	422	3.62	3.64	0	25.41

5. Empirical Model

In this section we provide the empirical model for this study, and present how the data outlined in the data section will be used to gain knowledge about municipal characteristics that improve the EV shares. The first parts of the framework consist of outlining how ANOVA and regressions will be used. Afterwards our regression models will be presented, and the tests performed in this study are done using the program RStudio.

5.1 ANOVA

To analyse some of our main variables, we want to perform an analysis of variance, also shortened to ANOVA, which is an analysis on the differences of means in the data. One usually differs between a one-way ANOVA, where one is exploring different independent variables within one factor, and a two-way ANOVA, where one explores different factorial variables of different categories.

As discussed in the literature and theory section, some of the variables we are most interested in are the variables regarding income, education, age, gender, presence of a major city and charging stations. Some of these categories consist of two or more variables. We created dummy variables giving 1 for every municipality that had higher than the 3rd quarter percentile value for the highest income, education and age variables in addition to the male variable. Both Presence of A Major City and Charging Stations are categories that already only include one variable and do not need to be adjusted. This enabled us to perform a two-way ANOVA to analyse the different categories in one analysis. The ANOVA analysis will help us see what categorical factor that explains the biggest part of variation. If the results are significant, they may also indicate which factors that will play a role in EV shares further in our analysis. After performing the ANOVA, it is beneficial to run a regression to examine which of the variables within the categories that affects our dependent variable, in addition to research how and to what extent the impact from these variables is.

5.2 Regression Model

To create a model that captures the effects of our collected variables, a multiple linear regression will be utilized. This model should give a result of the relationship between the independent and dependent variable. The data section introduced a set of variables because of the findings made by prior studies where a significant portion of these variables were deemed to have an impact on EV adoption, both positive and negative. Reducing relevant variables could also cause omitted variable bias. Our main regression model will therefore include all of the 30 variables we have obtained. In addition to the main regression model, two minor regressions will be performed to reduce complexity and gain knowledge on how some variables change with the inclusion of more variables. We will run one regression including all the variables related to individual characteristics of the population, and one with the variables related to the structure of the municipalities. This division is done because the structural variable to a larger extent is macro variables controlled by the government or institution, and some variables could therefore be affected by policies if shown to have an effect on the EV adoption. The variables we consider as related to individual characteristics are the variables related to income, education, age, gender, cars per household, voting and driving length. In comparison, the variables we consider to be related to the structure of the municipalities are the variables related to type of roads, temperature, charging stations, businesses, universities, distances and prices of electricity. When all the results are presented, we focus on using the main regressions findings and to use the part regressions only as a help in terms of the significant variable's changes between the two models. We aim to use the adjusted R-squared since the addition of independent variables increases the goodness of fit to the model when the new term improves the model.

For our regression regarding individual characteristics, the regression equation will look like this:

$$EV\ adoption_i = \mu + \mathbf{X}_i'\boldsymbol{\gamma} + \varepsilon_i$$

where $EV\ adoption_i$ denotes the dependent variable, μ denotes the interception point, ε_i denotes the error term, which pick up the part of the dependent variable that cannot be explained through the the independent variables, and $\mathbf{X}_i'\boldsymbol{\gamma}$ is a vector of the variables we consider to be related to individual characteristics.

Similarly, this is the equation for the regression regarding structural variables
$\text{EV adoption}_i = \mu + \mathbf{Z}_i'\boldsymbol{\gamma} + \varepsilon_i$
Where $\mathbf{Z}_i'\boldsymbol{\gamma}$ is a vector of the variables we consider to be related to the structure of the municipalities.

Finally, the full regression model is given by the following equation.

$$\text{EV adoption}_i = \mu + \mathbf{X}_i'\boldsymbol{\gamma} + \mathbf{Z}_i'\boldsymbol{\gamma} + \varepsilon_i$$

Given a one-unit shift in the independent variable, holding all other variables constant, the estimate β shows how much the mean of the dependent variable changes. This coefficient is estimated based on the method Ordinary Least Squares (OLS), which is a method that estimates the relationship between variables by minimizing the sum of squares in the difference between observed and predicted values. For the multiple linear regression, the goodness-of-fit is given by the adjusted R-squared, which explains how much of the variation in the dependent variable that is explained by the model.

Two common problems when performing multiple regressions are the presence of multicollinearity and heteroskedasticity. To control for these, we perform a Variance Inflation Factor-test and a Breusch Pagan test, see Appendices 1 and 2. Here we further explain the two limiting factors to a regression, and present our way of accounting for them in our research.

5.3 Standardization

We want to examine the determinants of the EV share in a municipality. Since many of the collected variables are measured at different scales, they are giving an unequal analysis contribution and we therefore want to standardize our variables to understand the relative importance of them. Gelman (2008) proposes that the numeric data should be divided by two times its standard deviation in order to get comparable data. The coefficients will be directly comparable for untransformed binary predictors as a result. In our dataset, we have all types of data ranging from percentages and numerical values, to valuta in NOK. Applying this formula will make our data easier to read in terms of their influence on the dependent variable, and also make the regression output comparable between each other.

6. Results

We have now presented the data we want to test in our analysis together with the data's summary statistics. The empirical method has also been revealed, showing how we will proceed with the regression analysis and how our data will impact the model specifications that we are also interested in testing as our part regressions. In this section we will present the results of the ANOVA analysis and the three OLS regression models.

6.1 ANOVA

Table 6.1: ANOVA

	Sum sq
Income	1543.8***
Education	671.7***
Age	98.7***
Gender	25.3*
Charging Stations	5.7
Presence Of A Major City	907.8***
Residuals	2340.3

From the results presented in Table 6.1, we see that income is the variable that explains the largest part of the variation with a Sum of Squared Residuals (SSR) of 1543.8 of the total 5 593 SSR. This means that the variable explains around 27% of the variation in the model. This variable is significant at a 1% level along with the variables representing Education and Presence of a major city, and both also explains a relatively large amount of the variation in the number of EVs in the municipalities. Therefore, we expect these variables to have a somewhat large impact on EV adoption. The remaining three variables explain less than 2% of the variation, and the only variable that is significant on a 1% level is the variable related to

Age. Therefore, we also expect that age has a small impact on EV adoption, but since the SSR and p-values are low for Gender and Charging stations, we cannot reject the hypothesis that these variables may have zero effect on the adoption of EVs.

