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Uncertain Electric Vehicle Incentives – Does It Affect Vehicle Choice?

An exploratory study on how uncertainty impacts the sale of new electric vehicles, using media intensity as a measure of uncertainty

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This thesis was written as a final part of our master's degree in Economics and Business Administration at the Norwegian School of Economics in the spring of 2022. We both find the field of behavioral economics particularly interesting, and conducting an exploratory study within this field has been exciting.

In this thesis, we wish to provide insight into how uncertainty regarding electric vehicle incentives affects vehicle choice behavior and provide possible explanations for this choice behavior. The political debate in Norway regarding benefits and incentives for electric vehicles is an ever-recurring hot topic, and we are excited to continue following the current affairs.

We would like to thank our supervisors, Morten Sæthre and Mateusz Mysliwski, for introducing us to the idea behind this thesis and for their insight into the literature and empirical methods. Finally, we want to express our gratitude for their continuous feedback and interest in our work.

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Abstract

This thesis explores whether uncertainty regarding electric vehicle incentives impacts electric vehicle sales. In the late 1990s, the first incentives for electric vehicles were implemented, and throughout the 2000s, more benefits were introduced. Since then, there have been several policy changes regarding the incentives, and there is an ongoing political and public debate about whether these incentives should be continued or not.

To measure uncertainty, we constructed uncertainty indexes. The indexes are based on newspaper frequency, and they measure monthly uncertainty regarding various electric vehicle incentives. They are standardized and will take a value between 0 and 100.

This uncertainty measurement was used in three case analyses to see if we could find any relationship between uncertainty and the sale of new electric vehicles. We conducted a time series analysis in an attempt to see how uncertainty regarding electric vehicle incentives, in general, has affected sales in the last decade. In this first attempt, we find no evidence that there is a relationship in the data. Furthermore, we conducted two specific case analyses with the difference-in-differences research method. In these analyses, we wanted to investigate how different levels of uncertainty regarding toll road fees and parking fees affected the sale. However, as in the first case, we do not get any statistically significant results, and we cannot conclude whether the uncertainty affects the sale.

Despite the inconclusive results, the thesis provides a framework for decision-making and offers a thorough literature review of what influences consumers' vehicle choices. Furthermore, we use this insight to discuss possible explanations for our results – both rational and psychological explanations.

As far as we know, no previous empirical studies have been conducted on the relationship between uncertainty regarding incentives and sales. We hope this thesis will contribute with some insight and inspire to further research on the subject.

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1 Introduction

People make countless decisions throughout their lives. Some of these decisions involve more significant investments and have a more lasting impact. Thus, they require that one invest more time and effort in assessing the situation and the various choice alternatives. This will be the case for durable goods costing a certain amount of money, and this thesis will focus on these types of decisions. Such decisions involve costs and benefits today as well as in the future.

Standard economic theory assumes that people make decisions in accordance with the fully rational "economic man." This implies that one has the ability to consider and process all relevant information and use it in calculated cost-benefit analyses that include both the present and the future. The result is that one ends up with the most rational decision in terms of own utility.

However, in real life, empirical evidence shows that people do not make choices that are consistent with this calculating "economic man." The field of behavioral economics incorporates insights from psychology and empirical evidence into standard economic theory. Furthermore, it has established several new assumptions regarding how people form beliefs and preferences and how decisions are made (Dellavigna, 2009). In this paper, we are particularly interested in how people form beliefs about the future based on available information and to what extent they consider uncertainty about the future when decisions are to be made.

To do this, we will look at the decision to invest in a new electric vehicle. This choice is particularly suitable because we have access to detailed sales data for new electric vehicles in Norway all the way back to 2010, and perhaps most importantly: there have been previous periods with great uncertainty related to the future benefits and costs of electric vehicles. The political debate in Norway regarding benefits and incentives for electric vehicles is an ever-recurring hot topic, and the media coverage is occasionally very high.

The following statements from the leaders in both the Norwegian and Danish electric vehicle associations indicate a common perception that uncertainty about future policies affects electric vehicle sales. At least among those who are supporters of electric vehicles.

"If you create uncertainty about the benefit schemes for electric vehicles, the consequences can be large" (Jakobsen, 2017).

> A vehicle is the most expensive purchase you make, second only to housing, and you are not willing to take great risks. This makes the electric vehicle market vulnerable [...] If there is also uncertainty about the benefit schemes, it is obvious that it could have negative effects also in such a mature market as the Norwegian electric vehicle market has become (Bu, 2017).

However, no empirical studies have been conducted on this alleged connection as far as we are concerned. With this thesis, we hope to contribute with some insight into this possible effect of uncertainty regarding incentives on electric vehicle purchases.

To measure the degree of uncertainty, we will use media intensity. Earlier studies have used news frequency as a measure of political uncertainty (Baker and Davis, 2016). We will adopt this method to determine the degree of uncertainty consumers face when considering buying an electric vehicle. Using this method, we hope that our thesis can also provide insight into how consumers respond to a stable policy path vs. a more volatile one.

1.1 Research Question

This thesis is an exploratory study of uncertainty's impact on the decision to buy an electric vehicle. Our research question is as follows:

How does uncertainty regarding electric vehicle policies affect consumer vehicle choice?

1.2 Outline

In the following part of this thesis, we will first establish the context by describing the market for electric vehicles in Norway and the different electric vehicle incentives. That will constitute section 2. Following that, in section 3, we will establish the theoretical foundation to provide the necessary intuition behind decision-making theory. We will also present relevant literature and previous studies that give us relevant insight into vehicle-choice behavior. In section 4, we conduct our empirical analysis, which includes a presentation of the data and the econometric methods we use. In section 5, we will discuss the findings from our empirical analysis using insights from the previous sections. Finally, in section 6, we sum it up in a conclusion and state the thesis contribution and limitations.

2 Electric Vehicles in Norway

This section will start with a brief description of the development of electric vehicles (EVs henceforth) in Norway and present the different policy tools available for the government to incentivize the sale of EVs. Further, we will give an overview of how the various incentives have been used over the years. Finally, we will present three cases we want to examine in our empirical analysis.

Norway has a stated climate goal that all new cars by 2025 will be zero-emission cars (Meld. St. 33 (2016–2017), pg.27, 2017). Norway is on the right track - sales of EVs began in earnest in 2010, and throughout the 2010s, the sale has increased rapidly. In 2021, 65 % of all new vehicles in Norway were electric (SSB). This makes Norway one of the leading countries in the use of EVs.

Figure 2.1: First time registered vehicles 2010-2021

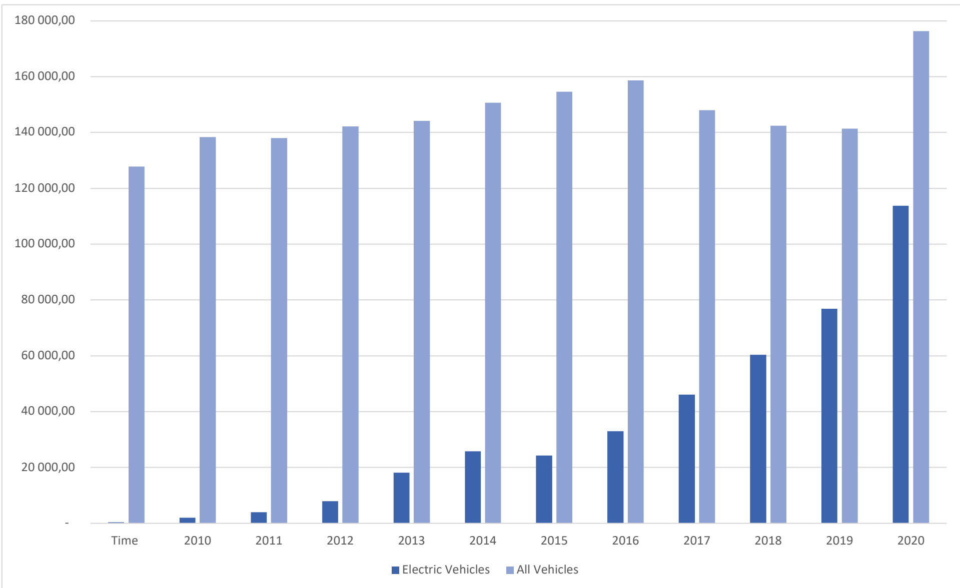
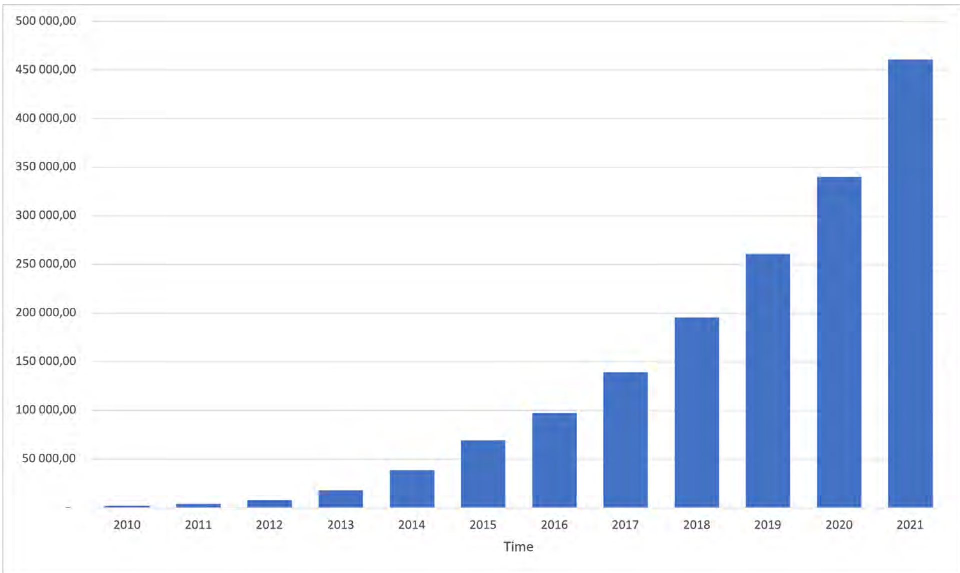


Figure 2.2: Registered electric vehicles in Norway 2010-2021



Fearnley et al. (2015) define two driving forces for the market for electric vehicles: technological development and political incentives. Technological development has made EVs increasingly attractive - the range is improved, and production prices have fallen. Still, it is not the technological development alone that has given EVs the position they have in Norway today. It is largely due to Norway's EV policy and the authorities' desire to shift demand from fossil cars to zero-emission cars, in line with the climate goals set[1].

2.1 EV Policies

To shift consumer demand and incentivize the purchase of EVs, the authorities can use several different political tools (hereinafter referred to as incentives).

We use the divisions of the various incentives in Figenbaum (2018), which divides the incentives according to how the incentives reduce costs for the consumer. Fiscal incentives reduce purchase costs and/or yearly costs, and here we find exemption from VAT and registration tax, reduced company car taxes, and reduced annual vehicle license fee. Direct subsidies to users reduce variable usage costs, and here we find reduced rates on parking, toll roads, ferries, and financial support for charging stations. Finally, we have user benefits that reduce time costs by giving access to bus lanes.

[1]The EV incentives also stimulate the development of EV technology since it makes more people demand the products and this makes it more attractive to invest in technology to further develop EVs

In Norway, there are both national and local incentives. The national incentives are regulated by the government. In this category, one have have fiscal incentives such as fees- and tax rebates, which affect the up-front capital cost. Parking fees, toll roads, ferry tickets, and access to public transport lanes (direct subsidies to users and user benefits), i.e., incentives that affect the usage cost, are, as of today, mainly regulated by each municipality. However, the municipalities must comply with the national "50 % - rule", which states that zero-emission cars should receive at least a 50 % discount on parking, road tolls, and ferry tickets. Beyond that, they can decide for themselves how big the discounts should be. This was decided in 2016, and before that, free parking was a national incentive. In other words, EV policies are frequently changing, and below, we will present a list that gives an overview of the various incentives Norway has had and/or still has. The list is not exhaustive, but it shows the incentives we consider to be the largest and which have the most impact on the consumer costs.

