What Drives Electric Vehicle Diffusion?

An Agent-Based Approach to Assess Factors and Market Effects in Norway

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Vad påverkar diffusionen av elektriska fordon?

En agentbaserad modell för att bedöma faktorer och marknadseffekter i Norge

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Abstract

Environmental sustainability and energy efficiency have over the previous years become important topics on the political agenda to reduce emissions and prevent global warming. Due to the demand for sustainable transportation, the interest in electric vehicles (EVs) has increased as the functionality is coming closer to par with the incumbent internal combustion engine vehicles. Norway is the frontrunner in EV adoption, why dynamics of the Norwegian car market have undergone a shift. In addition, EVs are now entering the used car market where the presence previously has been limited. Understanding the factors that affect the decisions to purchase an EV and thereby the diffusion, is non-trivial as technology advancements, political measures and consumer preferences are continuously changing. Stakeholders are closely monitoring the developments on the Norwegian market in order to gain insight on products, infrastructure investments, and measures to deal with the change.

This study investigates the diffusion factors for EV adoption in Norway by using an agent-based model to simulate the consumer behavior in different scenarios spanning until 2030. The model is initialized using data from 3962 individual responses in a Norwegian survey. Further, how the used car market is affected by the introduction of EVs is investigated using data from Norway’s largest online marketplace for used vehicles.

The results from the simulations show that EV diffusion are positively affected by combining political incentives and technology developments, while the perception of EVs created by social interactions between consumers can expedite adoption even further. If such factors are combined, the simulations show that 92% of the Norwegian fleet could be electric in 2030, coupled with low emissions. Moreover, the analysis of the used car market show that gasoline and diesel cars have experienced increased depreciation over recent years. The findings can be used by stakeholders as a guideline toward where the market is heading, and further research should include tailoring survey questions to fit the model as well as more extensive analysis of value retention for specific car models.

Keywords: electric vehicles, diffusion of innovations, agent-based model, market development, used car market
Sammanfattning

Hållbara utveckling och energieffektivitet har under de senaste åren blivit viktiga ämnen på den politiska agendan i syfte att minska utsläpp och förhindra global uppvärmning. Till följd av efterfrågan på miljövänlig transport har intresset för elbilar ökat kraftigt, samtidigt som funktionaliteten närmar sig den för de traditionella fordonen med förbränningsmotor. Norge är föregångare i att gå över till elbilar, varför dynamiken på den norska bilmarknaden har genomgått ett skifte. I tillägg har elbilar nu börjat ta plats på andrahandsmarknaden, där de tidigare varit nästintill obefintliga. Att förstå de faktorer som påverkar beslutprocessen att köpa elbil och därmed diffusionen är inte trivialt då teknisk utveckling, politiska åtgärder och konsumenters preferenser ständigt är i förändring. Intressenter bevakar denna utveckling ingående för att få insikt om produkter, infrastrukturstävlingar och åtgärder för att kunna hantera teknologiskiftet.

Det här examensarbeteet undersöker faktorerna som påverkar diffusionen av elbilar i Norge, genom att använda en agentbaserad modell för att simulera konsumenternas beteenden i olika scenarier fram till 2030. Modellen initieras med data från 3962 individuella svar från en norsk enkätstudie. Vidare undersöks hur andrahandsmarknaden påverkas av att fler elbilar introduceras genom analys av data från Norges största marknadsplatser för begagnade fordon.

Resultaten från simuleringarna visar att diffusionen av elbilar påverkas positivt genom kombinationen av politiska incitament och teknisk utveckling, samtidigt som bilden av elbilar skapad av social interaktion mellan konsumenter kan påskynda skiften än mer. När dessa faktorer kombineras, visar simuleringarna att 92% av Norges bilflotta kan vara elektrisk år 2030, resulterande i låga utsläpp av växthusgaser. Analysen av andrahandsmarknaden visar att bensin- och dieselbilar har upplevt ökade värdeförluster under de senaste åren. Resultaten kan användas av intressenter som indikation på vart marknaden är på väg. Framtida arbete inkluderar skräddarsydda enkätfrågor för modellen samt en djupgående analys av värdeäkta bilmärken på specifika bilmodeller.

Nyckelord: elbilar, diffusion, agentbaserad modell, marknadsutveckling, andrahandsmarknad
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Acronyms

**ABM**  
Agent-Based Model

**BEV**  
Battery Electric Vehicle

**COMPETT**  
Competitive Electric Town Transport

**EV**  
Electric Vehicle

**HEV**  
Hybrid Electric Vehicle

**ICE**  
Internal Combustion Engine (Vehicle)

**PHEV**  
Plug-in Hybrid Electric Vehicle

**STECCAR**  
Simulating the Transition to Electric Cars using the ConsuMat Agent Rationale

**TCO**  
Total Cost of Ownership

**VAT**  
Value Added Tax

**YoY**  
Year-on-Year
Foreword and Acknowledgements

This study is the derivative work of a master thesis conducted at the department of Industrial Economics and Management at KTH Royal Institute of Technology, Stockholm. The study was carried out during the spring 2017 in collaboration with Fortum Sverige.

(Part of) the data used here are taken from "COMPETT - Konkurransdyktig elektrisk transport i byer, 2014". The data is collected by Erik Figenbaum, Transportøkonomisk Institutt. The study is funded by the Norwegian Research Council. The data is formatted to be anonymous by NSD - Norsk Senter for Research Data AS. Neither Erik Figenbaum, Institute of Transport Economics, Research Council of Norway and NSD are responsible for the analysis of the data or interpretations that are made here in this study.

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Albin Gropp and Fredrik Ohlsson
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1 Introduction

This chapter presents the background for the problematization along with the purpose of the study. The purpose is followed by the research questions, contribution, delimitations and limitations, and the thesis structure.