In this analysis, the variables are representing the highest income, age and education. Even though income is the variable explaining most of the variation, it is possible that other variables would have explained more of the variables if the lower levels of these variables would have been used instead. However, our results give us a strong indication that a population with high income and high education will affect the number of EVs in the municipality to some extent. Since the variable representing the presence of a major city is also influencing the number of EVs, we note that this variable may be the most impactful variable when all factors are considered. The fact that charging stations do not seem to have a significant effect on EV adoption might indicate that our research will support the findings of Mersky et al. (2016), who found charging stations to only be significant on a county level. Despite their results, most other academic literature has found charging stations to be a significant factor for EV adoption, and this result was therefore a surprise.

6.2 Regression Analysis

This section will cover the presentation of the results from our regression models as shown in Table 6.2. We present the key findings of the three models and compare the degree of influence between each other in the Full Regression Model, along with differences from the part regression to the main regression. We will also look at the variables interpretation for their standardized coefficients presented in Table 6.2, and their unstandardized estimates.

Standardization was performed in order to make the variables comparable between each other, and also to see which variables impact EV shares the most given the same scale. Using the unstandardized coefficients afterwards to interpret the regression results in their real measurements, such as income in percent or the length of private roads in kilometers, can add additional engaging information about the variables.

Table 6.2: Regression Results

	(1) Population Characteristics Model	(2) Structural Variables Model	(3) Full regression model
Lowest Income	-0.0504 (0.03629)		-0.0341 (0.02980)
Second Lowest Income	-0.0778 (0.05980)		0.0134 (0.04638)
Second Highest Income	0.0443 (0.05394)		0.0256 (0.04745)
Highest Income	0.2796*** (0.06924)		0.2315*** (0.06051)
Primary School	-0.1093 (0.07443)		-0.0151* (0.06107)
High Education Short	-0.2719*** (0.07924)		-0.0978 (0.06805)
High Education Long	0.3320*** (0.09747)		0.1039 (0.09587)
Age 25-34	-0.1930** (0.06287)		-0.1606** (0.05992)
Age 35-44	0.1866** (0.05631)		0.0285 (0.05298)
Age 45-69	-0.0969 (0.06143)		-0.0701 (0.06102)
Age +80	-0.1988** (0.06140)		-0.1891*** (0.05625)
Men	-0.0025 (0.04025)		0.0571 . (0.03322)

One Car	-0.0037 (0.05942)		0.0028 (0.05410)
Two Or More Cars	-0.1008 (0.08578)		-0.0501 (0.06822)
V	0.0168 (0.05658)		0.0511 (0.05103)
Sp	-0.1136** (0.03960)		-0.0562 (0.03476)
MDG	0.1066* (0.04460)		0.0074 (0.036309)
Participation	-0.0152 (0.04864)		-0.0055 (0.03423)
Total Driving	0.0665 . (0.03794)		0.0523 (0.03831)
Presence Of A Major City		1.1389*** (0.13916)	0.7072*** (0.14446)
University		0.0837 (0.09196)	0.0563 (0.10203)
Toll Road		0.2925* (0.11560)	0.3730*** (0.09367)
Electricity Price		0.0151 (0.03284)	0.0147 (0.04031)
European Highway		-0.1955** (0.06935)	-0.1854** (0.06993)
Private Roads		0.3694*** (0.09703)	0.4130*** (0.10322)
Municipal Roads		-0.1593 (0.04604)	-0.0363 (0.03457)
Businesses		-0.1635**	-0.0637

		(0.05606)	(0.07541)
North		-0.4044*** (0.11040)	-0.0343 (0.10587)
No Coast		-0.2374** (0.08244)	-0.0706 (0.08866)
Charging Stations		0.0523 (0.05193)	0.04200 (0.03116)
Constant	-0.0249 (0.033800)	-0.0291 (0.03189)	-0.1452* (0.02891)
R^2	0.5998	0.5685	0.7174
Adjusted R^2	0.5784	0.5569	0.6926
Observations	355	409	343

Robust standard errors in parenthesis
. p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

The primary focus of this study is to find the largest predictors for EV share in a municipality, and followingly the full regression in Model 3 is the best model to use since it takes account of all variables. For all three models we notice that 18 of the 30 variables were significant in at least one of the three models. However, in the main regression only nine variables were significant on at least a 10% level. The inclusion of variables between the structural and population characteristics models to the full regression reduces the impact of several variables, and also reduces their significance since the other variables in the model interpret the same. For our result we use the full regression's significant results and interpret them. In addition, we will use Model 1 and Model 2 to present the changes these variables experienced between regression models. Model 2's adjusted R-squared of 0.557 is below the adjusted R-squared of 0.578 for the population characteristics. The adjusted R-squared of the full regression is close to 70%, meaning that the model explains 70% of the variation from the independent variables. Many of the variables can be explained by each other and dilutes their effect in the full model.

6.2.1 Comparing Estimates

The results of the structural regression show that Presence Of A Major City is both highly significant and has the highest impact with a coefficient value of 1.139. In the full regression model, the coefficient sees a reduction of 37.9% to the value of 0.707 but this is still a considerable amount higher than the next variable, Private Roads. The full regression presents an estimate of 0.413 for Private Roads, which is an increase from the structural regression of 11.92%. In this instance, the inclusion of demographic variables increased the impact the variable had on EV shares in a municipality. Toll Roads also increase between the two models, from 0.293 in the structural regression to 0.373 in the full model. High Income reveals a decrease of 27.5% in its estimate between the two models, from 0.280 in Model 1 to 0.232 in Model 3. The variable is still an impactful predictor of EV shares. The last variable with a positive influence is the gender variable Men, but the estimate of 0.057 is quite low.

The largest negative predictor of the number of EVs in a municipality is the Age +80 variable with a coefficient of -0.189 showing that a municipality with a higher share of inhabitants above the age of 80 reduces the share of EVs in the municipality. For this variable, the estimate sees a decrease of 5.03% from Model 2, and the inclusion of variables only slightly diminishes its influence. The variable's effect is closely followed by European Highway, which negatively impacts EV shares with a -0.185 coefficient and reveals a similar reduction to Age +80 in its estimate between the models. Surprisingly, the age group Age 25-34 is significant on a 1% level and has a negative coefficient of -0.160 in the full regression. Most prior literature found older ages to be negative predictors of EV share, but younger ages were mostly associated with a positive impact. In the part regression, the variable is also significant on a 1% level but has a coefficient of -0.193 which means that the inclusion of more variables decreases its effect by 16.78%. The last negative coefficient is education related to primary schools, with a very low coefficient of -0.015, and this variable was not significant in the part regression.