Table 1: Timeline - Incentives for Electric Vehicles

Year	Incentives
1990/96	Exemption from registration tax
1996	Reduced annual motor vehicle tax
1997	Free toll roads
1999	Free parking
2000	Reduction company car taxes
2001	VAT exemption
2003/2005	Access to bus lanes
2009	Further reduced company car taxes
2009	Reduced tax on ferries
2015	Exemption from VAT on leasing
2016/17/18	50 % rule decided
2018	Exemption road traffic insurance tax[2]
2022	Full annual motor vehicle tax[3]
2022	Company car tax rebate reduced[4]

The first incentives were implemented in the late 1990s, with the removal of registration tax and free municipal parking. Throughout the 2000s, more benefits were announced, including the introduction of the VAT exemption in 2001. This means that EVs are exempt from paying 25 % VAT on the up-front purchase price, which significantly impacts the vehicle price. The registration tax also considerably affects the purchase price, particularly for heavy (expensive) cars. The registration tax consists of three components: weight, CO2 emissions, and NOX emissions (Skatteetaten, 2022).

[2]The motor vehicle tax is replaced by road traffic insurance tax. Previously, the annual fee was NOK 500 which was approx. 16 % of the tax for conventional vehicles. 2018-2020: NOK 0. Low rate for EV in 2021.

[3]Full rate: NOK 2975

[4]The tax rebate is reduced from 40 % to 20 %

The Tesla Model 3 was the best-selling EV in 2021 (OFV), and the most affordable alternative currently costs NOK 349 900, with a weight of 1612 kg. The weight tax on a Tesla Model 3 as described above would have amounted to NOK 80 951.[5]. VAT on the same car would have amounted to NOK 87 475. Therefore, both of these fiscal incentives significantly impact the "up-front" capital cost of EVs and are of great importance for the competitiveness of EVs in the Norwegian vehicle market.

Moreover, the "50 % - rule" will ensure that the variable user costs of EVs are lower than for conventional vehicles, thus incentivizing the purchase of EVs. However, as of today, it has not yet been required by law to comply with the decision regarding parking, as the parking regulations have not been updated. In 2021, the Electric Vehicle Association published an overview showing that 39 municipalities did not follow the decision and demanded that EVs pay more than 50 % of the conventional rate for parking. Among them was Trondheim municipality, which demanded full payment (Rotevatn, 2022). According to Christina Bu, Secretary-General of the Electric Vehicle Association in Norway, this rule is essential for the predictability of consumers, and it provides reassurance that choosing an EV pays off. She further emphasizes that the members of the Electric Vehicle Association see this advantage as crucial in deciding whether or not to buy an EV (Rotevatn and Haug, 2021). To date, the rule has not yet been enforced through the parking regulations. This is even though the then-Minister of Transport, Jon Georg Dale, in 2019 stated that the Ministry of Transport "Intends to stipulate necessary changes in the parking regulations [. . .] in the autumn of 2019" in a public response.

In 2018, EV owners estimated that they save on average 14 150 NOK per year because of the local incentives (toll roads, parking, bus line & ferries) (Figenbaum and Nordbakke, 2019). The total savings will be a great amount when you add the other national incentives that affect the purchase price, such as exemption from VAT and registration tax.

[5]

Weight-fee:
0-500 kg: 0 NOK/kg 0
501-1200 kg: 27,15 NOK/kg NOK 13 468
1401-1500 kg: 211,49 NOK/kg NOK 20 937
>1500 kg: 245,97 NOK/kg NOK 27 549

2.1.1 Uncertainty Regarding EV Policies

As we pointed out in the introduction, this paper explores the impact of uncertainty on decision-making and is not about evaluating the effects of various EV policies. Hence, we do not consider it relevant to further explain the different policies and the introduction of those. Instead, we want to examine how uncertainty surrounding the above policies affects the consumers' choice of investing in an EV. We are now shifting the focus from the time of implementation of various policies to the period between the announcement of possible policy changes and clarification. The period before a clarification will, namely, be the period with potential uncertainty for the consumer. In what follows, we will present three cases that deal with different policies and uncertainties surrounding these. These cases will form the data basis for our empirical analysis, and they are presented thoroughly in section 4. Before proceeding to explore these cases in detail, it is necessary to introduce some theory and literature on decision-making and uncertainty, both in general and in the vehicle market, as well as other relevant studies.

3 Theory and Related Work

In this section we aim to establish an overview of existing theories and studies that address decision-making, both general choice theory and specific for our vehicle choice. We will also present literature on how consumers form beliefs about the future. To begin with, we will establish a framework for measuring political uncertainty.

3.1 Measuring Uncertainty and Media's Role

One can think of political uncertainty as a period where you do not know what the policymakers will do in the future, and the policy path is perceived as unstable with a lot of press coverage and policy debates. Media is an important channel for the distribution of news and information. It is called the fourth state power, and it is well known that the content of the media affects what both politicians and citizens are concerned about (Stortinget, 2022). A survey of EV-owners in Norway (Figenbaum et al., 2014) found that media was by far the most important source of information about EVs. A distinction can be made between editorial and social media. In the following, we will refer to the editorial media, which is newspapers, TV, and radio, managed by a responsible editor.

For our thesis, we investigate uncertainty related to EV policies. To determine uncertainty and define uncertain time periods, we will use newspaper frequency (media intensity) as a measure. We have adopted this newspaper approach from the article *Measuring Economic Policy Uncertainty* by Baker and Davis (2016). They found that newspaper frequency is a plausible measure of economic policy uncertainty (EPU). The study developed indexes for EPU based on newspaper coverage frequency. The indexes were based on different search terms and restrictions.

Baker et al. evaluated the newspaper approach in several ways to ensure it was a reliable approach. Among this, they compared the indexes they made with other economic and political uncertainty measures, and they tested the correlation between their computer-generated indexes and human-made indexes. The human-made indexes were made by recruiting students to revise 12 000 articles and make them assess how the articles discussed uncertainty based on the criteria for the computer index. They found a 0,93 correlation between the human and computer-generated index, making it a very plausible and precise approach.

To determine newspaper frequency, we have used Retriever Norge to provide us with detailed media analysis and insight. Retriever Norge is a media company that offers search in news archives, media monitoring, and analysis. Retriever gave us exact numbers on how many articles that were published in a specific time period based on different search terms. They also gave us the possibility to restrict the search to different newspapers. For instance, when looking at local policy debates, we could restrict the search only to show us articles from papers based in that area. This allowed us to experiment with searches across both policy debates and municipalities.

3.2 Decision-making: A General Framework

To start with, we will present the standard model for decision-making to use as a framework. We will look at hypothetical scenarios regarding EV policies and consider the rational model's implication for consumer decisions. In section 3.4, we will look at systematic deviations from this standard model that are relevant to the research question.

3.2.1 The Rational Choice Framework

We will use Dellavigna's (2009) modification of the standard model as a framework, which is based on Carness and Rabin (2002).

$$\max_{x_i^t \in X_i} \sum_{t=0}^{\infty} \delta^t \sum_{s_t \in S_t} p(s_t) U(x_i^t | s_t)$$

The model states that individual i, in time t=0, maximizes expected utility. x_i^t is the different choice alternative available to the consumer in state s_t. $U(x_i^t|s_t)$ is the utility from making choice x_i^t conditional on s being the state of the world. $p(s_t)$ is the probability that a state will occur based on rational beliefs. δ^t is a time-consistent discount factor reflecting the "price" on time. The rational agent in the standard model will update beliefs according to Bayes' rule and make choices consistent with the expected utility theory. Bayes' rule is a rational way of updating beliefs and understandings about the state of the world as more and more evidence (information) becomes available.

In our setting, the different states of the world are referring to different EV policies in the future. The probability related to the different future policies is the probability that the existing EV subsidies will be discontinued, and the new policies will come into effect. Let us hypothetically assume that all current EV policies will be protected for all time to come – that is the state of the world. For simplicity, we say that a consumer can choose between buying an EV, a fuel vehicle, or no vehicle at all within this state of the world. It can be discussed whether or not no vehicle is a feasible alternative. It will largely depend on where in Norway one lives and the public transport service available, the family situation, and areas of use for the mode of transport. The different choice alternatives will give different payoffs. We will discuss how the rational choice framework's implications change as the level of uncertainty regarding policies increases. We will look at both uncertainty in terms of whether policies will be changed and uncertainty regarding the timing of the change.

The starting point will be a situation with zero uncertainty - all EV subsidies are secured for the time to come. The rational consumer will choose the option that gives the highest utility for them based on different features of the vehicle types, own preferences, and cost concerns such as toll roads, annual vehicle tax, and purchase price. However, there is no uncertainty regarding the state of the world, the current benefits will be the future benefits, and one can therefore precisely estimate future usage costs. Then we introduce uncertainty. First, we consider a situation where the future benefits are no longer protected but will be reduced and/or discontinued. There is no uncertainty that this will happen and no uncertainty regarding the time of the change. The further ahead in time until the subsidies are discontinued, the less impact it will have on the decision because of the discount parameter δ , which reflects the cost of time. Future higher costs of EVs in the form of fewer benefits will be discounted to make them comparable today. Regardless of the timing of the policy, one thing is clear: reduced subsidies imply that the use of EVs will be relatively more expensive. Suppose there is no change in the other choice alternatives. In that case, the incremental buyer will choose not to buy an EV when there is a marginal increase in future operating costs.

In summary, the rational choice framework implies that one should see a reduction in the sales of EVs when such a policy change might happen sometime in the future, all else equal. This is in line with the standard assumption of a falling demand curve - demand is decreasing with the price. If we introduce uncertainty about the timing of the removal, the probability that the state will occur will still be equal to 1. However, how much the consumer will discount the future increased costs is hard to say since one does not know when it will be removed. If we also introduce uncertainty regarding the removal, the rational probability that the state will occur is less than one, and the decrease in sales will be smaller than if there is no uncertainty.

In studies of vehicle choice, the choice is often described as a dynamic discrete choice problem (Chen and Li, 2017). Similar to the rational expected utility framework presented above, dynamic discrete choice models construct the individual purchase decision as a utility maximization problem, where expected utility is the deciding factor.

3.3 The Vehicle Market and the Effect of Vehicle Policies on Decisions

A significant amount of literature on modeling vehicle markets aims to explain how equilibrium is determined in the market. Our thesis falls within the demand side of the market – how do consumers' demand for a new EV respond to uncertainty about future EV policies?

The early influential work by Berry et al. (1995) studied the market for new vehicles and developed techniques to analyze demand and supply parameters, which later can be used to analyze equilibrium in the vehicle market. The article emphasizes how insight into the market's cost and demand side is essential for analyzing policy issues. As for the vehicle decision, Berry et al. (1995) found that fuel economy was not a significant matter. Following this, the literature on the vehicle market and vehicle choice behavior has further developed. A study by Gillingham et al. (2022) is one of the most recent additions to the literature. The paper establishes a dynamic equilibrium model, which is later used to evaluate a Danish vehicle tax policy and show how hypothetical changes in tax policies will affect vehicle sales and vehicle decisions. This study also models the vehicle decision as a dynamic discrete choice, and the new contribution of the Danish study is that they have incorporated driving and associated driving costs in the utility maximization problem for the consumer. In contradiction to Berry et al. (1995), the study implies that policies that affect usage costs, such as fuel economy, will have an impact on the choice. Furthermore, it will therefore be interesting to look at what previous studies says about how consumer forecasts future expected operating costs when facing the choice of buying a vehicle or other durable goods. Before that, however, we will present some statistics from surveys of Norwegian vehicle owners that have investigated the effect of various policies and which factors are important to consumers when intending to buy a vehicle.