1.1 Background

Increasing demand of sustainable solutions for energy production, energy consumption, and transportation has in the few previous years led to an increased interest in electric vehicles (EVs). Nevertheless, EVs have previously been characterized by low functionality and high cost, which can be considered a consequence of the dominance of internal combustion engine (ICE) vehicles, the oil industry, transport networks, technologies, and institutions with which it has co-evolved (Struben & Sterman, 2008). This have in addition with the size of the automotive industry created large positive feedback loops and path dependencies that have provided advantage to the incumbent ICE technology. However, factors such as technological advancements and political incentives for clean transportation have over recent years improved EV sales despite the barriers to EV adoption, including: high initial cost, range anxiety, and scarcity of charging infrastructure among others (Adepetu et al., 2016; Boulanger et al., 2011; Struben & Sterman, 2008).

In the fourth quarter of 2015, the global cumulative number of EVs on the roads passed 1 million cars and is steadily increasing (IEA, 2016; BNEF, 2016a; Shepard & Abuelsamid, 2016). Cumulative sales already reached 2 million by the first quarter 2017 resulting in a 1.15% market penetration in new car sales in main markets (BNEF, 2017; BNEF, 2016a). In the leading Norwegian market, EV sales amounted to nearly 40% of new vehicle sales, with a fleet penetration of around 6.7% (OFV, 2017). This success is partly due to the favorable governmental policy schemes such as tax exemption of 25% VAT, free parking, access to bus lanes, in addition to high taxation on ICE cars (Figenbaum, Assum & Kolbenstvedt, 2015; IEA, 2016).

The increase in EV production and demand has intensified battery production and development, contributing to declining battery prices, dropping on average by 19% year-on-year since 2010. This is mainly due to technology improvement, economies of scale, and market competition between manufacturers (BNEF, 2016b). As a result, the previously expensive EVs are becoming more affordable, and closer to parity with ICEs, as the battery cost of a battery electric vehicle constitutes about a third of the total production cost. In addition, EVs are now starting to enter the used car market where these vehicles have not previously existed. This implies that EVs will become a viable option for used car market buyers, as prices come to par with ICEs. However, uncertainties regarding the life of used batteries exist, and many consumers await maturity of the technology (BNEF, 2017).

1.2 Problematization

Political incentives, both fiscal and non-fiscal, together with technology development have played a vital role for consumers to buy EVs. However, surveys of EV owners show that social interaction also has significant impact on the purchase decision (Figenbaum et al., 2015; Figenbaum & Kolbenstvedt, 2016; Kangur et al., 2017). Understanding the factors that affect the decisions and thereby the diffusion, is non-trivial as technology advancements, political measures and consumer preferences are continuously changing. Stakeholders have been uncertain of the technology shift and diffusion of EVs, and are closely monitoring the developments on the Norwegian market in
order to gain insight on product investments and measures to deal with the change. Therefore, to create sufficient and concurrent insights there is a need to investigate the dynamics of the new and used car market, including how consumer actions and interactions impact the choice of vehicle and fuel type.

As diffusion of innovations involves complex phenomena and is defined as "the process by which an innovation is communicated through certain channels over time among members of a social system" (Rogers, 2003), there is an inherent need to simplify the process in order to understand and describe it. Therefore, to study these complex interactions between individuals, different diffusion models have been developed. One of these is the agent-based model approach, which captures single individuals' needs and preferences and how they interact in the social system (Al-Alawi & Bradley, 2013). This allows for recreation of complex and emergent patterns of behavior that are not defined at the level of any individual, when data on aggregated behavior is limited (Adepetu et al., 2016). Therefore, the dynamics of the diffusion can be investigated by applying an agent-based model, creating insight into the market developments aiding stakeholders to make more informed decisions.

1.3 Purpose & Research Question
The purpose of this study is to investigate the diffusion of electric vehicles in the Norwegian market and assess the effectiveness of factors that affect the adoption rate. In order to address the purpose we aim to answer the following research questions:

1. How does an agent-based model describe the diffusion of electric vehicles?
   (a) How do policies, technological, and social factors affect the diffusion of electric vehicles?
   (b) What effects on the diffusion emerge when combining several factors simultaneously?

When investigating the diffusion factors and the different outcomes of their combination, insight into where the market is heading can be investigated. In doing so, another question arises for the operationalization of the purpose:

2. What can we learn about future developments in the Norwegian car market?
   (a) What will the diffusion of electric vehicles look like until 2030?
   (b) How is the used car market affected by the diffusion of electric vehicles?

1.4 Limitations & Delimitations
First of all, we delimit ourselves to the Norwegian market as the nature of the study requires a confined setting and consumer experiences with EVs. As the country with the highest EV penetration, there is comparatively much data available. However, EVs are in a relatively nascent state and sufficient data is sometimes limited. Hence, the study puts emphasis on analytical assessment of factors, rather than to yield quantitatively accurate predictions, which would be premature at this stage and out of the scope of the project. Nevertheless, the aim is to create as statistically accurate results as possible. Just as for many other volatile dynamic technologies, it is not easy to predict accurate sales and/or market penetration. However, the simulated results provide indications on future developments on which conclusion are drawn upon. For limitations regarding the model used in this paper, i.e. the STECCAR model, we refer to Kangur (2014), who describes the model's limitations in depth.
As the study regards diffusion of innovations and consumers behavior, we delimit the term electric vehicles to only include battery electric vehicles and plug-in hybrid vehicles. Hybrid vehicles without a plug-in feature are more similar to internal combustion engine vehicles, and are therefore omitted as they do not require the owner to charge the vehicle’s battery.

For the duration of this project, there have continuously been numerous developments in the area of electric transportation. These changes were accounted for at the highest level possible when analyzing literature and putting the results in context. However, in terms of access to data, vehicle data span years until the start of 2017 (start of the project). Naturally, any later incorporated data would require major rework and changes in the analysis, which the time frame of the project does not allow.

1.5 Contribution

Being one of the world’s largest industries, the automotive industry is under constant investigation both from politicians, the academic perspective, consulting firms, media as well as the public. Car sales have been closely monitored and projected on a global scale for an extended period of time, but EV adoption is in the context a relatively new phenomenon. Due to the rapidly changing environment, data and assumptions in literature quickly can become obsolete. Hence, there is a gap in incorporating the latest trends in for example policy and technology, when trying to understand the main drivers for EV adoption. Furthermore, the connection to the used car market is of interest when deliberating if an EV is a viable purchase option.