6.2.2 Interpretation of Variables

The High Income variable is both highly significant and positive in both the Population Characteristics Model (1) and the Full Regression Model (3). The results show that a two standard deviation increase in the highest income group is associated with a 0.3941% increase of a standard deviation in EV shares in the smaller model. In the full model, a two standard deviation increase means a 0.3263% of a standard deviation increase in EV shares. The unstandardized coefficient for Model 3 reveals a value of 0.164. The interpretation of the significant effect is that if the number of people in a municipality in the highest income group increases by a percentage point, then the EV share increases by 0.164 percentage points.

The estimate of the variable capturing primary school education is as mentioned -0.015 in the main model. The negative sign suggests that a two standard deviation increase in people with a primary school education as their highest level, holding everything else constant, is related with -0.022% of a standard deviation decrease in the number of EVs. A one percentage point increase in people with primary school as their highest finished education reduces EV shares in a municipality by -0.010 percentage points. In the smaller model, the coefficient is not statistically significant at a reasonable level.

Age 25-34 presents a statistically significant coefficient of -0.193 in the Population Characteristics Regression, and a coefficient of -0.161 in the Full Regression Model. According to both models, the age group negatively impacts EV rate in a municipality. The coefficients reveal that a two standard deviation increase in the percentage of people between ages 25-34 relates to a -0.099% and -0.083% of a standard deviation decrease in EV adoption for the two models respectively. The unstandardized coefficient from Model 1 is -0.376, and from Model 3 its -0.313. Interpreting this in real scale reveals that a one percentage point increase in the inhabitants between ages 25-34 in a municipality reduces EV adoption by -0.376 and -0.313 between Model 1 and Model 3 respectively.

Age +80 has a coefficient of -0.199 in the part regression, and the estimate is slightly reduced due to the inclusion of variables with a coefficient of -0.1891 in the full regression. The variable presents that a two standard deviation increase in people above the age of 80 reduces EV share of -0.074% of a standard deviation in the full regression. Age +80 proves to be significant on a 1% level in Model 1 and on a 0.1% level in Model 3. In the full regression, Age +80 has an unstandardized estimate of -0.481. A one percentage point increase in inhabitants above the age of 80 is related to a negative impact on EV growth of -0.481 percentage points between and Model 3.

The gender variable Male has a coefficient of 0.0571 in the Full Regression Model and shows that a two standard deviation increase in the percentage of men increases EV growth by 0.017% of a standard deviation. Male is significant and positive on a 10% level in Model 3. The unstandardized coefficient of the variable proves that a one percentage point increase in the share of men in a municipality is related to a 0.194 percentage point increase in EV adoption rate. Total Driving revealed an insignificant result in the main regression and is not a good predictor for EV shares. On average, a municipality has a ratio of about 3.62% electric vehicles according to our descriptive statistics from Table 4.2.

In Model 1, High Education Long, Age 35-44 and MDG all have a significant, positive impact on the number of EVs, with coefficients of 0.332, 0.187 and 0.107. In addition, Total Driving also impacted the EV shares positively, but with a low coefficient of 0.066. On the other hand, High Education Short, SP, and Age 35-44 all had a negative impact on our dependent variable. Both variables related to education were significant at a 0.1% level, while the Total Driving variable was significant at a 10% level. However, none of these variables turned out to be statistically significant on at least a 10% level in our main regression, meaning that the effect from these variables are explained by others when more variables are included.

The coefficient of Presence Of A Major City in Model 2 was 1.139 and 0.707 in Model 3, and the variable is significant on a 0.1% level in both. Since the dummy variable has not been standardized, this can be interpreted as it is. For a municipality with presence of a major city, EV shares increase by 1.139 percentage points in Model 1 and 0.707 percentage points in Model 3 when compared to municipalities with no presence of a major city. The Model 3's estimate shows that 4.33% of the vehicles are electric in a municipality in close proximity to a large city. This is a percentage change of 19.54% from municipalities that are not close to a major city, and reveals that the variable is highly significant and impactful in this study. Another significant infrastructural variable is Toll Road, which is significant on a 5% level in the structural part regression. The variable is seen as significant on a 0.1% level in the full regression however, and the dummy variable can be interpreted immediately. The presence of a toll road in a municipality increases EV growth by 0.293 percentage points in Model 2, and 0.373 percentage points in Model 3. For Model 3, the average of electric vehicles in a municipality grows from 3.62% to 3.99% in a municipality containing one or more toll roads.

The two road variables that presented significant results are European Highway, significant on a 1% level for both models, and Private Road which is significant on a 0.1% level for both models. These two variables deviate from each other, as European Highway has a negative coefficient while Private Road has a positive impact. While the estimated coefficient for the Private Road variable changes from 0.369 to 0.413 with the inclusion of other variables, the European Highway variable is barely impacted, with a change in estimate from -0.196 in Model 2 to -0.185 in Model 3. Interpreting the standardized values reveal that for European Highway, a two standard deviation increase in the length of highways in a municipality has a negative impact on EV adoption of -0.018 % of a standard deviation for Model 3. In this model, the variable denoted to highways gives an unstandardized coefficient of -1.865 percentage points. For the Private Road variable, a two standard deviation increase in the length of private roads in a municipality increases EV shares 0.109 of a standard deviation in the full regression. The variable has an unstandardized coefficient which means that a one percentage point increase in the length of private roads in a municipality is positively related with EV share increase of 1.566 percentage points.

In the structural regression, the two variables used to capture temperature in an indirect way, North and No Coast, had a negative impact on the EV shares in the municipalities. Their coefficients of -0.405 and -0.270 respectively reveal that they have an influence on the dependent variable, and both are significant in the smaller regression. Additionally, the Business variable also impacts EV shares negatively with a coefficient of -0.164. However, with the addition of more factors in the full model, these variables turned out to not be significant.

7. Discussion of the Results

This chapter is going to provide a discussion of the results presented in chapter 6. Both structural macro factors and demographic variables are statistically significant impactors of the number of EVs in a municipality. Below, Table 7.1 reintroduces the hypotheses proposed in chapter 3.3, and gives an overview on whether the hypotheses are supported or not. We further discuss the findings of our ANOVA model and the regression model's, and their implication on the hypotheses.