3.3.1 What Influences Vehicle Choice

In a study on policies that influence future usage price and their influence on the decision of what type of vehicle to buy, Busse et al. (2013) point out "that a policy must influence something that people pay attention to in order to actually affect the choices consumers make" (p.221). As stated, we are not going to study the effect of policies. Still, in order to see how uncertainty regarding future policies affects decisions today, we must investigate policies that we know are important to the customers and which have previously been shown to influence sales.

The Institute of Transport Economics (TØI) in Norway has, over the years, conducted surveys among Norwegian vehicle owners, both electrical and conventional vehicle owners, to understand what influences them when deciding what car to buy (Figenbaum et al. (2014); Figenbaum and Kolbenstvedt (2016); Figenbaum (2018) and Figenbaum and Nordbakke (2019)). In both 2016 and 2018, exemption from registration tax and VAT (reduced purchase price) as well as energy- and operating costs were among the most important factors for purchasing an EV (Figenbaum and Nordbakke, 2019). In 2014, 81%[6] of the EV owners reported that the vehicle's operating costs were of "very large" or "large" significance on the purchase decision (Figenbaum et al., 2014). When asked about the importance of the different incentives[7] , exemption/reduction of toll road fees was considered "great" or "crucial" importance for buying an EV by respectively 50% and 63%

[6] N= 2241

[7] Registration tax exemption and VAT exemption not included in this question because they are embedded into the purchase price

of the respondents in 2016 and 2018[8] – which makes it the most important local incentive. The second most important incentive was reduced annual tax/insurance, with 49% both years. Furthermore, 25% and 24% reported that free/cheaper parking was of great or crucial importance - making it the third most important incentive.

To sum up - the results from these surveys indicate that EV policies influence people's decisions. In 2014, the respondents were also asked if uncertainty regarding future incentives "was a disadvantage or an advantage." 69%[9] of the respondent thought of the uncertainty as a disadvantage (31% thought it was a big disadvantage, and 38% thought it was a small disadvantage). This indicates that periods with a lot of uncertainty might influence the sale. The statements regarding uncertainty presented in the introduction confirm this perception.

3.4 Consumer Behavior When Investing in Vehicles and Other Durable Goods

In this section, we will present more literature and studies that aim to explain consumers' vehicle-choice behavior and what influences the decision to buy an EV. First, we look at how people forecast future expenses and savings and how they incorporate the future operating costs into their decision today. Furthermore, we look at studies that apply dynamic discrete choice models to the vehicle decision to analyze how the consumer choice will change if there are changes to the models' input.

3.4.1 Discount Rates and Myopic Consumers

As we saw in the rational framework, consumers discount future expenses and savings to make them comparable today with the discount factor δ. Several studies have estimated the size of this discount factor in various settings, and the first to investigate this for energy-using durables was Hausman (1979). He modeled the decision to buy an energy-using durable as a trade off between the initial purchase price and the future expected operating costs, in other words: a trade off between expected future costs and present costs. Hausman also modeled the decision as a dynamic discrete choice. He found that

[8] 2016: N=3111, 2018: N=3653
[9] N=1721

the individual discount rate was about 20 percent and that it varies inversely with income: discount rates decrease when income increases. The discount rate level he found cannot be directly transferred to our case. First, it is about different durables: vehicles vs. room air conditioners. Second, the study was conducted 40 years ago, and interest rates and other factors that affect individual discount rates have changed a lot since then. However, what we bring from this study is that he was one of the first to investigate whether consumers are myopic when purchasing durables that have future operating costs.

Inspired by this study, there are several new contributions to the question of consumer myopia in vehicle purchases.In their natural experiment of vehicle purchases, Gillingham et al. (2019) find that consumers act myopically regarding future fuel costs. With a discount rate of 4% they are indifferent between a $1 discount on future fuel costs and a 15-38 cents discount on the purchase price.In contrast to this, Busse et al. (2013) find no evidence for consumer myopia in vehicle purchases, and their estimated discount rates are, in many settings, equal to zero. A lot of literature has investigated this effect, and the results are ambiguous.Some find evidence of higher discount rates and some consumer myopia (Kahn (1986); Killian and Sims (2006) and Allcott and Woxny (2014)), while others Goldberg (1998) find no evidence of consumers undervaluing expected future fuel costs, similar to Busse et al. However, what is clear from these studies is that the higher the discount rates on future expected usage costs, the smaller impact policies regarding usage costs have on the vehicle buying decision.

Anderson et al. (2011) studied how consumers forecast future gasoline prices and emphasized the importance of information about consumers' beliefs on future energy prices. They find that the average consumer belief is that they expect the future price to be equal to the current price. Furthermore, they find that, historically, this is a reasonable forecast.

Kim et al. (2014) use an extended discrete choice model to investigate what influences the EV decision. They find that cost consideration influences the utility of the vehicle the most. They also find that social influence matters for the choice when the public opinion of EVs is positive and when large shares of friends and family also have EVs. Furthermore, attitudes towards environmental concerns and technology acceptance matter as well. These results align with the TØI surveys of Norwegian EV owners. The environment was listed as the second most important reason for vehicle purchase by EV owners[10], only behind economy concerns (Figenbaum and Nordbakke, 2019).

3.5 Deviations from the Rational Choice Framework

As stated in the introduction, people do not behave according to the rational framework in many settings. This section will list and briefly describe different deviations and biases relevant to our thesis, which will later be used to help discuss our empirical findings.

The rational choice model implies a narrow self-interest where individual utility is solely determined by own payoff. But as we saw in the last section, people do not only consider their own payoff in monetary terms when estimating the utility they will derive from a choice alternative. They care about the environment when choosing vehicle types, and in that way, they increase utility by behaving environmentally friendly. This behavior could be due to maintaining a good self-image as an environmentally friendly person or because of peer pressure and trends among friends and family, as indicated by Kim et al. (2014). Social pressure and social signaling are shown to influence consumers' decisions in various settings (Akerlof, 1991).

The standard model assumes time-consistent preferences, but behavioral economics studies have shown that people behave present biased; that is, the future is discounted too much, and they place too much value on the immediate utility they get today. The disproportionately high discount rates in some of the studies presented above might indicate such behavior. Green (2011) also considers hyperbolic discounting, which is the same as present biased, a possible explanation for high discount rates.

Another deviation from the standard model is related to the well-known prospect theory by Kahneman and Tversky (1979). They found that when consumers evaluate the utility of something, they make relative judgments rather than absolute ones and will evaluate the utility they derive relative to a reference point. One says that consumers have reference-dependent preferences. Furthermore, it is established that negative deviations from this reference point, perceived losses, affect people more than equivalent positive deviations from this point, perceived gains. This will affect consumer decisions when considering a

[10]They were asked what the most important factor was for buying a particular type of vehicle, and they could only answer one factor.

choice that involves risk and uncertainty. A general approach is that losses have a twice as large impact as gains on the consumer decision (Dellavigna (2009); Green (2011)). The consumers' reference point at the time of purchase can therefore influence the decision. If the consumers' reference point is the current EV benefits, the future uncertainty regarding benefits is perceived as a possible loss. However, suppose the reference point is the rates for conventional vehicles. In that case, the future benefits for EVs are still perceived as a gain, potentially just a smaller gain if the benefits are reduced in the future.

The context-dependent preferences can explain why we see people buying value-size candy in an electronic retail store with a price per kilogram that is higher than the price of regular size in the grocery store. Relative to the expensive TV you are about to buy, a value-size can of candy that costs, for instance, NOK 99, is perceived as very cheap in comparison. The same might be the case for the up-front capital costs of the vehicle and the usage costs such as parking fees or toll roads. Even if these might be higher in the future due to reduced incentives, the unit price of toll roads is still perceived as small compared to the purchase price, and thus, uncertainty regarding these does not influence the decision.

Because of limited attention, consumers behave bounded rational in many settings. Instead of solving complex maximization problems as presented in section 3.2, people use heuristics to make a decision (Kahneman and Tversky, 1979). These shortcuts are not random but are systematically biased, and the behavioral economics field has revealed several of these biases. One of these psychological mechanisms is salience. In a decision context, customers may pay too much attention towards some features and information that is salience and are inattentive to features of the decision that is less salient. One overweighs the available information, and information that is further into the future is less likely to be salient to you (Dellavigna, 2009). Related to this is the self-attribution bias; individuals tend to discount information that is not consistent with their prior beliefs and overvalue information that confirms their beliefs. One can say that individuals behave motivated inattentive; they might only be attentive to the features of a vehicle type that confirms their wishes and provides them with a justification to buy (or not to buy). There is also evidence that informational overload leads to a slower response to the information(Hirshleife et al., 2009). All of these are examples of deviations from Bayesian rational updating.

Kreps and Porteus (1978) has created a model for dynamic choice under uncertainty which also includes that the time at which the uncertainty is resolved is important for the individual. For instance, a consumer may prefer early resolution over late resolution even though the two alternatives' expected utility is the same. This deviates from the assumption in the standard model that consumers are strict utility maximizers.

3.6 Summary

Based on the literature review, we can state that consumers emphasize EV incentives when they buy a car - at least they say they do. That is important for our further analysis. If consumers do not pay attention to the incentives in the first place, it is not meaningful to investigate uncertainty regarding these policies. In the following, we want to use data to see if there is any evidence of a relationship between uncertainty about future usage costs (through incentives) and EV sales.

The rational framework for decision-making, the expected utility theory, implies that uncertainty about future usage costs should affect sales. This is because the marginal buyer will not want to buy today when future expected costs increase, given that there is no change in the utility from the other alternatives. The dynamic discrete choice studies also suggest that cost considerations influence the decision the most.

On the other hand, we have seen that people in many settings do not behave in line with the assumptions in the rational choice model, such as excessive discounting of future costs, other things than their own payoff determine the utility, and emotions influence the decision.

The following part of the thesis moves on to explore the effect of uncertainty on the investment decision by using data to investigate if we can find some evidence of a relationship between the two conditions.

4 Empirical Analysis

As indicated earlier, we will begin this section with a brief introduction of the three different cases we are going to investigate and state why we have chosen these. Furthermore, we will describe the different data variables we include in our analysis and the empirical methods we will apply. In section 4.4, we will describe the various cases in detail and present the associated descriptive statistics and regression results. Finally, in section 4.5, we will discuss potential weaknesses with the empirical analysis.

4.1 Cases of Interest

After reviewing the changes in EV policies during our chosen investigating period, we decided to focus on five of the largest municipalities in Norway: Oslo, Bergen, Stavanger, Trondheim, and Kristiansand. The first and somewhat obvious reason why these were chosen is that these are municipalities with large populations and many EV users, and that the nationwide newspapers primarily cover policy changes in the larger municipalities. Secondly, we noticed that political debates and significant changes in EV policies occurred at different times in several of these municipalities. This is something we can take advantage of this in our research design. The municipalities that do not experience a high degree of uncertainty can act as a counterfactual state and will allow us to control for changes in EV sales that are not caused by uncertainty. The empirical methods we use for our analysis will be explained in section 4.3.

Our first case investigates the general impact of uncertainty regarding EV incentives through a time series analysis. We look at the general uncertainty regarding national incentives over the last decade (2012-2022). The second and third case is specific case analyses that investigate uncertainty regarding specific local incentives (toll roads and parking fees) using panel data and the difference in differences research design.