In this study, we use an agent-based model to make an indication of the future development and assess factors that affect the adoption rate of EVs in the market. The model that is utilized was developed for the market in Netherlands, and modified it to fit the Norwegian consumer and market, our aim is to contribute to literature regarding agent-based modeling for diffusion of electric vehicles. Moreover, this study could provide valuable insight and implications of the diffusion of EVs for stakeholders in society, automakers, policy makers, and infrastructure partners such as energy companies providing the electricity for charging.

1.6 Thesis Structure

The remaining parts of the thesis are presented as follows: Chapter 2 provides an overview of the current electric vehicle market setting, including policy schemes, technological development and purchase behavior. In Chapter 3 the theoretical framing and literature review are presented. Then follows Chapter 4, which describes the agent-based model and its components. Chapter 5 provides a description of the study’s methodology along with a discussion about the validity and reliability. In Chapter 6 the results derived from simulation runs in different scenarios are presented. The results are then analyzed in Chapter 7. The results and analysis are discussed and concluded in Chapter 8. Lastly, in Chapter 9 there is a discussion of further work and stakeholder implications.
2 Electric Vehicles

This chapter presents an overview of the current setting on electric vehicles, including policy support, technology development, and consumer purchase behavior. As this study mainly concerns Norway and the Norwegian setting, the focus of the chapter’s content is put there.

2.1 Overview

An electric vehicle (EV) uses an electric motor for propulsion, compared to internal combustion engine (ICE) cars that rely on fossil fuels to power the powertrain. The categorization of EVs constitute both battery electric vehicles (BEVs), and plug-in hybrid electric vehicles (PHEVs) (BNEF, 2016a). The former uses a battery for the electric engine; and the latter both have an electric and internal combustion engine. However, it is important to recognize that there is a difference between a PHEV and hybrid electric vehicle (HEV), which combines a conventional ICE propulsion system with an electric powertrain to achieve better fuel economy. Hence, it is not possible to charge and drive using only the electric engine in a HEV. As HEVs do not have a plug-in feature, we chose to omit them from this study and focus on BEVs and PHEVs as they share the all-electric drive and require the owner to charge the vehicle’s battery.

Many automakers are adding EVs to their product mix. At the Paris Auto Show in September 2016, the Chief Executive Officer for Daimler, Dieter Zetsche said: “We’re ready for the launch of an electric product offensive that will cover all vehicle segments, from the compact to the luxury class” (Nussbaum et al., 2016). The availability and performance of models are increasing, and as of today PHEVs have a battery capacity around 8 kWh, which translates to approximately 30-50 km of pure electric drive, only sufficient for shorter travels. BEVs on the other hand, have a battery capacity ranging between 30-100 kWh, allowing ranges between 200-500 km, enough for most daily travels. Nevertheless, there are more nuances to consumer choice than range and models. Figenbaum & Kolbenstvedt (2015b), identify two main dimensions affecting the diffusion of electric vehicles, i.e. Technology and Policy. Furthermore, the results in their study indicate that the Social aspect, i.e. consumer-to-consumer interactions, plays an imperative role for the purchase decision for alternative fuel vehicles.

2.2 Policy Support

The need for global reduction of carbon dioxide (CO\textsubscript{2}) emissions has over the previous years led to increased policies and incentives for “green transportation”. These policies include, but are not limited to, regulatory measures (e.g. emission regulations and fuel economy standards), financial levers (e.g. taxation on vehicles based on emission level (gCO\textsubscript{2}/km)) and other consumer direct incentives (IEA, 2016). The Norwegian Parliament has since 1990 provided policy support in various areas for an emergent EV diffusion. Compared to many other countries these incentives favor EVs over ICEs, where EV drivers enjoy several benefits such as free parking, access to bus lanes, exemption from taxes, toll fees (Figenbaum, Assum & Kolbenstvedt, 2015). Norway’s policies have led to an unmatched EV market share of new sales with 29% in 2016, moving towards 40% the first quarter of 2017 (EAFO, 2017). What is more, an interim goal is set by the National Transport Plan that all new passenger vehicles in Norway shall be emission free by 2025 leading up to the overall climate goal of carbon neutrality by 2030 (Norwegian Government, 2017).
2 ELECTRIC VEHICLES

2.2.1 Emission Standards

In the race of becoming the most environmentally sustainable and complying with regulations, automakers have put lots of efforts in combustion engine R&D in the strive for the lowest tailpipe emissions and fuel efficiency. The Volkswagen emission scandal of 2015 is an example of this competition, where VW went to great lengths to beat their competition, in this case fraudulently.

As BEVs have zero tailpipe emissions and are becoming more energy efficient, they have an advantage compared to ICEs in benefiting from regulations. However, it is only local pollution that is reduced in a shift towards EVs as the electricity needs to be produced elsewhere. For many countries, reaching climate change benefits is challenging due to a power generation that is dependent on coal, and thereby the whole EV vehicle life cycle needs to be assessed (IEA, 2016). In Norway, on the other hand, about 96% of the electricity generation comes from renewable sources, why the positive environmental effects of EVs are conceded. The Norwegian goal is to be carbon neutral by 2030 (Stortinget, 2016), where the interim target of 2020 for new passenger vehicles is to have average emissions of 85 gCO₂/km (Figenbaum et al., 2015) and as mentioned, the interim target of 2025 is that all new passenger vehicles will be emission free as proposed in the National Transportation Plan. This can be compared to the EU target of 95 gCO₂/km for 2021 which represents a 40% reduction from the 2007 fleet average of 158.7 gCO₂/km (European Commission, 2014), making Norway's goal a comparative 46% reduction.

The interest in climate policy is strong as over recent years, Norwegian cities have not been able to comply with local air quality legislation leading up to a ban on diesel cars in the Oslo city centre on January 17th 2017 (see e.g. Bugge & Ridar, 2017). In addition to the temporary ban in Oslo, four of the largest cities in the world; Paris, Madrid, Athens and Mexico City will ban diesel cars and vans permanently by 2025 (Harvey, 2016), acting as frontrunners for other cities, paving the way for increased electrification of transports.