Table 7.1: Support for the hypotheses

Hypothesis	**Supported?**
H1: Income has a positive effect on the adoption of electric vehicles	**Supported for higher income**
H2: Education has a positive effect on the adoption of electric vehicles	**Not supported**
H3: Income has a larger impact than education on the adoption of electric vehicles	**Supported**
H4: Presence of a major city will have a positive effect on the adoption of electric vehicles	**Supported**
H5: Infrastructure such as private roads will have a positive effect on the adoption of electric vehicles	**Supported**
H6: Access to charging stations will have a positive effect on the adoption of electric vehicles	**Not supported**

H7: Presence of a major city will have a larger impact than infrastructure and charging stations on electric vehicle adoption	**Supported**
H8: Toll roads will have a positive effect on the adoption of electric vehicles	**Supported**

The results from our ANOVA-analysis is consistent with the findings for our structural variables in the regression model, as charging stations do not explain the variation in EV shares in any of the models, while Presence of a Major City has an impact in both models. In the ANOVA-analysis, Income is the category that explains most of the variation, but in the regression analysis, other variables seem to have a bigger impact on EV shares than high income. This may be explained by other variables included in the regression, but could also be explained by how the dummy-variables were created for the ANOVA-analysis as discussed in section 6.1. Inconsistent with our main regression analysis, high education is significant and explains some of the variation in our dependent variable in the ANOVA-analysis, but the variable for the highest education level is not significant in our full regression analysis. The variable is, however, significant in our Population Regression Model, which is consistent with the ANOVA-results, indicating that other variables would have captured the effect from this variable if included in the ANOVA-analysis. Both Age and Gender explains a small part of the variation in our ANOVA-analysis, which also is the case for our full regression model where Age seems to have a larger impact than expected from the ANOVA-results. As both primary school education and Age 25-34 are significant variables in our main regression model, this may explain the differences in the result for ANOVA because the dummy variables mainly capture people with high age and people with high education.

The main regression model's adjusted R-squared increases with the inclusion of all the variables. This makes sense as both models separately gave a goodness of fit above 55%. The part regressions had variables that explained some of the variation in the data, and adding all together gave an adjusted R-squared of just below 70%. Despite capturing a lot of the relevant variables according to prior literature, the goodness of fit for the structural model is lower than in the individual regression. This could be explained by the individual regression containing seven more explanatory variables. For the three regression models, either seven or nine variables turn out to be statistically significant even though the number of total variables differs. This uncovers that several variables were never significant for the overall fit, and that some of the significant variables in the smaller regressions are explained by other variables that are included in the main model. The adjusted R-squared of just below 0.7 means that our data explains close to 70% of the model's variation. This also means that about 30% of the dependent variable remains unexplained, and shows that there could be improvements to our variable choices.

When proposing our testable hypotheses, we suggested that high income and high education should have a positive impact on EV adoption on the basis of prior related literature. Given the results of our main regression, we can confirm hypothesis one that income does have a positive effect on the adoption of electric vehicles. Because of the luxury associated with EVs in the early stage, the effect from High Income is consistent with the discrete choice theory, as consumers choose the good with the vector of attributes that gives the highest utility. Attributes will in many cases be monetary. Therefore, the consumers who can afford EVs will often prefer them because the luxury attributes maximize their utility. Even though the Norwegian government has made EVs as affordable as possible given total costs of ownership according to Lévay et al. (2017), the lower income groups do not impact the EV adoption in this study. This opposes the theory that price and luxury attributes are the attributes that give most consumers the highest utility. Possibly, this is caused by our low bar for the variable representing highest income, or that the income variables are not properly capturing people's purchasing power. This indicates that the budget constraint or individual preferences for this group fails as the explanation for the EV adoption. Because of the luxury associated with several EVs in the early stage, the findings from our income variable is consistent with the idea that consumers prefer attributes like comfort and appearance when purchasing an EV. The lower income levels are insignificant in both models and we can only support our findings that higher income levels increase EV shares, not that lower income levels reduce EV shares.

Our result from the Population Characteristics Regression suggests that it does not matter what level of income or education an individual has, as long as the individual is in one or both of the highest income and highest educated groups. In the full regression, surprisingly, neither the Highest Education Long or Highest Education Short variables had any significant impact on EV adoption. The variable representing the highest form of education in Norway had a p-value of 0.15 and was close to significant on a 10% level, but is not seen as a significant explanatory factor in this study. Another change in the variables is the Primary School variable that has a negative impact on EV shares in the full regression and becomes significant. A possible explanation for the increase in significance of the variable is that it correlates with other impactful variables included in the full regression. The substantial differences on educational variables between models shows that they are sensitive to the inclusion of other variables. We must be careful to reject the fact that education plays a part in EV adoption, but our results still do not give us enough evidence to reject the null hypothesis of hypothesis two. Our results give enough evidence to support hypothesis three, which stated that income has a larger impact on EV growth than education.

In the main regression, the variable for people above the age of 80 and the variable for the age group between 25-34 had a negative impact on EV adoption. The age group of 35-44, which had a positive impact in the minor regression, is explained by other factors in the full regression. Both the distinct, negative coefficients for the age group of +80 and the age group between 25-34 remained largely the same for both regression, meaning that the estimates hold well when more variables are included. This contradicts the findings by Sovacool et al. (2018) and Hidrue et al. (2011), who found that younger or middle-aged individuals prefer EVs compared to other age groups. A possible explanation for this is that individuals, despite high income, might not have enough money saved up to attain EV at this age. The budget constraint from chapter two shows that even if a consumer prefers the attributes for a good, the person cannot buy it if the price of the good is higher than his or her income. Simultaneously, the age group segmentation in our data might not have been optimal since our age groups cross over the age groups used by the studies mentioned. Our findings of the age group +80 is consistent with the idea that older people likely are less interested in technology and driving compared to younger age groups, and consistent with prior literature expecting older generations to be less interested.

None of the voting variables turned out to have a statistically significant impact on EV shares, meaning that the effect from the minor regression is captured by the inclusion of variables in the full regression. This was also the case for the variable representing average driving length in the municipalities. The full regression does, unlike the individual regression, indicate that the variable Male has a positive impact on the number of EVs at a 10% level. This is consistent, to some extent, with the findings from Sovacool et al. (2018) who found that men between the age of 30-45 with higher levels of education in full time employment are more likely to purchase an EV. However, the coefficient is low relative to others at 0.0571 and the impact is therefore quite low compared to our other significant variables.