4.2 Data

4.2.1 Variables of Interest

4.2.1.1 EV Sale (First Time Registered Vehicles)

Our dependent variable is the sale of new EVs. We use first-time registered EVs as a measure of EV sales. We received data from OFV, the Norwegian road traffic information council, on the registration of new EVs and other vehicles from January 2010 to February 2022. We received data nationwide and for the five largest municipalities in Norway. The data we received from OFV were monthly. In case 2 and 3, we compare outcomes in different municipalities. Since they are of various sizes, they will have different levels of first-time registered vehicles. To account for this skewed distribution, we will use the natural logarithm of first-time registered EVs as the dependent variable for case 2 and 3.

After receiving the data, we noticed that from 2010 to 2011, there was a minimal number of EVs being sold, especially in some of the municipalities. Based on this, we decided to shorten our investigation period from 2010-2022 to 2012-2022. The first uncertain period we are interested in investigating happened in 2015, and we consider 2012 to 2015 a sufficient amount of time to see a trend before an uncertain period occurs.

It is important to point out that there is a difference between when the purchase was made and when the vehicle was registered. If there is delivery time on the vehicles, the registration will occur later than the sale. An earlier master thesis by Lium and Sanne (2021) also obtained data on first-time registered vehicles from OFV. They contacted car dealerships to get an overview of the different delivery times. It turns out that there have been significant variations in delivery time over the years and between vehicle brands, ranging from immediate delivery to a six-month waiting period. If all the EVs had an equal delay, we could have more easily taken this into account in the analysis, but since this will differ from month to month and between vehicle models, it is more difficult to control for. The implications it will have for our analysis are discussed in section 4.5. However, we note that OFV itself refers to this data as sales in its own analyzes and statistics, and we will in the following continue to refer to first-time registered EVs as sales of EVs.

4.2.1.2 Uncertainty Index

The other variable of interest is the level of uncertainty. To measure this, we have created an uncertainty index as described in section 3.1. We created an index for each of our cases of interest since we are investigating uncertainty regarding different policies. We created an index for each of our municipalities of interest for the local policy changes parking and toll road fees.

In case 1, the index is based on the intensity of the keyword combination "Elbil" and "Fordeler" in the Norwegian media over our investigation period. The index for case 2 is based on the intensity of the keyword combination "Elbil," "Parkering," and "Municipality." For this case, we have created an index for each of the municipalities we are investigating. The approach for making the index for case 3 is the same as for case 2; we just switch the keyword "Parkering" with "Bompenger."

Since the volume of articles varies across time, we need to control for changes in the general media intensity. To do this, we collected the total number of articles published each month from Retriever. Then we divided the number of articles about our cases of interest each month by the total number of articles published that month. Furthermore, we standardized these numbers such that our uncertainty index takes a number between 0 and 100. Where 0 is no uncertainty, and 100 is the highest uncertainty regarding the policy incentive and EVs.

4.2.2 Control Variables

In addition to our variables of interest, we have collected data on income and population, both nationwide and for the municipalities of interest. These will serve as control variables in the regression models and are included to avoid omitted variable bias in the regression results. We use income and population as we expect these to have an impact on the sale and consider them suitable control variables as they should not be affected by a policy change for EVs. The data for our control variables are collected from Statistics Norway (SSB), the Norwegian statistical institute and the main producer of official statistics.

The observations for our control variables are only available on a yearly basis. Since we want to analyze the sale monthly, we are dependent on monthly data for our control variables. Hence, the values for population and income will be the same for each month in the year. Therefore, our observations will be independent across the municipalities(group) but repeated within the municipalities(group). A requirement for our empirical method is that the observations must be independent. That being the case, we allow the error terms to be intragroup correlated and use clustering on income and population. This affects the standard errors and the variance and relaxes the requirement that the observations must be independent.

4.2.2.1 Income

For the income variable, we collected data on income after taxes for all municipalities and Norway. We got our data from table 12558 from SSB (Statistics Norway, 2022b). This table divides the income level into ten equal groups, from deciles 1 to 10. The table shows the number of households that are in the different deciles. Decile 1 is the tenth of all working with the lowest wage, and the 10th decile is the tenth with the highest wage.

The study by Figenbaum et al. (2014) found that the owners of EVs have high education and high income. Therefore, we use the number of households in the municipalities that are in the 10th decile as a control variable. Another argument for using the number of high-income households as a control is that we are looking at the sale of new vehicles. Buying a new car will have a higher cost than a used car.

4.2.2.2 Population

The population data was collected for the same municipalities and time as the income data. We collected the data from table 07459 from SSB(Statistics Norway, 2022a). This table shows the population in our five municipalities of interest in each of the investigation years. When controlling for population, we take into consideration the size of the municipality. We assume that when the population increase, the sale of EVs will also increase. Figenbaum et al. (2014) also show that most potential buyers and EV owners live in big municipalities and densely populated areas. It is also natural to think that the population in a city impacts the sale of EVs, as a higher population gives a larger consumer mass.

4.3 Empirical methods

4.3.1 Time Series Data Analysis (Case 1)

Our time series data consists of monthly observations of the EV sale, uncertainty index, income, and population from January 2012 until December 2021. The variables are thoroughly described in the previous section. Several methods can be used to analyze the relationship between variables over time. Which one is appropriate depends on the properties of the time-series data.

Checking for stationarity (unit root test)

The time-series data are stationary if the mean is constant over time. Non-stationary time series then implies that the mean increases or decreases over time. For our dependent variable, EV sale, we know it has an upward movement over time (the mean increases). To check for stationarity in our variables, we conducted a unit root test, more specifically an Augmented Dickey-Fuller (ADF) test. The test concluded that we do not have stationary data.

4.3.1.1 First Differences and Distributed Lag Model

The first difference regression is a method that solves the problem with non-stationary time series data. By taking first differences, the data is made stationary. Instead of doing a regression on the raw data, we will use the change in data from one point to the next, for instance:

$DeltaEVSale = EVSale_t - EVSale_t{-}_1$

The intuition behind this method is that if there is a relationship between uncertainty (UI) and the EV sale, we should also see it after removing time trends and seasonality. For instance, if UI increase from one period to the next, sale should decrease. After converting the non-stationary variables by taking first difference, we do an OLS regression. This will be our model (1).

$$EVSale_t - EVSale_t{-}_1 = \beta_0 + \beta_1(UI_t - UI_t{-}_1) + \beta_2(X_t - X_t{-}_1) + u_t \qquad (1)$$

An extension of this basic model is made by including lagged values of UI. The first model assumes that the change in uncertainty will affect sales in the same period (month). How quickly consumers respond to uncertainty, if at all, we do not know, but it is reasonable to assume that not everyone will react in the same month. Therefore, the second model we estimate will be a distributed lag model. This model allows for previous values of the independent variables to impact EV sales. To decide how many lag lengths that are optimal to include, we use the Akaike Information Criteria (AIC). The first differences distributed lag will conduct our model (2): First differences distributed lag

$$(FD - DL) \tag{2}$$

A weakness of the first differencing method is that one removes the information of a possible long-run relationship between the variables and only looks at the short-run change. In the next section, we present a method that can be applied to time series with both non-stationary and stationary data and that can be used to test for long-run relationships.

4.3.1.2 Autoregressive Distributed Lag Model

This method is similar to the distributed lag model, but one does not have to difference the data, and it also includes lagged values of the dependent variable, hence the name autoregressive. We will test for the long-run relationship by conducting a Bounds test (Pesaran et al., 2001). This will be our model (3): Autoregressive distributed lag

$$(ARDL) \tag{3}$$

4.3.2 Panel Data Analysis (Case 2 and 3)

The Difference-in-Differences design (DiD)

For our panel data analysis, we will use difference in differences. This method is often used to investigate whether a policy implementation or a change has the intended effect. In our analysis, we are interested in the effect of uncertainty regarding EV policies on EV sales and not the effect of a policy change itself. The method splits the units into a treatment group and a control group and estimates the differential effect between the two groups. We form two groups; The treatment group that experiences uncertainty regarding an incentive (an unstable policy path) and the control group that does not experience uncertainty regarding that incentive (a stable policy path).

To be able to say that the estimated difference in the two groups comes from uncertainty, in other words, that there is a causal relationship between uncertainty and EV sales, the assumption of parallel pre-trends must be fulfilled. This means that the two groups must follow the same trend in sales prior to the uncertain period, such that in the absence of uncertainty the two groups would have continued to follow the same trend (Wooldridge, 2019). This can be assessed through a graphical representation of historical EV sales and will be done for each case later.

In the simplest case, uncertainty is indicated by a dummy variable. We call it U_{it} and it will take the value one if the municipality is in our treatment group and zero otherwise. The second dummy variable is $UTime_t$ which is created based on when our treatment groups are experiencing uncertainty. We are interested in the effect of uncertainty on sales and need to create an interaction variable. This variable is called DiD_{it} and will take the value one when our treatment groups are experiencing uncertainty and zero otherwise. Based on this, we create regression (4).

Our second approach is a difference in differences with continuous treatment. This approach is based on the paper by Callaway et al. (2021). In our simple case, we have a strict measure of uncertainty where it either takes the value of one if there is uncertainty or zero if there is no uncertainty. However, this is a gross simplification of reality. In this setup, we have two periods. The first period is our pre-period, where none of the municipalities experience uncertainty. Our second period is the post-period, where some of the municipalities experience uncertainty with various intensities.

We define the post-period in each case from the time when the uncertainty regarding the specific incentive arises. When the parallel pre-trend assumptions hold, we simply compare the outcome changes among municipalities that experience a certain level of uncertainty in the time period to outcome changes in the municipalities that do not experience uncertainty. The level effect is the treatment effect of a level of uncertainty, which equals the difference between a unit's potential outcome under uncertainty and its untreated potential outcome. The slope effect is the causal response to an incremental change in the uncertainty index. When we have continuous treatment, the causal response and the treatment effect will be the same.