2.2.2 Fiscal Incentives

Taxes and subsidies have proven to be important in the diffusion of EVs. As mentioned, the sales figures of EVs in Norway are evidence of successful incentive schemes. Mock and Yang (2014) conclude that the total fiscal incentive in 2013 provided in Norway for BEVs were about 55% of the vehicle base price, and in the case of the Netherlands, the PHEV incentives were equivalent of about 75% of the vehicle base price. However, the authors also conclude that fiscal incentives are important, but it is not the only factor. In the United Kingdom the market share for both BEVs and PHEVs were low compared to the high fiscal incentive of 50% of the vehicle base price. Figenbaum and Kolbenstvedt (2015a) state that the effective tax system in Norway along with the extended time frame for incentives might explain the discrepancy.

In relation to other countries, Norway’s vehicle taxes are high. Firstly, vehicles have a progressive registration fee where weight, engine power, CO₂ and NOₓ emissions are taken into account. Moreover, owning a vehicle implicates paying numerous taxes including; vehicle purchase tax VAT of 25%, fuel tax, annual registration tax, scrap deposit tax, income tax on company cars as well as road tolls (Norwegian Tax Administration, 2017). Measures to promote BEVs have been exemption from the registration tax, while smaller PHEVs often had no registration tax due to the low CO₂ emissions. Today, EVs have a low annual registration tax, around 85% cheaper than ICEs (Norwegian Tax Administration, 2017). What is more, BEVs have an exemption from the VAT of 25% on the list price. Figenbaum and Kolbenstvedt (2015a) argue that the latter is an important fiscal incentive due to the fact that BEVs are and have been comparatively
expensive to produce, resulting in higher list prices. Hence, if the VAT exemption did not exist, BEVs would have a harder time competing with ICEs. Free toll roads is another incentive that have had large impact on the EV adoption in Norway. Costs can amount up to €2500/year for commuters, making BEVs favorable and emergent in cities as well as remote areas such as islands connected to the mainland with underwater tunnels (Figenbaum & Kolbenstvedt, 2015a). However, the increase of EVs on toll roads have now led to the conclusion that they should contribute as well, and from March 2017 EVs in Oslo need to pay toll during rush hour of 10 NOK (58 NOK for diesel, 48 NOK for gasoline). Plans to raise fees from 2018 and make EVs pay at all times from 2020 are also on the table. Most likely, other cities will follow Oslo’s example and impose toll on EVs (Hegvik, Ertesvåg & Newth, 2016). Similarly to the toll, local municipalities can decide if EVs should be exempted from parking fees and have access to bus lanes. Before 2017, these initiatives were in effect nationwide and were according to Figenbaum and Kolbenstvedt (2015a) the most important incentives for EV uptake along with the VAT exemption.

2.3 Technological Development

Over recent years, the EV demand and production (along with other technology such as tablets, laptops and phones) has put more pressure on battery manufacturers to increase capacity and lower prices. Thanks to economies of scale, technology improvement, and market competition, battery prices per kWh have been dropping on average 19% year-on-year since 2010 (BNEF, 2016b). Notable in the strive for cheaper batteries with better capacity, is that several manufacturers plan to expand their current line or build new factories, such as Tesla’s “Gigafactory” in Nevada, U.S. As one of the leaders of EV production, Tesla supposedly will have a battery pack cost reduction by 30%, thereby enabling the lower cost of €32,500 for the Model 3 making Tesla more affordable in comparison to the Model S which is twice as expensive to the end customer (Dyer & Bryce, 2015). In addition to the U.S. factory, Tesla plans to build another Gigafactory in Europe and will compete with other manufacturers joining in the intensified electrification.

As battery capacity and range of BEVs increase, the interest in building charging stations follow and the number of charging points in Norway are close to 9000, even though most EV owners charge their car at home (Nobil, 2017). To realize the possibility to take long-range trips above a single charge, incentives have been taken from both manufacturers and politicians. In Norway, charging stations have been subsidized from the government and the goal is to establish fast charging stations along the main roads every 50 km. On the automakers side, Tesla’s net of fast chargers are increasing and have up until 15th January 2017 been free of charge, but will ahead have a nominal fee for new Tesla owners in order to fund an expansion of the network (Tesla, 2016). In addition to conventional plug-in charging, more electric concept cars are equipped with wireless charging capabilities to relieve the customer of the cable in the future. Building charging networks is not all, as manufacturers try to reduce the perception that the battery is short-lived by offering warranties or utilizing lease plans for the battery thereby easing anxiety for vehicle life span as well as the secondhand value. For example, both Nissan and Tesla offer up to 8 years warranty on their batteries for capacity degradation (Nissan, 2017; Tesla, 2014).
In addition to technological advancements on the powertrain of the EVs, business model reinvention, and autonomous driving are gaining more attention. Car sharing schemes are becoming more frequent and may have impact on EV adoption on a global level as they utilize a relatively high share of EVs, around 7% compared to the 1% in main markets (BNEF, 2016c). Customers who would not consider an EV for their personal use would then be exposed to them and form a better educated opinion. Moreover, the concept of shared economy is becoming more adaptable to people as it is realized by digitalization. The entrance of autonomous vehicles with great connectivity will perhaps allow for increased car sharing where vehicles constantly can be in motion instead of being parked (Gao et al., 2016). Recent developments of the autonomous technology shows that these vehicles might be on our streets in the near future, for example NIO plan to have its fully autonomous car in the U.S. in 2020 (NIO, 2017). However, there are many regulatory requirements that need to be resolved before fully autonomous vehicles are allowed, while the current advanced driving-assistance systems will have significant impact on how both consumers and regulators will be prepared for autonomous vehicles. A progressive scenario shows that fully autonomous cars could amount up to 15% of passenger vehicles sold globally in 2030 (Gao et al., 2016). In the analysis, this type of ownership and driving is left out due to the high uncertainty and chosen constraints in the model.