As expected, toll roads turned out to be both statistically significant and positive in terms of EV shares. If we consider driving as a part of the price for vehicles, this finding is consistent with economic theory, assuming that cars are normal goods, because the price reduction from toll roads increases the demand for EVs. Therefore, we fail to reject hypothesis eight. Even though Mersky et al. (2016) could not find the variable to be significant, Zhang et al. (2016) did find it significant. Our more recent data compared to the previous studies reveals that it might have a relatively large and positive impact on the number of EVs in a municipality. This could be explained by the increase in toll roads in the period between the studies, and the fact that individuals can drive freely through these when they use an EV compared to the cost of driving an ICE vehicle. This variable also indicates that price is an important attribute for consumers in the purchasing decision. Results from the Toll Road variable show that one of the most logical solutions to implement further EV growth would be the introduction of more toll roads in coordination with keeping the discounts or free passes for EVs. The variable is heavily affected by the inclusion of other variables, with an around 27.30% increase in estimated coefficient, from 0.293 to 0.373. In the structural regression, the variable was significant at a 5% level, but in the full regression the variable is significant at a 0.1% level. A possible explanation for the increase is that the variable correlates with one or more of the included variables, and now is capturing some of those variable's impact on the EV adoption. Even though the variable is sensitive to the inclusion of others, both the main regression and the structural regression results in Toll Roads as a positive predictor for EV shares which supports our hypothesis.

The second most impactful variable in the main regression is the Private Road variable with a positive and significant result, while the Europe Highway variable contrasts Private Road, and gives a negative significant result. These results make intuitive sense, as areas with more private roads usually are less distant. Compared to the structural regression, the Europe Highway variable's estimate has dampened a bit in the full regression, from -0.196 to -0.185, while the Private Road variable has been amplified by 11.80%. The variables were divided by the area of the municipality and they present the notion that the infrastructural factors of private roads and highways are some of the most important factors on EV shares. They are not very sensitive to the inclusion of new variables, which strengthen the variables as EV adoption predictors. We fail to reject hypothesis five, and conclude that type of roads in municipalities impact EV adoption positively with Private Roads, but we can also conclude that Europe Highways affect EV adoption negatively.

Consistent with the findings in the ANOVA-analysis, Presence Of A Major City had the largest positive impact on a municipal level, being significant at a 0.1% level in both regressions. However, the variable saw a reduction in estimate of 37.9% between the two regressions, which might be due to the other independent variables picking up some of the effect for this variable in the main model. Still, we can remark that hypothesis four is supported. Since no other variable in our regression has a larger impact on the EV adoption, we also state that hypothesis seven is supported. This corresponds to the findings made by Mersky et al. (2016), who also found this variable to be the most impactful predictor of EV growth on a municipal level in Norway. This could stem from several dynamics integrated in a large city, such as the smaller distances, larger pool of charging stations and free parking spaces for EVs, close proximity to the person's home and other factors.

To our surprise, Charging Station did not turn out to have a significant impact on EV adoption. Even though it was positive and significant at a 15% level in the Structural Model Regression, there is not enough evidence to confirm that charging stations impact EV adoption positively on a municipal level. Many of the prior studies deemed charging stations as the best predictor of EV growth, and the findings in this regression are surprising. A reason could be that many EV owners decide to charge their vehicle a majority of the time in their own home, and that the charging stations provided by the government is just a plus for the owners (Lorentzen et al., 2017). Moreover, individuals might not be using the charging stations in the same municipality they are located in because of their habit of charging at home when possible. Despite previous literature findings, Mersky et al. (2016) found the same result on a municipal level as in this study. While charging stations were the greatest indicator of EV growth on a county level and on a regional level according to Mersky et al. (2016) and Schuitema et al. (2014), it was not significant on a municipal level. An explanation of the phenomenon having an impact in certain countries could be related to their population size, since Norway is a small country in population size. Considering our findings, it seems that on a municipal level, the type of roads together with the presence of a major city and toll roads are the best measures for EV adoption as they might capture the effect of range anxiety better than charging stations. Hypothesis six can therefore not be supported in this regression, as we fail to reject the null hypothesis.

Both variables related to temperature had a negative and significant impact in our Structural Model regression. These results could imply that temperature has an effect on EV adoption, but the results may be caused by other factors than just temperature such as geographic and infrastructural factors. As an example, areas in the northern half of Norway and areas without a coastline seem to be more distant between each other than elsewhere in the country. This might also explain why these effects are captured by the other variables in the full regression.

The variable related to businesses in a municipality also had a significant, negative impact in Model 2. This was surprising, and might indicate that the variable should not have been adjusted by population. The variable is not significant in the main model however. This might show that technology for a city is not necessarily picked up by the number of businesses in it. Simultaneously, the type of businesses might be an important factor to note in terms of EV shares. It therefore seems that Zhang et al. (2016) found that technological improvements on the EV itself is the greatest predictor of EV growth, and that technological improvements in the city will not affect this much if at all.

8. Limitations and Suggestions for Future Research

This section will cover the limitations of our thesis, along with suggestions for future research.

8.1 Limitations

Some of the main limitations of this regression analysis is the lack of precision in some of the variables. Municipal-level data is limited in itself, and there are even limits in the available data for several municipalities. As an example, we wanted to include temperature as a variable, and to explore the effect it potentially has on EV shares. Considering the lack of relevant and credible data capturing this, we created two dummy variables to indirectly grasp the effect of temperature. Our hopes were that this would capture the municipality's characteristics geographically through their location in the country, including their climate and temperature. In addition, the merge between counties and municipalities at the end of 2019 certainly provided issues with the data collection part. In general, it was challenging to obtain data from several of our variables in different municipalities. Some of the variables included in this study with a focus on a municipality's infrastructure and technological aspects could have been excluded for others, since they ended up having no impact on the EV shares.

The full model regression explains close to 70% of the variation, and evidently some of the variation remains unexplained. There is a possibility that a confounding variable is affecting an independent variable together with the EV share variable. An example would be that distances may be impacting EV share and the type of roads. Thus if we managed to obtain a variable that solely captures distances, a possible outcome would be that the variable was among the most influential ones. Consequently, the impact from the road variable would drop. A category of variables that could explain some of the variation is environmental factors. Gathering variables with sustainable aspects on a municipality level proved to be hard, and the addition could have added further explanations to EV shares in a municipality.