The dummy variables for our treatment group and uncertain time will be the same as in the simple case. However, our interaction variable will be a continuous number. We call this interaction variable $ContinuousDiD_{it}$, and it will take a value between 0 and 100 for a municipality experiencing uncertainty in the period that we have defined as uncertain. The variable is created by multiplying the two dummy variables with our uncertainty index. X_{it} is the set of control variables. From this, we get regression (5). This regression is constructed based on regression (1) in the paper by Callaway et al. (2021).

$$LNSaleEV = \beta_0 + \beta_1 U_i + \delta_0 UTime_t + \delta_1 DiD_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{4}$$

$$LNSaleEV = \beta_0 + \beta_1 U_i + \delta_0 UTime_t + \delta_1 ContinuousDiD_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{5}$$

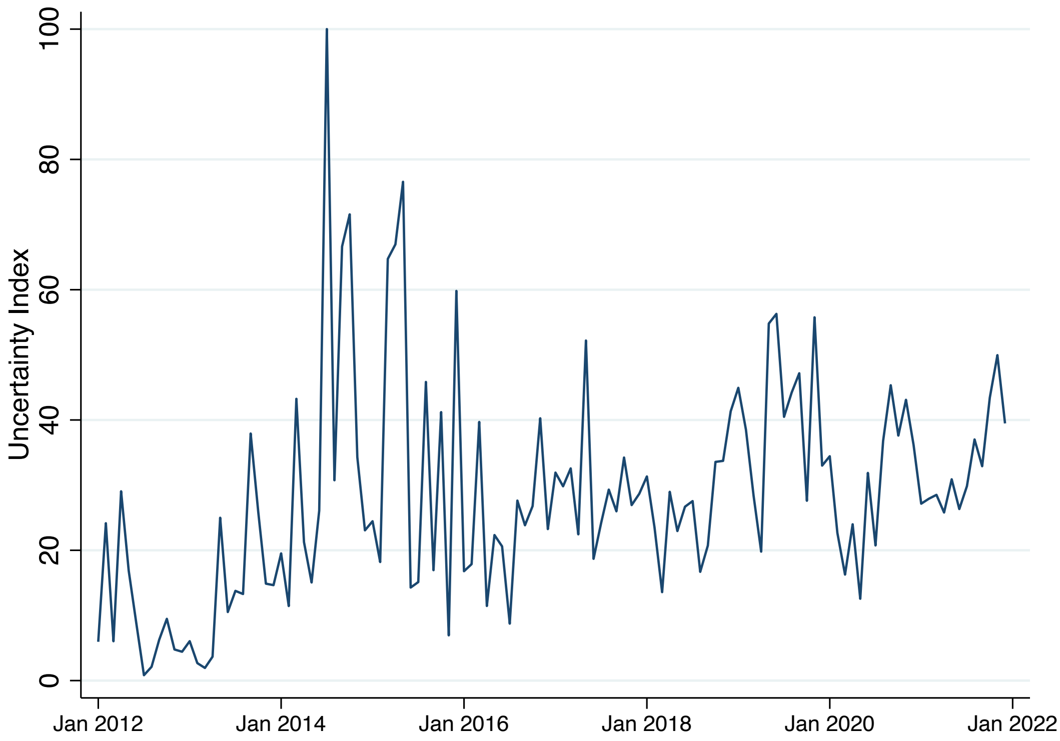
4.4 Case Analysis

4.4.1 Case 1: National Incentives - A Time Series Analysis

Our first case investigates the impact of uncertainty regarding general nationwide EV incentives. All the incentives aim to give EVs advantages relative to conventional vehicles, but over time we have seen that the scope of these benefits is steadily up for discussion and debate. As a result, some benefits have been removed altogether, and other benefits have been diminished, while some have remained unchanged.

To determine uncertainty, we have established an uncertainty index as explained in section 4.2. The index for this case analysis consists of the keywords “elbil” and “fordeler,” and we have used articles from all Norwegian newspapers in the period 2012 to 2022.

Figure 4.1: Uncertainty Index 2012-2022



The graphical representation of the UI index shows that there are some periods with greater levels of uncertainty than others. The period with the greatest level of uncertainty is the period around 2015, and in the following, we will give a closer description of what happened in this period.

When the Norwegian government introduced the climate agreement "Klimaforliket" of 2012, it was stated that: "The current tax benefits for the purchase and use of zero-emission cars will be continued until the next parliamentary term (2017), as long as the number of zero-emission cars does not exceed 50.000" (Stortinget, 2012). After 2012, there was tremendous growth in the sales of zero-emission cars. On the 20th of April 2015, car number 50.000 was sold in Norway. This raised a nationwide debate on whether the EV benefits should be continued.

Already prior to the sale of car number 50.000, the newspapers started writing about the consequences of the rapid growth in EV sales. At the end of March 2015, the newspapers started writing about the current benefits and whether they should be continued or removed. On the 6th of May 2015, the government decided to continue the current tax benefits (Mæland, 2015).

Since then, there have been periods where our uncertainty index indicates high uncertainty. This implies that EVs and their benefits are something that concerns both the media and consumers. This is also confirmed by the TØI surveys presented in section 3: EV incentives matter to consumers and are something they pay attention to. The question is whether they care sufficiently about the incentives so that uncertainty regarding them influences the investment decision.

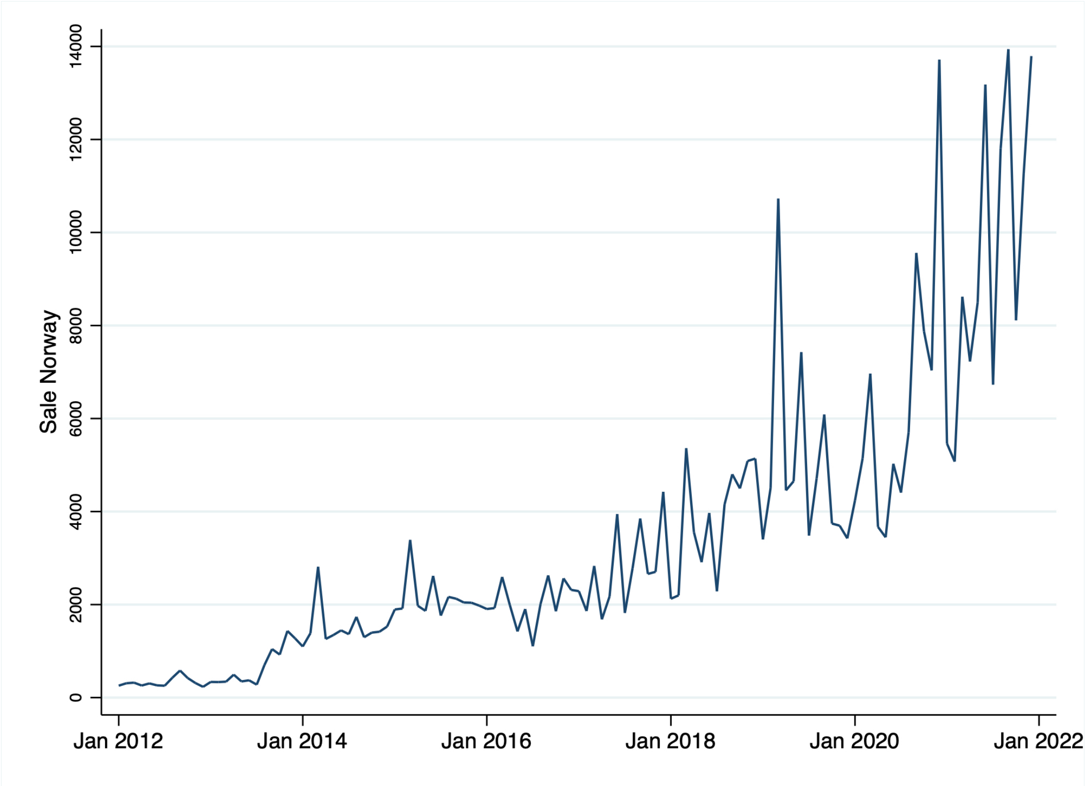
4.4.1.1 Descriptive Statistics

Table 2: Descriptive statistics, Case 1

	Mean	SD	Min	Max	N
Sale	3415.508	3136.524	232	13941	120
Uncertainty Index	28.433	16.950	0	100	120
Income	234894	7130.075	224547	246733	108
Population	5199099	142765.3	4985870	5392161	120

We have monthly observations from 2012 to 2022, which gives us 120 observations. The exception is income, which has 108 variables due to a lack of income data in 2021 from SSB. The UI variable ranges from 0 to 100, as explained earlier.

Figure 4.2: National sale of electric vehicles 2012-2022



As we see in figure 4.2, the sale of EVs has increased significantly during the investigation period.

4.4.1.2 Results

Table 3: The effect of uncertainty on the sale of Electric Vehicles

	Dependent variable:	
	LN Sale	LN Sale
	(FD)	(FD-DL)
D.Uncertainty Index	1.800	2.158
	(3.979)	(8.061)
L1 D.Uncertainty Index		9.263
		(9.335)
L2 D.Uncertainty Index		-6.042
		(8.105)
D.Income	-0.295	-0.339*
	(0.173)	(0.196)
L1 D.Income		0.119
		(0.198)
L2 D.Income		0.743***
		(0.198)
L3 D.Income		-0.911***
		(0.178)
L4 D.Income		-0.092
		(0.179)
D.Population	0.005	0.007
	(0.004)	(0.007)
L1 D.Population		-0.006
		(0.007)
L2 D.Population		-0.003
		(0.007)
Constant	166.802	240.606
	(94.052)	(167.515)
Observations	107	103
R^2	0.018	0.364
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 4: Autoregressive Distributed Lag Model

	Sale
	(ARDL)
Uncertainty Index	0.473
	(6.404)
L1 Uncertainty Index	1.304
	(6.449)
L2 Uncertainty Index	1.885
	(6.358)
Sale	ν
Income	ν
Population	ν
Constant	-1.64e+04
	(9952.989)
Observations	104
R^2	0.839

Note:
*p<0.1; **p<0.05; ***p<0.01

Our first model, the OLS on first differences, has a very low R^2 and no significant results. When allowing the lagged independent variables to have an impact (model 2: FD-DL), R^2 increases to 36% and we get some significant results on income. It is logical that lagged first differences will increase the explanatory power since people do not react immediately. The included lags will also solve some of the problem with the registration delay, as it estimates the effect of lagged values. For instance, if we assume a two-month delivery time, one will see the effect on sales in an uncertain January on the vehicles registered in March. In model 2 and 3 (FD-DL and ARDL[11]), we allow UI for January to affect the sales variable in March. However, none of the three models gives significant results on the UI variable, and the p-value is very high. This is a first indication that we do not find any relationship between uncertainty and sale. The results from the bounds test for the ARDL model indicate no long-run relationship either.

[11] See Appendix for complete ARDL regression output

4.4.2 Case 2: Local Parking Fees - A Panel Data Analysis

Our second case of interest is the debate on free public parking. The public parking regulation from 1993 is a law that allows zero-emission and hydrogen-powered motor vehicles to be parked without paying a fee in places where paid parking is introduced Forskrift om offentlig parkeringsregulering mv, 1993, §8a. (1993) . As we saw in section 2, the parking regulations were revised in 2016. The new law now states that a municipal can introduce payment exceptions for electric and hydrogen-powered motor vehicles in paid municipal parking spaces (Parkeringsforskriften, 2016, §34, 2016). The law was implemented on the 1st of January 2017. After this date, it was up to each municipal to decide whether zero-emission and hydrogen-powered motor vehicles could park without paying a fee.

The revised law was announced on the 18th of March 2016. Already in the first quarter of 2016, there was a lot of media coverage about this topic. However, the highest media coverage was in the fourth quarter of 2016, with 347 articles including the search words “elbil” and “parkering.” In comparison, it was 252 articles in the first quarter. In this period, Bergen, Stavanger, and Trondheim notified that there would be an end to free parking. On the contrary, Oslo and Kristiansand announced that they would continue the free parking and thus continue the stable policy path. Since there are differences across municipalities and regions, this is an interesting period to investigate. We will use the difference-in-differences design to compare municipalities and see if the different level of uncertainty provides a difference in sales.

We define the uncertain period from February 2016 to February 2017. As mentioned above, Bergen, Trondheim, and Stavanger implemented a parking fee in this time period. However, we find a low level of uncertainty in Bergen regarding parking fees in this time period. The level of uncertainty is based on our uncertainty index for parking fees for all municipalities during the period we have defined as uncertain. A graphical representation of the index is presented below.