2.4 Purchase Behavior

Along with the global interest for environmentally sustainable solutions the demand for EVs has risen along with the number of models manufacturers supply. EV owners have various preferences about their vehicles but according to the most recent survey by Norwegian Institute of Transport Economics (TØI) by Figenbaum and Kolbenstvødt (2016), Norwegian owners share common motivation in the economy of use, the environmental factor and that the technology is future proof, where BEV owners also are motivated by incentives such as the free toll roads. Most of the EVs are bought new from a brand dealer constituting about 85% of sales, where a small portion of 4% BEV is peer-to-peer market and other markets are from used brand dealers as shown in Figure 1. Indirectly, this suggest a future consolidation towards a similar balance as for ICEs, presuming ownership structures will remain the same as the EV fleet grow. However, this might change with car sharing and autonomous cars; but as mentioned, due to the limitations of this study, this aspect is excluded and similar structures as of today are assumed.
2. ELECTRIC VEHICLES

The surveys on Norwegian car owners showed that in addition to the location of purchase, a large influence on the decision to buy a BEV was word of mouth (Figenbaum, Kolbenstvedt & Elvebakk, 2014; Figenbaum & Kolbenstvedt, 2016) why it is important to include network effects in the decision making process for EV purchases. Recommendations from the contact network of the BEV buyer had the most impact on the decision followed by information obtained from the brand or dealer. For PHEV and ICE the primary source of information was the dealer, with word of mouth as second for ICEs and third for PHEVs (Figenbaum & Kolbenstvedt, 2016).

2.4.1 The Used Car Market

The used car market in Norway experienced around 460 000 transactions in 2016 (OFV, 2017). As seen in Figure 1, the market for used ICE vehicles is larger than the one for EVs. What they have in common is that vehicles often are sold at a price difference compared to a new vehicle due to depreciation. The depreciation rate is the difference between the list price of a new car and the resell price of the car after a period of time, i.e. the value difference. Many factors affect the depreciation such as: driven kilometers, maintenance costs, brand perception, vehicle features, and more. In addition, the depreciation is often one of the largest parts in the total cost of ownership (Hagman et al., 2016).

Although the market for used EVs is limited in Norway, the asking prices for the most popular models, the Tesla Model S, Nissan Leaf, and Mitsubishi Outlander PHEV have been strong. However, the average BEV lose about 15% more of the value compared to ICEs (BNEF, 2017). The general depreciation models used by financial institutes and developed for ICEs, set the expected depreciation rate at 50% after owning a car three years, and driving 45 000 km (Hagman et al., 2016). Between the two types of EVs, PHEVs and BEVs, generally retain more value due to concerns regarding battery life and range concerns which do not affect the PHEVs in the same sense. Even though consumers might be uncertain about purchasing used EVs, the Norwegian market is stable compared to other countries, for example the U.S. where residual values of EVs are significantly lower (BNEF, 2017).

Figure 1. Source of purchased vehicles for survey participants (Figenbaum & Kolbenstvedt, 2016)
This chapter presents the theoretical background and literature review on which the study is based. First, general theory on diffusion of innovations which constitute the foundation for the subsequent theories is explained. Secondly, vehicle adoption models are evaluated and discussed. Focus is subsequently put on the method of choice, namely agent-based models. The chapter is concluded with a reflection on previous research in the field, and a summary of agent-based diffusion models.

3.1 Diffusion of Innovations

Diffusion could be defined as “the process by which an innovation is communicated through certain channels over time among members of a social system” (Rogers, 2003). Communication referred to in this definition is a process in which individuals create and share information with each other, to attain a shared understanding of a subject. This implies the communication is a converging process as individuals consolidate toward a mutual interpretation ascribed to certain events, or the opposite, diverge and move further apart. Hence, this process implicitly makes complete diffusion unrealistic in the real world, as all individuals within the system would have to select the same behavioural option (Kangur, 2014). Therefore, the objective of a diffusion model is to indicate the adoption rate of an innovation, amongst a population, over time (Mahajan et al., 1991).

The heterogeneity of the population and the converging communication process, imply that not all individuals in a social system adopt to an innovation at the same time. Depending on characteristics, an individual’s propensity to adopt to a new technology is time dependent. Rogers (1962) classifies different adopters into categories, based on when they first adopt to a technology. The innovativeness, or in other words, the degree to which an individual is prior to other members within the system to adopt to a new technology is what separates the different categories. The first two groups, i.e. Innovators and Early Adopters, constitute a relatively small part of the total market share and often have more to gain from the functionality of a new product, whereas the two subsequent groups, Early Majority and Late Majority, put more value on normative influences. It is first when these groups adopt to the new technology that it becomes the social norm, and self-sustaining. The last group to adopt is classified as Laggards.

It is important to acknowledge the various characteristics and preferences between the adopter groups, as different policies will be more or less effective during the diffusion process. In Figure 2, the normal distribution, i.e. bell-shaped frequency curve, represents number of individuals adopting per time unit; whereas the S-shaped sigmoid function, illustrates the same data on a cumulative basis.
Figure 2. Rogers diffusion of innovation. The bell-shaped frequency curve represent the number of individuals that adopt to a new technology per time unit, and the S-shaped curve is the cumulative basis (Rogers, 1962;2003)

As social phenomena involve complex interactions between individuals, that make decisions independently without any reference point; there is an inherent difficulty to understand and predict future outcomes such phenomena, e.g. vehicle diffusion. Therefore, researchers have developed models that try to simplify and illustrate this complex phenomenon. In the literature on diffusion models there are, in a broad sense, two categories of models; those that describe adopters as groups, rather than individuals; and models that account for the heterogeneity of the population (Geroski, 2000). The former builds on the premise that what is limiting the rate of adoption is the scarcity of information about the technology, how to use it, and what it does. The latter builds on the assumption that different parts of the population is likely to adopt to a technology at different times, due to the various attributes. To extract insights from the complex environment which characterize diffusion of innovations, models and computer simulations can provide environments which are appropriate to investigate the emergent processes.