Considering the early adoption of EVs and our key findings on the effect of income, we could obtain improved results if we were able to collect data from an even wealthier group, or if we made the income level groups different. Then, we could study the impact of the EV adoption for this group as our highest income variable only represented households earning more than

750 000 NOK after taxes. For several municipalities, more than 33% of the population belonged to the given group, so ideally we would have obtained more detailed variables regarding income. This could also explain why middle and lower income groups did not have an impact on EV adoption in our study.

Wold & Ølness (2016) were motivated to focus on the county level because they found that the study by Mersky et al. (2016) resulted in a lower goodness of fit for their model on a municipal level. Despite the recent municipality mergers in Norway, the country still has some small municipalities both considering area size and population size. One may argue that the sales of EVs somewhere in Norway are too low to find significant effects (Wold & Ølness, 2016). However, the sample size we obtained from including several variables for hundreds of municipalities strengthened our model. Particularly considering that there has been an increase in EV sales since these studies were written. Accordingly, we consider our choice of researching on a municipal level is justified.

8.2 Future Research

Our full regression model explains around 70% of the variation in the EV adoption, meaning that 30% of the variation cannot be explained by the model. If we were able to obtain more relevant data, we could have created a model that explained even more of the variation in the EV adoption. For example, we wanted to collect more variables capturing the effect of subsidies from the government, but as we were unable to find data for all municipalities on factors like free parking and subsidized prices of EVs, we chose to only include the toll road variable.

The study was only performed in Norway, and it would be interesting to include other countries whose EV growth has been rapidly changing recently such as France. This could broaden the research and reveal more findings than this study managed to on the Norwegian market. Many of the variables included were not optimal and should be excluded or replaced by data that can better capture the effect it has on EV growth. This includes many of the structural or technological variables.

For most of the data, there appeared to be small changes over time, and followingly, most of the data ended up being from 2018. Most of these variables were demographic and changed little between years. Some of the structural variables such as charging stations and toll roads have been growing increasingly in recent years, and an analysis with our variety of variables over several years could provide interesting patterns relating to EV growth. Moreover, doing a study with hybrids and EVs to pinpoint differences and similarities in the variables would be an interesting research idea.

9. Conclusion

During this research we anticipated testing several hypotheses regarding EV shares to answer our research question: "How do characteristics of the municipalities affect the adoption of electric vehicles in Norway?" Our analysis searches for aspects of municipalities in Norway that create a higher chance of increasing the number of EVs.

The study was performed using data mostly from 2018. Two approaches were used, regression models and ANOVA. In both models, a variable denoted to capturing the electric vehicle share of all vehicles in a municipality was used as the dependent variable. Information on 30 variables spanning demographical, geographical, infrastructural and financial aspects were used to create a model that would be able to capture all relevant variables seen by previous literature as predictors of EV growth. To capture the changes the variables could have between different models, two sub-regression with population characteristics and structural variables were performed.

Our analysis found the presence of a major city to be the greatest predictor for EV growth in a municipality. For a municipality with presence of a major city, EV shares increase by 0.707 percentage points in comparison to municipalities with no presence of a major city. The study indicates that the range of the EVs still might be an issue for the consumers, despite the increased battery range technology for EVs. Private roads and toll roads were also positive explanatory variables of EV adoption, while the highest income level was the only demographic variable that showed a positive relation towards EV adoption in our study. All four variables were significant in both regression models. The structural variable for highways was negative and significant in our model. Demographic variables such as individuals above the age of 80, individuals between 25-34 and people with a primary school education as their highest level of education were significant and negatively impacted EV shares as well. The variables capturing highways and private roads contrast each other completely, revealing that a municipality's total amount of road type is highly significant of the number of EVs. Our results illustrate that structural factors are of great importance towards a positive growth of EVs.

The findings in our research contributes to prior studies on EV adoption on a municipal level. The ANOVA model provides an overview of which variables that explains the biggest part of the variation in EV shares. Simultaneously, the main regression model reveals significant and clear results of several variables shown in previous literature as significant. Our results towards the age group 25-34 is of great interest as it does not concur with prior academic findings. The regression results present that government incentives are still of great importance for individuals in terms of increasing the interest of EVs. Additionally, we capture road types as a significant predictor for EV shares in a municipality. Followingly, those who live close to a major city with numerous private roads are the likeliest to purchase an EV according to our findings. These areas are consequently large cities in Norway for the most part, where the average salary often is higher compared to rural areas. This makes it difficult to apply the factors towards the rural areas of Norway in order to further increase the growth there.

To apply the results found in this study towards other countries, some considerations have to be made. The growth for EVs and hybrids in Norway over the past 10 years is a result of reduced taxes on the environmental vehicle options, toll road exemption or lower costs, bus lane access and increased charging stations around Norway. These incentives advanced the contemporary growth in Norway, and other countries would need to apply most, if not all, benefits Norway currently gives EV drivers to be able to have a similar increase in their own countries.

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Appendices

A1 Multicollinearity

A common problem when performing multiple regressions is the presence of multicollinearity, which is present when there is high correlation between the independent variables. When multicollinearity is present, the coefficients are estimated to be sensitive to small changes in the model (Wooldridge, 2015). Correlation between variables also reduces the precision of the coefficients, thereby weakening the statistical power of the regression model. This creates a problem with P-values that cannot be trusted despite variables showing statistical significance. To identify multicollinearity, one of the most common methods is the Variance Inflation Factor test, shortened to VIF-test. (Wooldridge, 2015). This test identifies correlation between the independent variables and the strength of this correlation. The VIF value starts at 1 and has no upper limit, and the formula for the VIF test is outlined as:

$$VIF_i = \frac{1}{1 - R_i^2}$$

In the formula, is the value obtained from the regeression's ith predictor. A VIF of 1 tells us that there is no correlation between the ith independent variable and the remaining independent variables. There are uncertainties about the limit of how high the VIF-value can be before the variable creates problems in the model. Sometimes, a VIF value of more than 4 or 5 is regarded as moderate to high, and values above 10 or more is regarded as very high. In this study, we have decided to resolve issues with variables that have a VIF above 10 since this value signals serious multicollinearity between the variables.