Figure 4.3: Uncertainty Index for Parking fees

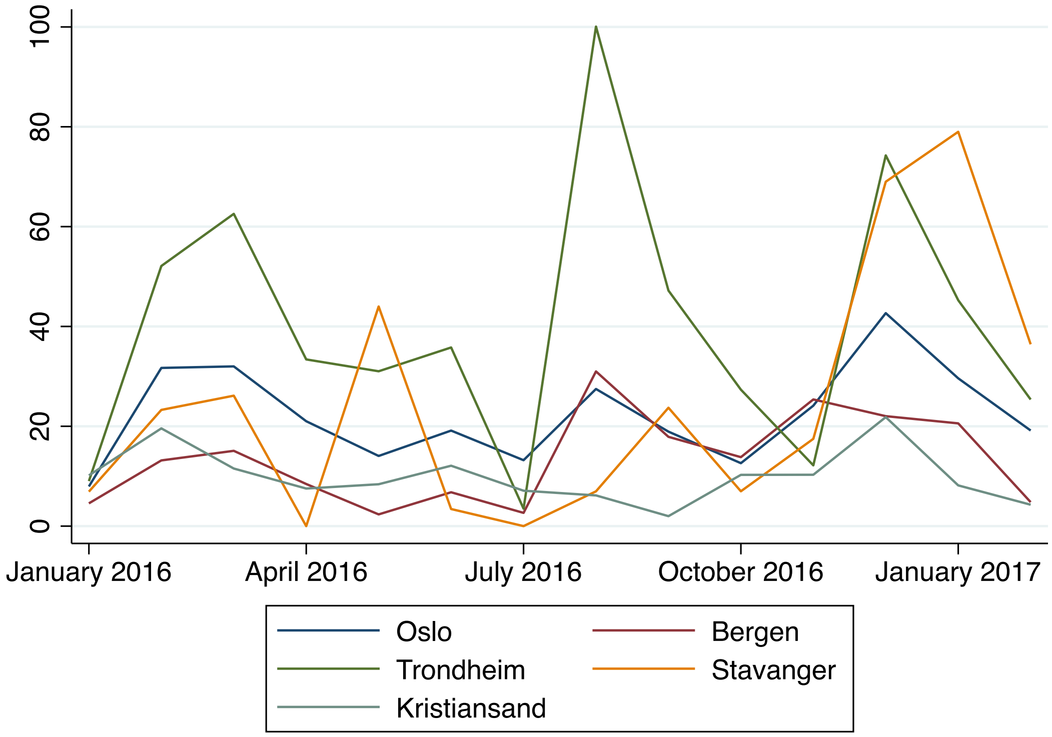


Table 5: Implementation of parking fees and the level of uncertainty from February 2016 to February 2017

Municipality	Implemented parking fee	Level of uncertainty
Oslo	No	Low
Bergen	Yes	Low
Trondheim	Yes	High
Stavanger	Yes	High
Kristiansand	No	Low

4.4.2.1 Descriptive Statistics

Table 6: Descriptive statistics, Case 2

	Mean	SD	Min	Max	N
LN Sale	4.446	1.090	1.792	6.760	310
Uncertainty Index	12.572	16.412	0	100	310
LN Income	9.274	0.753	8.091	10.513	310
LN Population	12.226	0.685	11.329	13.410	310

Table 4.5 shows the descriptive statistics for the variables included in our analysis for case 2. In this case, we have included all the five municipalities and the time period reaches

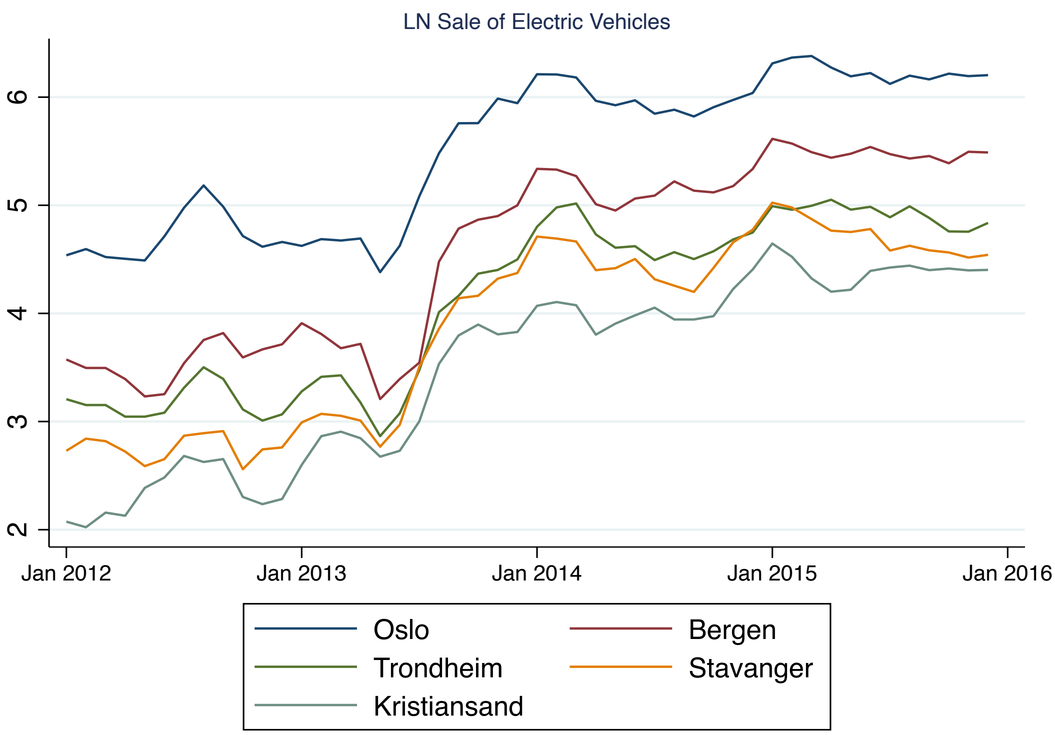
from January 2012 to February 2017, which gives us a total of 310 observations. All the variables that are included are monthly.

4.4.2.2 The Parallel Pre-trend Assumption

In this section, we will check if the parallel pre-trend assumption holds. The Parking law was revised in 2016, and we have in earlier sections defined the uncertain time from February 2016 to February 2017. For our analysis to make sense, we need our treatment and control groups to follow the same trend before 2016. To get a smoother graph that represents the trends better, we use the three-month average LN sale of EVs as shown in the equation below.

$$LNSaleEV_{it} = \frac{LNSale_t -_1 + LNSale_t + LNSale_t -_1}{3} \tag{6}$$

Figure 4.4: Testing for parallel pre trends, parking fees



Based on the graphical representation of the sale of EVs over time, we conclude that the parallel pre-trend assumption holds. We see that all the municipalities move together, and none have significant deviations from the others. We have defined the treatment and control groups for this case in the table below. The control and treatment groups are based on the level of uncertainty presented in table 4.4 and from manually reading through the articles published in local newspapers. The treatment groups have an unstable policy path with high levels of uncertainty, while the control group has low levels of uncertainty and stable policy paths.

Table 7: Treatment and Control groups, Case 2

Group	Municipality
Treatment	Stavanger and Trondheim
Control	Kristiansand, Oslo and Bergen

4.4.2.3 Results

Table 8: The effect of uncertainty regarding parking fees on the sale of Electric Vehicles

	Dependent variable:	
	LN Sale	LN Sale
	(1)	(2)
Treatment group	-0.051	-0.083
	(0.413)	(0.393)
Uncertain Time	0.754***	0.695***
	(0.216)	(0.180)
Interaction	-0.148	
	(0.346)	
Continuous treatment		-0.000
		(0.005)
LN Income	-0.011	-0.007
	(0.739)	(0.747)
LN Population	1.045	1.040
	(0.851)	(0.862)
Constant	-7.865**	-7.857**
	(3.272)	(3.273)
Observations	310	310
R^2	0.506	0.505
Note:	*p<0.1; **p<0.05; ***p<0.01	

The regression estimates from the simple difference in difference model show that Stavanger and Trondheim had 14,8% lower sales than Kristiansand, Oslo, and Bergen in the uncertain period. These results indicate that uncertainty has a negative impact on the sale of EVs.

Although the DiD coefficient indicates that uncertainty has a negative effect on sales, it is non-significant. Therefore, the results are inconclusive.

For our second regression, the difference in difference with continuous treatment, the results show a negative sign with the value of -0,000043. This indicates that a one-unit change in the uncertainty index for Stavanger and Trondheim will lead to a 0,0043 % decrease in sales compared to Kristiansand, Oslo, and Bergen in the uncertain time. Just as for the simple difference in difference regression, the coefficient is non-significant, and we have inconclusive results.

For our control variables, income and population, we would expect both of these to positively impact sales, as a higher income gives people more to spend, and a higher population will increase the demand. The coefficients have the same signs in both regression models and similar values. The results show that income has a negative sign and population has a positive sign. As in the variables before, we cannot interpret much from these results as they are not statistically significant.

4.4.3 Case 3: Local Toll Road Fees - A Panel Data Analysis

In section 3.3.1, we introduced various TØI rapports, which stated that toll road fees were by far the most important local incentive for consumers. In 2016 50 % of the EV owners said the incentive was of significant importance for the purchase decision. In 2018 the share had increased to 63 % (Figenbaum and Nordbakke, 2019).

Our next case of interest is the changes in toll road fees for EVs. Norway has toll roads all over the country, and there are large price differences. From 2016 it was up to each municipality to decide whether they wanted to introduce toll road fees for EVs. Before this, every EV passed the toll roads for free. However, the nationwide "50 % - rule" restricts municipalities from charging EVs toll road fees over 50% of the rate for conventional vehicles. Beyond this, it is up to each county to decide what percentage they will charge. Since the municipal decides the price of toll roads, there are variations across municipalities. Toll road fees are also one of the topics that have made many headlines in the media over the past years. Local differences allow us to compare across municipalities with the same pre-trends to investigate the effect of uncertainty.

We find that Bergen and Stavanger have uncertainty regarding toll roads over the same time period, and these two municipalities will make up our treatment group. Since the uncertain period for Oslo overlaps with the uncertain period for Bergen and Stavanger, it will not be a part of the control group, and we remove Oslo from our dataset for Case 3. Our potential control groups will be Trondheim and Kristiansand, which had implementation and an uncertain period years later than Bergen and Stavanger. We will look at the parallel pre-trend assumption and define our treatment and control groups in the following case analysis.

Figure 4.5: Uncertainty Index for Toll Road fees

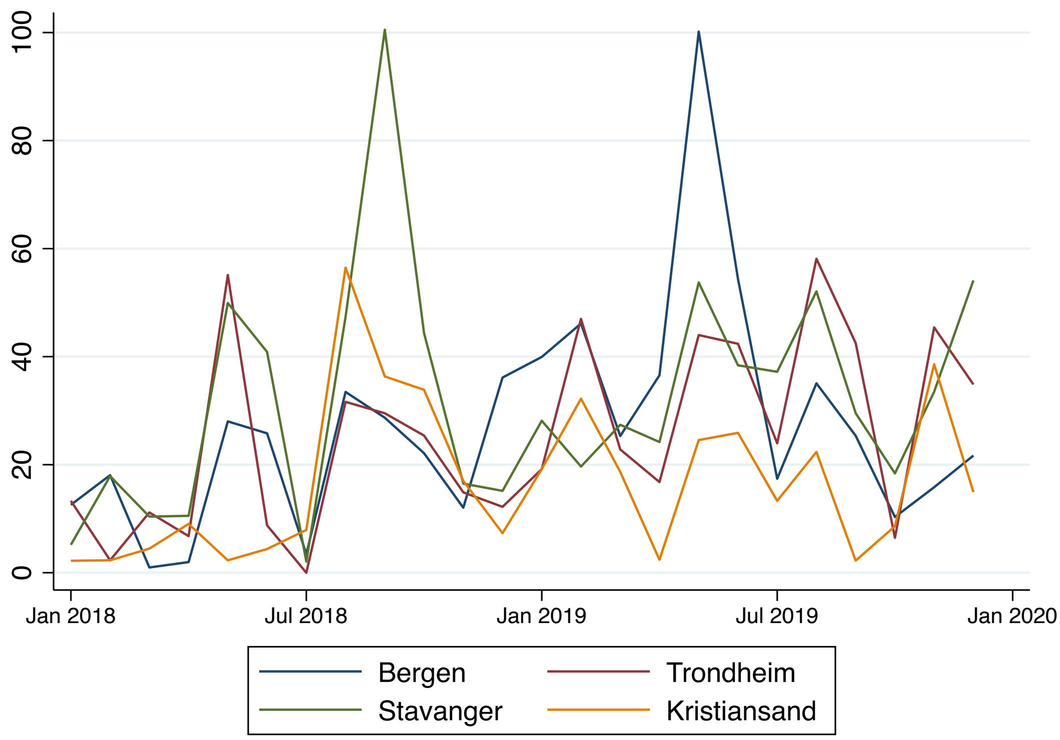


Table 9: Implementation of toll road fees and the uncertain period for each municipality

Municipality	%	Date of implementation	Uncertain period
Bergen	40%	06.04.2019	August 2018 - May 2019
Trondheim	20%	01.11.2021	September 2020 - May 2021
Stavanger	50%	10.02.2020	August 2018 - May 2019
Kristiansand	50%	01.09.2021	March 2021 - November 2021

The uncertain periods in the table over are based on the level of our uncertainty index and from manually reading through the articles published in local newspapers. In the graph, we present the uncertainty index for the municipalities included in this case in the period August 2018 to May 2019. We define Trondheim and Stavanger as uncertain in this period, while the other municipalities have their uncertain time later.