3.2 Vehicle Adoption Models

Prior research assessing the market diffusion of EVs mainly constitutes three major modeling techniques; agent-based, consumer choice, along with diffusion and time series models (Al-Alawi & Bradley, 2013). Most of these studies regarding the diffusion of EVs are based on diffusion and time series models, which focus on average driving patterns (see e.g. Becker et al., 2009; Jeon, 2010; Lamberson, 2008; McMann & Senter, 2010; Struben & Sterman, 2008). These models assume a proportional adoption rate between the number of adopters and the remaining population, and are applied by calibrating Rogers’ market diffusion curve to new data or predict hypothetical growth rates (Gnann et al., 2015). However, as the individual driving and purchasing patterns constitute large heterogeneity these models tend to form inaccurate results (Smith et al., 2011; Gnann et al., 2015); especially as the procedure is sensitive in nascent states when limited amount of data is available (Gnann et al., 2015). Lately there has been an increase of
agent-based and consumer choice models, where the heterogeneity of the adopters is accounted for (see e.g. Sullivan et al., 2009; Neubauer et al., 2012; Gnann et al., 2015; Eppstein et al., 2011; Brown, 2013; de Haan et al., 2009; Mueller & de Haan, 2009; Cui et al., 2011; Kangur, 2014; Kangur et al., 2017). As contended by Axelrod & Tesfatsion (2005):

> Understanding an economic system requires more than how individuals behave within the system, but also how interactions of many individuals leads to large-scale outcomes. It requires more than to understand the individuals that comprise the system. It also requires understanding how the individuals interact with each other, and how the result can be more than the sum of the parts.

Furthermore, Gnann et al. (2014) among others, argue that agent-based models are more suited for complex and expensive purchase decisions. However, Al-Alawi and Bradley (2013) discuss result sensitivities on individual data which can have an impact if not assessed. Although, considering the complex economic system which characterizes the automotive market and the expensive nature of vehicle purchases, we thus intend to use an agent-based model for this study as it allows us to investigate emergent behavior that emanate from agent interactions, in a case where empirical data on an aggregated level is limited. Consequently, the literature review focuses on this type of diffusion model.

### 3.3 Agent-Based Modeling

Agent-based modeling (ABM) is a computational simulation method where a virtual environment is constructed in which actions and interaction between autonomous, proactive, reactive, and heterogenous agents are simulated (Al-Alawi & Bradley, 2013). This modeling technique is referred to by several common names, including: Agent-based modeling and simulation (ABMS), Agent-based Simulation (ABS), and Individual-based modeling (IBM). Nonetheless, the founding principles of the systems are the same. Agents are defined as entities or individuals that have control over the interactions, i.e. have the capability to make decisions, in the system. These decisions are either based on simple conditional rules (i.e. *if-then* statements) or by adaptive techniques, which assumes that certain situations and environments will affect the nature of different decision strategies, e.g. simple heuristics (Glöckner et al., 2014). Characteristics are defined for each agent which dictate their interactions among other agents and the environment, whereas the environment is defined with state variables that are representative for all agents within the model (Al-Alawi & Bradley, 2013). A representable structure of an agent-based model is depicted in Figure 3. The models’ bottom-up design enable the ABM to recreate and predict the appearance of a complex phenomena and emergent patterns of behavior that are not defined at the level of any individual agent (Adepetu et al., 2016). Further explanation of the model is described below.
3.3.1 Agents

Agents, as the name suggest, are the main building blocks in agent-based models. They represent decision-making entities, which are dictated by certain rules and interact with each other and with the environment. The literature lacks a formal definition and consensus about what constitutes an agent. However, this characterization has been deemed useful for understanding what an agent is (Jennings, 2000): 'An agent is an encapsulated computer system that is situated in some environment and that is capable of flexible, autonomous action in that environment in order to meet its design objectives.' Wooldridge and Jennings (1995) provides an explanation in line with this definition by the following points:

(i) clearly identifiable problem solving entities with well-defined boundaries and interfaces;
(ii) situated (embedded) in a particular environment - they receive inputs related to the state of their environment through sensors and they act on the environment through effectors;
(iii) designed to fulfill a specific purpose - they have particular objectives (goals) to achieve;
(iv) autonomous - they have control both over their internal state and over their own behaviour;
(v) capable of exhibiting flexible problem solving behaviour in pursuit of their design objectives - they need to be both reactive (able to respond in a timely fashion to changes that occur in their environment) and reactive (able to act in anticipation of future goals)

Agent-based simulations can be made with single agents within an environment, but due to the inherent complexity in most social phenomena, simulations mostly require multiple agents; to represent both the decentralized nature of the problem, and the multi-level and nonlinear interactions (Jennings, 2000). Following (iv), agents have control over its actions and are designed to fulfill an explicit purpose (iii). The interactions that arise between agents, in a multi-agent
simulation, could either be to achieve individual goals or to cope with the dependencies that emanate from the common environment. As seen in Figure 3, agents receive inputs from both the environment and other agents, which in turn affects the agent’s state, and subsequently its actions. It is from these interactions, and changes in behavior due to other agents that complex phenomena emerge from otherwise simple deterministic rules.

As seen in Figure 3, an agent has a State that is defined by a collection of parameters and information about what the agent is at the moment. These states can either be internal, local or global. The internal state is what defines the specific agent, and comprise all agent properties (van Dam et al., 2012). An agent representing a consumer in a vehicle diffusion model could have internal state consisting of age, income, driving distance and current vehicle type etc. A simpler agent could be a light switch agent with the binary states on and off.

Furthermore, agents perform actions based on the decision rules derived from their current state. In simplified terms, the agent in a vehicle diffusion model evaluates its needs and state, and subsequently form a decision to buy a new vehicle or not, based on a set of rules. For example, ‘If current vehicle age > 9 years, set state = buy new vehicle’. It is from these state changes and actions, the agent behavior emerge as a result of the cumulative interactions between internal, local and global states and decision rules (van Dam et al., 2012).