Table Appendices 1: VIF results

	(1) Population Characteristics Model	(2) Structural Variables Model	(3) Full regression model
Lowest Income	1.877235		2.006957
Second Lowest Income	3.568915		3.794142
Second Highest Income	2.423567		2.796870
Highest Income	5.568532		7.282101
Primary School	4.271525		5.320609
High Education Short	5.579875		6.481626
High Education Long	5.369195		6.460444
Age 25-34	4.021514		4.319669
Age 35-44	4.050859		5.274057
Age 45-69	4.652844		5.029553
Age +80	4.142968		4.446453

Men	1.604684		1.889512
One Car	2.971979		3.401518
Two Or More Cars	4.729086		5.615475
V	1.149160		1.224085
Sp	1.958340		2.300252
MDG	1.651497		1.788921
Participation	1.681350		1.878490
Total Driving	1.739093		2.036311
Presence Of A Major City		1.292276	2.017223
University		1.146255	1.754162
Toll Road		1.173059	1.323731
Electricity Price		1.651867	2.905203
European Highway		2.518904	3.006961
Private Road		3.901949	4.355674
Municipal Road		2.190970	2.276114

Business	1.468201	2.767207
North	1.907003	2.778921
No Coast	1.293313	2.205326
Charging Station	1.230440	1.288716

Above is a presentation of the VIF-values computed by our regressions. The population regression shows some correlation between variables, and three of them have a VIF > 5. Still, no variables get any higher than 5.580 so the first regression model's variables do not correlate enough for us to have major concerns that multicollinearity could be present in the regression. The structural variable regression has no variables above a VIF value of five, and the regression shows that the variables included do not correlate between each other to a high degree. When all variables are included in the main regression, we see that seven variables have a VIF > 5, with the largest value at 7.282. However, the value is still well below our threshold of VIF > 10, where variables cause major concern towards the data's correlation. Since none of the variables is above the critical number of 10, the VIF-results give us the insight that there is some correlation between the variables but not enough to impede the regression analysis.

A2 Heteroskedasticity

An important assumption for OLS regressions is that homogeneity is present in the variance of the residuals.Heteroskedasticity impacts the t-values precision negatively which increases the chances that the estimated value is wrongly calculated. It also leads to issues with the p-values, usually resulting in a smaller p-value compared to what they should be. This is because the variance of the residuals is not constant given any value of the explanatory variables (Wooldridge, 2018). Using methods to map if there is heteroscedasticity present together with methods to deal with it is crucial to make the model's results as trustworthy as possible. One method to illustrate heteroscedasticity is to produce a residual plot of the regression, using residuals by fitted value plots. The plot should be producing random residuals that are uncorrelated with no patterns. In many cases plots with heteroskedasticity produce a fan or cone shape in the residual plots. A great indicator to look for is that when the fitted values increase, the variance of the residuals also increases. This is a sign that heteroskedasticity is present. Using residual plots to illustrate is therefore a good measure to find patterns of heteroskedasticity in the regression.

A different measure to test for heteroscedasticity are methods such as Breusch-Pagan and White-test (Wooldridge, 2018). The Breusch-Pagan test finds if the variance of the errors in a regression is dependent on the values of the independent variables. The null hypothesis (H_0) tests if homoscedasticity is present, and the alternative hypothesis (H_A) tests if heteroscedasticity is present. If the results produce a p-value below $\alpha = 0.05$, then the null hypothesis is rejected, and we can conclude that heteroscedasticity is present in the regression. The Breusch-Pagan test can only test for linear forms of heteroscedasticity. The White-test differs and can also test for nonlinear forms, but the degree of freedom is increased as a result. This means that the White-test is less likely to give a significant result compared to the Breusch-Pagan test. The presence of heteroscedasticity leads to imprecision in the variables significance. If the previously mentioned methods indicate heteroscedasticity in our regression, the standard errors will be adjusted by using robust standard errors. Robust standard errors is a method to collect unbiased standard errors of ordinary least squares coefficients under heteroscedasticity.

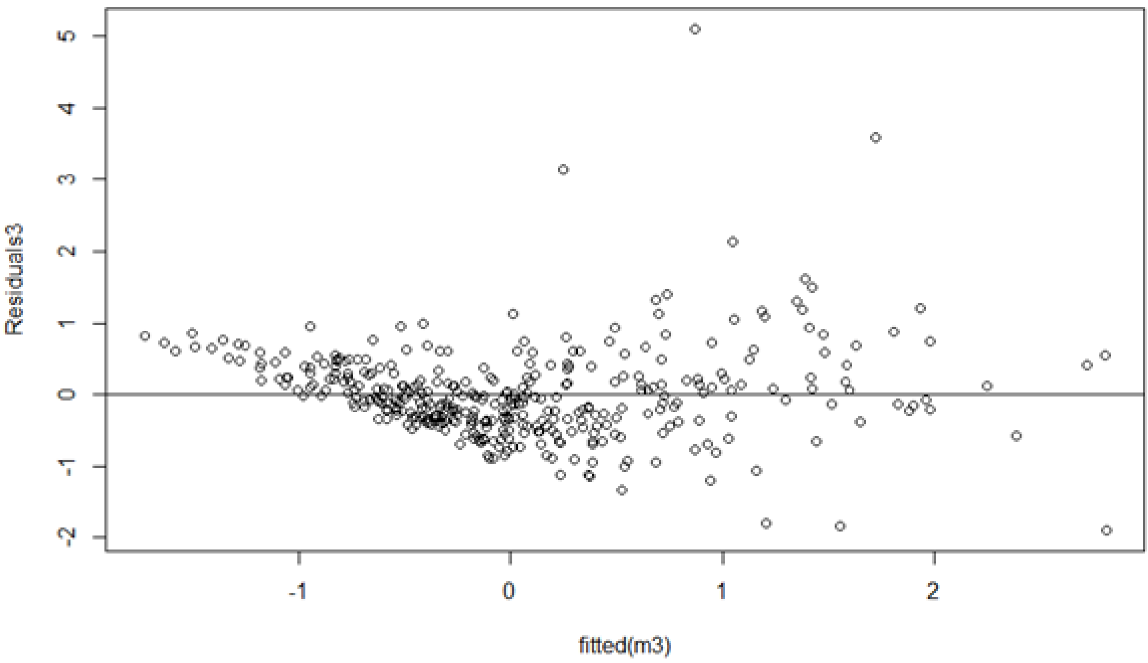

Figure Appendices 1: Residual plot of population characteristics regression model