4.4.3.1 Descriptive Statistics

Table 10: Descriptive statistics, Case 3

	Mean	SD	Min	Max	N
LN Sale	4.279	0.988	1.791	6.871	356
Uncertainty Index	9.533	15.613	0	100	356
LN Income	8.980	0.526	8.092	9.550	356
LN Population	11.552	0.424	11.330	12.545	356

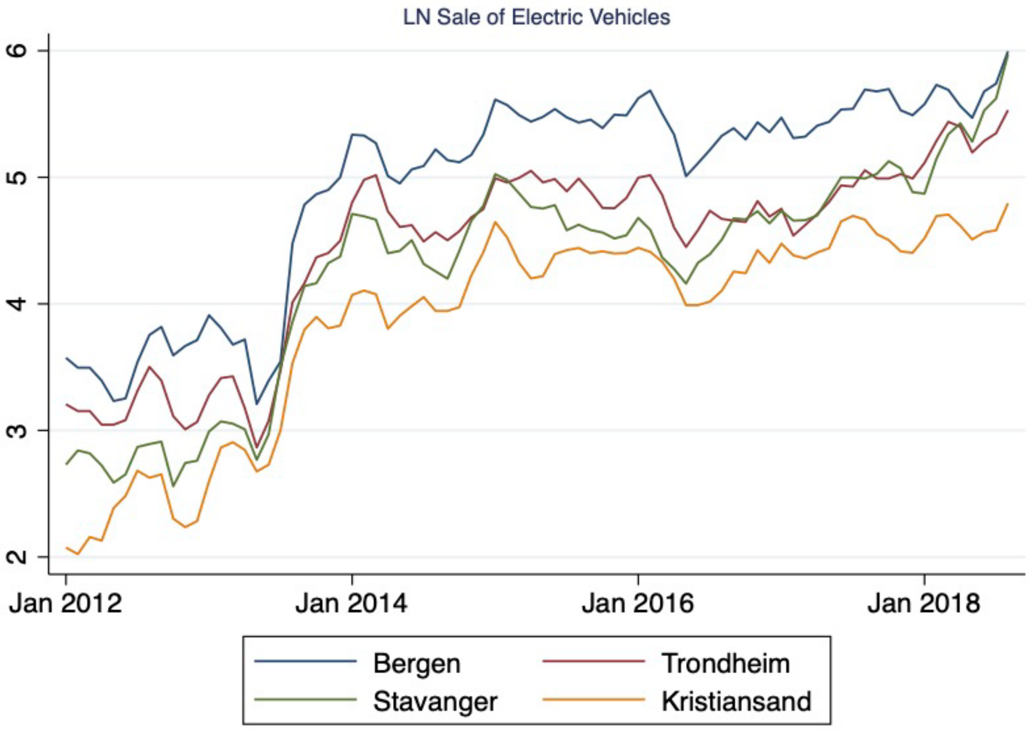
Table 4.9 shows the descriptive statistics for the variables included in our analysis for case 3. In this case, we have included Bergen, Trondheim, Stavanger, and Kristiansand, and the time period reaches from January 2012 to May 2019. All the variables that are included are monthly. This gives us a total of 356 observations.

4.4.3.2 The Parallel Pre-trend Assumption

As in case 2, we check for parallel pre-trends. For this case, we are investigating the time between August 2018 to May 2019 when our treatment groups had high uncertainty regarding toll road fees. For our analysis to make sense, we need our treatment and control groups to follow the same trend before August 2018. The graph below shows the sale in all the municipalities in the time-period 2012 to 2018. To get a smoother graph that better shows us the trends, we have used the three-month average LN sale of EVs, as illustrated in the equation below.

$$LNSaleEV_{it} = \frac{LNSale_t -_1 + LNSale_t + LNSale_t -_1}{3} \tag{7}$$

Figure 4.6: Testing for parallel pre trend for Toll Road Fees



Based on the graphical representation of the sale of EVs over time, we conclude that the parallel pre-trend assumption holds. We see that all the municipalities move together, and none significantly deviate from the others. In the table under, we have defined our treatment and control groups.

Table 11: Treatment and Control groups, Case 3

Group	Municipality
Treatment	Stavanger and Bergen
Control	Kristiansand and Trondheim

4.4.3.3 Results

Table 12: The effect of uncertainty regarding toll road fees on the sale of Electric Vehicles

	Dependent variable:	
	LN Sale	LN Sale
	(1)	(2)
Treatment group	0.423	0.442
	(0.457)	(0.445)
Uncertain Time	1.110***	1.180***
	(0.212)	(0.186)
Interaction	0.261	
	(0.337)	
Continuous treatment		0.003
		(0.005)
LN Income	-0.765	-0.771
	(0.834)	(0.834)
LN Population	1.565*	1.569*
	(0.833)	(0.834)
Constant	-7.710*	-7.711*
	(4.431)	(4.434)
Observations	356	356
R^2	0.362	0.361
Note:	*p<0.1; **p<0.05; ***p<0.01	

The regression estimates from the simple difference in difference model show that Bergen and Stavanger had 26,1% higher sales than Trondheim and Kristiansand in the uncertain period. These results indicate that uncertainty positively impacts the sale of EVs. Although the DiD coefficient indicates that uncertainty has a positive effect on sales, it is non-significant. Therefore, the results are inconclusive.

For our second regression, the difference in difference with continuous treatment, the results show a positive sign with the value of 0,003. This indicates that a one-unit change in the uncertainty index for Bergen and Stavanger will lead to a 0,3 % increase in sales compared to Trondheim and Kristiansand. Just as for the simple difference in difference regression, the variable is non-significant, and we have inconclusive results.

For our control variables, income and population, we would expect both of these to positively impact sales, as a higher income gives people more to spend, and a higher population will increase the demand. The variables have the same signs in both regressions and similar values. Income has a negative sign, but there is no significance as in the previous variables. For population, we have a positive sign and statistical significance at the 10 % level. The simple DiD model estimates that a one percent increase in population leads to a 1,565 % increase in sales. In the continuous treatment model, the estimated effect is a 1,569 % increase.

4.5 Weaknesses of the Analysis: Limitations and Sources of Error

The purpose of this analysis was to investigate whether uncertainty regarding EV incentives affects the sale of EVs. In this section, we will discuss the limitations of our analysis based on the approach we have chosen and the data we have used. Also, we will assess factors that make the analysis exposed to possible sources of error. In particular, we will explain the implications of our chosen measure of uncertainty and the data we use to measure EV sales. Furthermore, we will look at the DiD-method and discuss how our analysis might violate some of the method's assumptions. However, first, we will discuss the general problem with omitted variables in our econometric models.

4.5.1 Control Variables

As presented earlier, several things contribute to an increase in the EV fleet. We control for some of this by including population and income as control variables in our models. However, we are aware that there might be other things affecting sales that are not included in the model, and this can cause biased estimators. For our specific cases, control variables such as the number of public parking places and the number of toll booths in the municipalities could be of importance. Regarding all of our cases, an omitted control variable that could be of importance for our results is the charging infrastructure in Norway. We believe that an improvement in the available charging possibilities contributes positively to the sale, and we know that this has been continually improved. In section 5.1, we will highlight the overall development of EVs and improved charging infrastructure in Norway.

4.5.2 The Uncertainty Measurement

Our results are based on our chosen measure of uncertainty, which is media intensity. The survey by Figenbaum et al. (2014) showed that media was the most important source of information about EV, and thus we consider our approach a good measure. Nevertheless, the non-significant results imply that this measure of uncertainty does not have an impact on EV sales either way. It is important to point out that it is only this specific measure of uncertainty that gives no indications of a relationship between the two variables. Even though this was a good measure for economic political uncertainty in the study by Baker and Davis (2016), it is not given that this is the best approach for consumer uncertainty. There might be large individual differences in the perception of uncertainty regarding EV incentives. Similar to Baker and Davis (2016), it would have been interesting to further validate this measure of uncertainty or come up with alternative measures of the uncertainty consumers face. This could have been done by following a group of consumers over time and having the selected consumers assess the level of experienced uncertainty based on their own perceptions. Consumers considering buying an EV would have been the most ideal, as it is reasonable to assume that these are consumers who are interested in the EV policy and are more attentive to what the media writes about the topic compared to other consumers. With the limited time we had on this thesis, we had no opportunity to observe and interview a group of consumers over time. Thus, we used historical data and considered the news frequency approach the best for our use.

Additionally, we only used a particular set of keywords, respectively "Elbil" and "Fordeler" / "Parkering"/ "Bompenger." It cannot be ruled out that we would have gotten different levels in the uncertainty index if we had used slightly other keywords, which in turn could lead to other results in the analysis.

To some extent, we have checked whether the articles found by Retriever contain relevant information for our analysis or if they only contain the keywords but do not have much relevant content beyond that. We have taken some random samples, and most of the articles we checked had relevant content. For the specific cases, we controlled the relevance of almost all of the articles. However, in the general case 1, we have not been able to control everything and weed out all the articles that do not contain any relevant content due to limited time and a large number of articles. Thus, the uncertainty index will to a certain extent also contain articles that do not have much significance for the degree of uncertainty the consumers face.

4.5.3 Delivery Time – A Possible Delay in the Vehicle Registration

As discussed in section 4.2.1.1, we cannot rule out that the potential long delivery time on some of the EVs will interrupt our estimates. Variation in delivery time makes it difficult to assess when the EVs sold during uncertain times will appear in our data. Some vehicles are delivered immediately and are thus registered immediately, while others have a longer delivery time and have a delay in the registration. When working with the time series data analysis, we experienced with different lags of UI, but there were no indications that lags on three to six months back gave any other results. Since the delivery time differs between the different car brands and models, the effect of uncertainty may be split into different months in the dependent variable. In the ARDL model, we checked for a long-time relationship with different included lag lengths, but there were no indications that the overall effect of uncertainty influenced the sale.

For the DiD-model, we have not included any lags, and the delay in vehicle registration can cause disturbances and displacements in the data. Therefore, our estimates must be interpreted with caution.

4.5.4 The DiD-setup

The difference in differences approach assumes no uncertainty in the control groups. For the DiD-estimators to give causal effects, one needs a control group that gets no treatment. As we saw from the uncertainty index, the municipalities that serve as the control group does have some uncertainty regarding the incentives, just significantly less than the treatment municipalities. However, the index is based on articles that include the search term "elbil" and the incentive, so we further investigated the wording of the various articles in the different municipalities. From that, it was made clear that the treatment municipalities were exposed to articles that expressed much more uncertainty. We have also validated the division into treatment and control municipalities by investigating the municipalities' statements and changes in resolutions and laws.