3.3.2 Previous Research in Agent-Based Diffusion Models

There have been numerous studies using agent-based models to describe vehicle adoption: Adepetu et al., 2016; Brown, 2013; Cui et al., 2011; de Haan et al., 2009; Eppstein et al., 2011; Gnann et al., 2015; Kangur et al., 2017; Plötz et al., 2014; Shafiei et al., 2012; Sullivan et al., 2009. Eppstein et al. (2011) introduce a spatially explicit agent-based vehicle consumer model that measures the sensitivities and nonlinear interactions between various factors on PHEV market penetration. Each agent (consumer) is assigned specific attributes such as age, income, miles traveled per year, and typical years of ownership. Additionally, the model accounts for social effects (i.e. homophily and conformity) and media influence. The assigned “spatial neighborhood” works in conjunction with social networks to estimate agent network externalities in the model. However, the authors make numerous simplifying assumptions due to the nascent state of the EV market in 2011 and therefore assert they are not able to yield quantitatively accurate predictions. Despite the limitations of the model, qualitative insights into system behavior could be gained to assess which policies and procedures that may render most effective, and identify which data that may be important to examine. Still today, the EV market is in an early stage, however, more data is available to provide more accurate predictions and assumptions. This model serves as the basis for many subsequent papers within the field of vehicle adoption i.e. Adepetu et al. (2016), Gnann et al. (2015), and Plötz et al. (2014).

Adepetu et al. (2016) develop a spatial agent-based model that aims to determine how different policies and battery technologies affect EV adoption, using San Francisco as a test city. This model comprises both vehicle adoption and usage, making it suitable for policymakers, utility operators, infrastructure providers, as well as EV manufacturers. However, certain limitations arise due to the rather compact geographical size of San Francisco, thus affecting the quantitative applicability of the study, why future research should intend to study a more representative geographical area that incorporates a larger variety of driving profiles. Additionally, the model presented by Adepetu et al. (2014) study is limited by a rather simple total cost of ownership (TCO) estimation process, and does not account for long-distance trips in the decision process. Cui et al. (2011) also introduce a spatial ABM with focus on a local residential area limited to
Knox County, Tennessee, similar to Adepetu et al. (2016). However, it focuses more on charging infrastructure rather than EV adoption in the different scenarios.

More comprehensive TCO estimations and driving profile data are used by Gnann et al. (2015) and Plötz et al. (2014) in their studies on EV market evolution in Germany until 2020. Driving profiles are based on individual measurements, and differentiated into three different user groups; i.e. users of private, fleet vehicle, and company cars, due to noteworthy differences in driving behavior for the different profiles. The authors assert that distribution and regularity of trip lengths vary greatly between agents, which have a large influence of the TCO and subsequently the potential use of EVs over conventional vehicles. Although, uncertainties in future exogenous developments, i.e. oil and battery prices and the inherent challenge to estimate fuel usage and cumulative driving distance makes it difficult for consumers to calculate and weigh the environmental and financial trade-offs between different vehicle alternatives (Eppstein et al., 2011). This lack of knowledge by consumers is supported by several consumer purchase studies regarding alternative fuel vehicle purchases which asserts that consumers tend to make decisions on non-financial reasons (i.e. image, “perceived greenness” etc.), rather than rational reasoning on e.g. total cost of ownership and fuel economy (Heffner et al., 2007; Turrentine & Kurani, 2007). However, despite the tendency of non-rational reasoning several studies illustrate the weight of fiscal incentives (directly affecting the TCO), play an imperative role for diffusion of EVs (see e.g. Figenbaum & Kolbenstvedt, 2015b; Gnann et al., 2015; Adepetu et al., 2016; Struben & Sterman, 2009). This is especially important as EVs historically have not been in parity with ICEs regarding performance and functionality, why incorporation of both rational, i.e. financial, and non-financial decision reasoning, i.e. social aspects, is important to investigate.

A study that incorporates a more comprehensive decision process is Kangur (2014) that models the EV penetration in the Dutch market using a spatially explicit ABM, which builds on the “Consumat framework” developed by Jager (2000). The Consumat framework captures the main behavioral principles of consumer decision making by a collection of psychological meta-models. As contended in the study, this approach enables inclusion of more complex behavioral rules in a multidisciplinary context, where technology development, policies, and behavioral effects are studied simultaneously (Kangur, 2014; Kangur et al. 2017). The agent-model, named STECCAR short for ‘Simulating the Transition to Electric Cars using the Consumat Agent Rationale’, in which the Consumat framework is applied, comprises an elaborate process that explores scenarios and diffusion patterns depending on different technology developments and policy stringencies. This model constitutes the most comprehensive and elaborate process we have found in the literature and is well aligned with the limitations and domain of our study. Furthermore, as both the Consumat framework (see e.g. Acosta-Michlik & Espaldon, 2008; Jager et al., 2001; Brouwers & Verhagen, 2003) and the STECCAR model (Kangur, 2014; Kangur et al., 2017) have been successfully implemented in several different consumer domains, and most recently for vehicle purchase decision. Therefore, we contend it serves our purpose well and thus chose to adopt it and use it as the basis for this study.

3.3.3 Summary Agent-Based Modeling

In summary, agent-based models facilitate the ability to capture complex structures and dynamics, in the absence of the knowledge of global interdependencies; meaning that you may know very little about the effects on an aggregate level, but have a perception of how individuals of the process behave (Borschehev & Filippov, 2004). This allows investigation of emerging global behavior from simple deterministic rules. The main advantage with an ABM is that it accounts for the heterogeneity of the population and thus capture emergent phenomena and provide a
natural description of the system (Bonabeau, 2002). It also facilitates a degree of flexibility, where e.g. agent complexity can be modified, or the level of aggregation i.e. subgroups or individuals. However, the complexity and heterogeneity are twofold; they also constitute the main disadvantages with the modeling technique, as it becomes harder to validate and verify. Furthermore, individual data and elasticities can have large impact on the results if sensitivities are not assessed (Al-Alawi & Bradley, 2013). Although considering the inherent complexity of socio-economic phenomena, it is rather a characteristic of the socio-economic systems than the model itself. Even though there are challenges with agent-based models, it is increasingly being realized in the literature, that the social world needs to be looked upon as a complex adaptive system, where interactions between entities, i.e. consumers, in this case, are multi-level and nonlinear (van Dam et al., 2012).
4 Model Description

While Chapter 3 provided a brief overview and a review of agent-based modeling, this chapter describes the underlying the chosen agent-based model, STECCAR, and the framework it is built upon. First, the framework is presented, then the model, and last how the data was parameterized to fit the model.