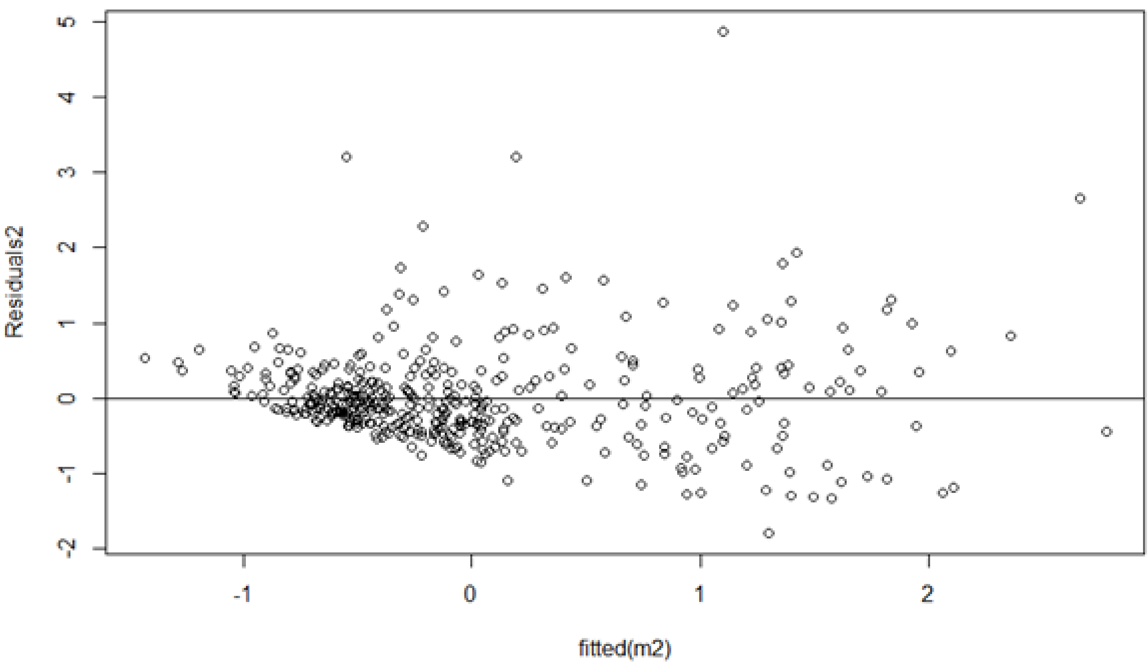

Figure Appendices 2: Residual plot of structural regression model

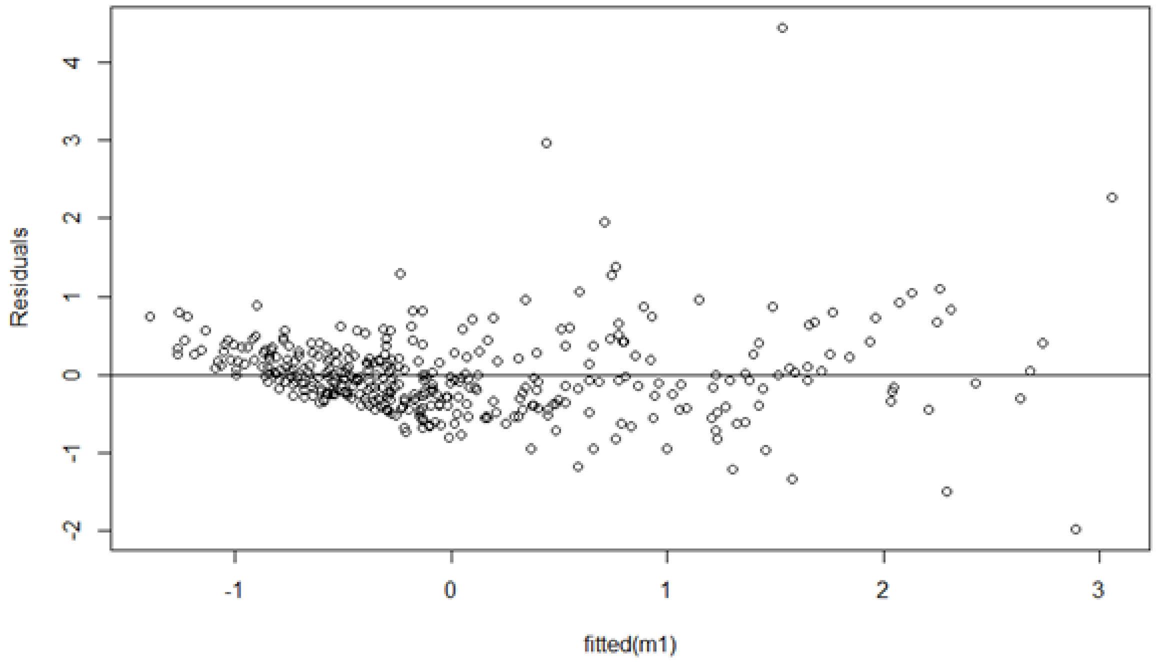

Figure Appendices 3: Residual plot of full regression.

Table Appendices 2: Population regression test for heteroscedasticity

	Breusch-Pagan test	White-test
Chi2	42.072	54.1
Prob > Chi2	0.001733	0.0435

Table Appendices 3: Structural regression test for heteroscedasticity

	Breusch-Pagan test	White-test
Chi2	31.735	36.7
Prob > Chi2	0.0008409	0.0256

Table Appendices 4: Full regression test for heteroscedasticity

	Breusch-Pagan test	White-test
Chi2	60.298	74.7
Prob > Chi2	0.0008494	0.0952

To prove that the assumption of constant variance of the errors from the regression persisted, we made a residual plot graphically with Figure Appendices 1, 2 and 3. These tests were performed on all three models, and in the figures there is a small but distinct pattern. The cone-like pattern tells us that heteroscedasticity might be present in all three models. To be sure that there is heteroscedasticity in our data, we perform two tests in Table Appendices 2, 3 and 4 for each model. The Breusch-Pagan test justifies a rejection of the null hypothesis in all three models, meaning that there is heteroscedasticity in the models. The White-test has a higher probability, and the full regression is above the alpha level 0.05 in this test meaning that there is homogeneity in the variance of the residuals. However the rest of the tests result in the rejection of the null hypothesis'. These results tell us that heteroscedasticity is a present problem in the regression models, and this will be solved by adjusting for robust standard errors.