Additionally, we strived to find cases and periods with little uncertainty regarding other local incentives during our investigation period. Still, as we saw in the time series, there will always be some uncertainty regarding EV policies nationwide. It is reasonable to assume that this might also affect consumers' perception of uncertainty.

5 Discussion

This section aims to link the previously presented theory and literature with the empirical findings to answer the research question. We will review the empirical results from a behavioral perspective and try to explain consumer choice behavior in light of the theories and studies previously presented.

Our results make it difficult to give an answer on the importance of uncertainty for the vehicle decision. We find no empirical evidence in our data that indicates a relationship between uncertainty and EV sales. Neither do we have any empirical evidence to reject that there is any relationship. In the time series analysis, we wanted to assess the general impact of uncertainty regarding EV benefits on the sales of new EVs. In this first attempt to see some relationships in the data, we find no evidence that uncertainty influences the sales of EVs. Similarly, in the second and third case analysis, we do not find evidence in the data that there is a connection between uncertainty regarding specific EV incentives and EV sales.

In the following, we will analyze these findings both in light of rational explanations, that is, behavior that in the standard model can be classified as rational, but also in light of alternative "psychological" explanations: the so-called deviations from the rational choice framework.

5.1 Rational Explanations

In this section, we will describe potential explanations for our findings that are not due to any behavioral biases but rather due to rational utility-maximizing behavior. As stated in the theory section, the standard model implies a reduction in EV sales when uncertainty regarding future operating costs increases. Despite this statement, there can be rational behavior explanations as to why we do not see any impact of uncertainty on sales. First, we consider the savings and costs aspect of the different incentives and see how the variations can provide rational explanations for the results. Furthermore, we will discuss how technological development and changes in the EV infrastructure might explain some of our results. Finally, we will discuss how changes in the choice alternatives available to the consumer can explain why we do not see any results.

5.1.1 The Saving Aspect

As we saw in section two, the different incentives can be classified depending on how they reduce costs for the consumer. Within each type of incentive, there are large individual differences in terms of how much savings the incentives provide. Of the estimated NOK 14 000 in annual savings in 2018 from direct subsidies, reduced toll road fees are estimated to account for 68 % while reduced parking fees only account for 18% . Similarly, in 2016, the numbers were 49 % and 16% . The relatively low annual savings due to parking incentives make this incentive less important for the vehicle decision as it has a low impact on the individual's total utility. Thus, the non-significant result in case 2 might be explained by this rational behavior: uncertainty regarding parking incentives does not impact sales because they are of low importance to the annual costs and thus the investment decision. By following this line of thinking, one should, on the other hand, expect to see some significant effect of uncertainty regarding toll roads since they are the direct subsidy that, by a large margin, provides the highest annual saving. Nevertheless, we do not get any significant results here either.

5.1.2 Purchase Price vs. Future Prices

When it comes to the fiscal incentives, VAT exemption, and the exemption from registration tax, these reduce the purchase price of the EV. We saw that these exemptions constitute large lump sums. Based on a Tesla Model 3, they were 87K and 80K, respectively. These incentives differ from the direct subsidies (reduced toll road and parking fees) in that they only affect the price you pay at the time of purchase and not the future price. In the theory section, we modeled the purchase decision as a maximization problem, including both current prices and future prices. Since these fiscal incentives only affect the purchase price, uncertainty regarding these incentives should not affect today's decision as long as they still apply at the time of the purchase. From the TØI surveys, we know that these incentives are of major importance to the customers, and as of today, these exemptions still apply. The no-effect indications from the time series data can thus be explained by this rational behavior. Furthermore, one can argue that uncertainty about these specific incentives should actually have the opposite effect: consumers accelerate the purchase decisions to utilize from the benefit before it is gone. However, we do not find any empirical evidence for such behavior.

While writing this discussion, the revised state budget was presented. A proposal was made to remove the VAT exemption from the 1st of January 2023 and replace it with a subsidy scheme, but only for EVs under NOK 500 000. The expensive EVs will not receive any subsidy. It would have been interesting to examine the change in the sale of expensive EVs now that the removal of the exemption has been announced and until implementation. That way, we can see if there are any tendencies that people accelerate the purchase now and that we will see a reduction in sales after the decision has been implemented. According to the rational choice model, this would have been the rational thing to do. The results from this could have provided valuable insight into how consumers react to such information.

5.1.3 Technological Development and Improved Infrastructure for EVs

As discussed earlier, there are two main driving forces for the increased EV fleet, one is the incentives, and the other is the technological development. Previously we have shown how the EV sale has rapidly increased. In the first case analysis, we controlled for this upward trend by taking first differences and applying ARDL models. Even though we have controlled for this trend, one cannot rule out that the development in the characteristics and attributes of the EVs have made them competitive even without the incentives. The range is significantly improved, and increasingly more charging stations becomes available all over Norway. Even though there is some uncertainty regarding the future benefits of EVs, the overall utility consumers derive from choosing an EV might still be greater than the utility of the alternatives due to the EV development. Thus, the uncertainty won't affect the vehicle decision.

5.1.4 Changes in the Substitute Product

When we stated that the rational model implies a substitution away from EVs when there is an increase in uncertainty about future benefits, it was with the assumption that the utility from the other alternatives is kept constant. This is a strict assumption, and in most cases, it does not reflect the reality. Conventional vehicles will be the key substitute product in most cases. If one thinks of the current situation with rising gasoline prices and the climate goal set that by 2025 all new vehicles are zero-emission vehicles, it will be rational for the consumer to believe that conventional vehicles will not get any cheaper in the future. Therefore, it cannot be ruled out that the consumers actually behave rationally regarding EV policies and take into consideration the possible future higher costs, but since the choice alternative also has uncertainty about future costs, they do not substitute, and thus, we do not see any change in the sale.

5.2 Psychological Explanations

The standard model for decision-making implies that increased uncertainty regarding future EV benefits decreases the current expected utility, and the incremental EV buyers will then choose not to buy. In our empirical analysis, we get no indications that this is the case. In this section, we will look at possible explanations for this that are due to behavior that deviates from the standard model.

5.2.1 Biased Probabilities and High Discount Rates

When the consumer is in the decision process, they must evaluate many aspects, and our results suggest that future cost aspects are paid little attention to and/or is undervalued. The several studies about discount rates in the decision to buy durable goods (Hausman (1979):Gillingham et al. (2019)) support the explanation that future costs are undervalued through high discount rates and that people care more about the present than the future.

The salient mechanism could also explain it: The uncertainty regarding future costs is perceived as less salient to the consumers and is being undervalued. Purchase price and attributes of the vehicle are information that is easier to obtain, and due to limited attention, one will pay too much attention to this and think little of the cost aspects in the future. The TØI-surveys and statements from the EV council suggest that people pay attention to the EV policies and that uncertainty regarding this will make fewer people buy EVs. Despite this, there is a great chance that people behave according to the self-attribution bias: In a digital world with a lot of information available, one overweight the information that confirms their beliefs, for instance, that the current benefits will also apply in the future or that they constitute minor sums.

5.2.2 Context-dependent Preferences: Relative Judgment and Loss Aversion

As we stated earlier, the reference point is crucial when a consumers value the utility of an outcome. Our results suggest that consumers think of the EV benefits as a gain relative to other types of vehicles. If there is uncertainty that some of these benefits will be the same in the future, they are still perceived as a gain relative to conventional vehicles. If the uncertainty of the future benefits were perceived as a potential loss, it would have a more significant impact on the purchase decision since consumers value losses higher than equivalent gains, and they will try to avoid experiencing losses due to loss aversion.

The relative judgment can contribute to more explanation for our results. In the purchase decision, one might fail to value the absolute costs of parking fees and toll roads. Instead, the consumers perceive these costs as small and non-significant relative to the up-front purchase price, and uncertainty regarding these future costs will not influence the decision.

5.2.3 The Complexity of Utility

The surveys of EV owners have shown that cost concerns are of major importance when deciding to buy an EV. In the standard model, it is assumed that utility is only determined by your own payoff, but in the theory section, we established how this is not the case in many settings. Since we do not see any effect of this uncertainty on EV sales, it is reasonable to assume that the uncertainty toward future cost plays a minor role for the consumers' utility and that other things influence the utility as well. This is in line with what Figenbaum and Nordbakke (2019) and Kim et al. (2014) found in their studies: environmental concerns are shown to be of importance to EV owners and friends and family as well as the public opinion has been shown to influence the vehicle decision.

6 Conclusion

In this section, we will summarize the findings, state the thesis contribution, and propose some interesting further research paths.

The purpose of the thesis was to explore the effect of uncertainty regarding EV incentives on the sale of new EVs. That way, we wanted to contribute with some insight into how consumers respond to stable policy paths vs. more unstable ones. To do this, we conducted three case analyses. We created an uncertainty index based on media coverage and used this to see if there were any indications of a relationship between sales and this measure of uncertainty. However, we do not get any statistically significant results in either of the case analysis.

Despite its exploratory nature and slightly disappointing results, this study offers some insight into a highly topical issue that gets a lot of news coverage and occupies the political debate throughout Norway. We have provided detailed data on the EV policies debate and shown how EV owners and enthusiasts consider uncertainty regarding EV policies a major problem and crucial for EV sales. We have carried out a first attempt to explore if there is any relationship. With our chosen approaches, data material, and research methods, we have not found any evidence to conclude if there is a relationship between the two variables or not. We have discussed the thesis limitations due to our chosen uncertainty measurement and possible errors in the vehicle registration data, as well as the method we have used.

Furthermore, we have provided a theoretical framework for decision-making and done a literature review to explore what influences the consumers' vehicle decisions. Based on this, we have presented both rational and psychological explanations for the no-effect indications.

We emphasize the need for further research on the topic to be able to give a conclusion on the effect of uncertainty regarding EV incentives on EV sales. Our thesis has provided some insight and indications, but it is limited to the chosen uncertainty measurement and the possible errors in the data due to delivery time and delayed registration.

6.1 Further Research Paths

A rather obvious research path forward is to supplement this thesis uncertainty measurement with other measures of uncertainty. It would be interesting with a qualitative research approach that follows both consumers and car dealers and examines their perception of uncertainty over time and how it affects the purchase decision. Contact with car dealers directly can also provide precise sales figures so that the problem of registration delays is solved.

In the discussion section, we provided several psychological mechanisms that can be used to explain why one might not see any effect of uncertainty of sales. If one in later studies finds evidence that the uncertainty has no effect, it would have been interesting to investigate empirically which of these mechanisms are most prevalent.

Nevertheless, we once again stress the importance of further research on the topic to be able to give an unambiguous answer to the research question.

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Appendix

Table A0.13: Autoregressive Distributed Lag Model

	(ARDL)
L1 Sale	0.599***
	(0.114)
L2 Sale	-0.036
	(0.099)
L3 Sale	0.610***
	(0.096)
L4 Sale	-0.356***
	(0.116)
Uncertainty Index	0.473
	(6.404)
L1 Uncertainty Index	1.304
	(6.449)
L2 Uncertainty Index	1.885
	(6.358)
Income	-0.058
	(0.139)
L1 Income	0.073
	(0.177)
L2 Income	0.714***
	(0.177)
L3 Income	-1.116***
	(0.196)
L4 Income	0.470***
	(0.156)
Population	-0.000
	(0.003)
Constant	-1.64e+04
	(9952.989)
Observations	104
R^2	0.839

Note:
*p<0.1; **p<0.05; ***p<0.01