4.1 Consumat Framework

Purchase decisions are often made by influences from social networks. Consumers may also rely on habits, making comparisons, imitating others or using their social network to get advice. In the STECCAR model, the Consumat framework is applied to these aspects of purchase decisions. The framework, depicted in Figure 4, aims at connecting the decision making behaviors by accounting for the needs and abilities of agents, including when an agent switches their source of decision strategy. The main components of the revised Consumat framework (Consumat II) suggested by Jager and Janssen (2012) are presented here. For further reading, we refer to Jager (2000), and Jager and Janssen (2012).

Figure 4. Consumat framework overview (Jager, 2000)

4.1.1 Behavior Drivers

The drivers for behavior in the model are needs, that when fulfilled result in satisfaction. In this case, the needs are satisfied by the purchase of a new vehicle. The needs can be divided into three behavior-driving forces: existence, social belonging and personal preferences. Existence refers to the acts by agents of having means of income, food, or housing. In order to avoid loss of existence, agents act to renew their resources. Social belonging refers to interactions in the agent’s network, group affiliation, and social status. Personal preferences refers to satisfying the subjective taste and liking of an individual. Differences between agents are the balancing between these needs, as some are more motivated by the existential needs and others by the
influences of their social network, i.e. other agents. The behavior options that agents perform relate to the abilities of an agent, i.e. the actual capacity to carry out an action. As agents carry out choices, the behavioral opportunity is connected to the abilities where for example resources can be used when choosing to buy a new vehicle. In addition, agents possess a memory where previously made choices are affecting new states of behavior and abilities.

4.1.2 Decision Strategy

The Consumat framework has a simple structure for decision making, which is an important element in the approach. The satisfaction level of the agent indicates the success of previous choices, so if an agent has a high degree of satisfaction, the need for decision making at the moment is low. However, when an agent is dissatisfied, the urge to make decisions becomes higher in order to increase satisfaction. Moreover, when there are numerous choices to decide from, one might be uncertain of the outcome of the decision. By looking at other people’s experience and their behavior, the uncertainty can be eased. Most often, these interactions occur when people share similar attitudes, values etc. Likewise, the Consumat framework accounts for similarity by basing chances of interaction on similarity, and thereby a social network can be constructed. As agents’ behavior change over time, the dynamic network will follow. The level of satisfaction and uncertainty of the agent corresponds to the choosing of one of the four ‘cognitive processing’ strategies, as shown in Figure 4.

When satisfaction is high and uncertainty low, repetition occurs, which drives habitual behavior. If, however, uncertainty would be high while satisfaction remains high, agents engage in imitation. Low satisfaction requires agents to put more effort in bettering their state. Therefore, when agents are certain but not satisfied they will assess viable options and start optimizing and thereby maximizing the utility of a choice. If agents are uncertain while having low satisfaction, inquiring occurs where the agent will compare behavior to similar others and copy it if the expected outcome increases satisfaction.

4.1.3 Memory

The experiences from choices combined with behavior make up the memory of the agent. Information gathered from inquiring and optimizing is stored in the memory and used next time agents make decisions. Hence, the memory is updated only when agents are engaged in optimizing or inquiring, making it possible for a satisfied agent to stay in repetition without updating its information on better opportunities. By combining status of capacity and requirements for consuming a certain opportunity, the behavioral control is formalized in the memory, meaning the agent knows for example if it can financially afford a new vehicle. The individual agent’s behavior is collectively aggregated from the impacts affected by the environment, and/or other agents.

4.1.4 Framework Evaluation

The Consumat framework has previously been successfully applied in various domains, e.g. adaptation to climate change by farmers, flood management, household dynamics, and most recently in the STECCAR (Kangur, 2014; Kangur et al., 2017). Hence, we know that it is a useful tool for modeling diffusion affected by social processes. However, Kangur (2014) argues that one concern regarding the framework is that needs are not ordered but balanced in line with a personal weighing function. The result would be, however unlikely, that symbolic and financial aspects outweigh the car’s ability to meet the driver’s behavior. If so, a person would buy a vehicle for
environmental or financial reasons, even if the vehicle does not meet the daily travel distances. Therefore, the assumption is that being able to travel the required distance is a basic need and failure to do so will result in a penalty in the overall satisfaction level of the agent. Moreover, another assumption accounted for is the influence from social networks regarding the purchase of a vehicle. As it is a substantial investment, it is unlikely that an individual would replace his or her car to a model similar to a peer as soon as uncertainty arises. Hence, the heuristic-based decision strategies can be viewed more as information seeking strategies (Kangur, 2014).

4.2 The STECCAR Model

The previous section presented the Consumat framework II on which the STECCAR model is built. This section will review how the model is constructed using the Consumat framework. The model that we utilize was developed by Kangur (2014), which we refer to for a more in-depth description.

4.2.1 Overview

The STECCAR model builds on a set of agents that own a vehicle that satisfies their personal needs. The model is written in Java and is executed with Repast Simphony, an open source agent-based modeling platform. The original model was parameterized using data from a nationwide survey in the Netherlands in June 2012, similar to the COMPETT survey (see Figenbaum, Kolbenstvedt, & Elvebakk, 2014; Figenbaum & Kolbenstvedt, 2015b) in Norway we use in this study. Both surveys capture data including individual characteristics, vehicle model, type of ownership, driving behavior and perception of EVs and the likeliness to purchase an EV in future. Necessary modifications have been made to the original code to fit the Norwegian setting and the market conditions.

In the model, there are three types of fuel technologies available: internal combustion engine (ICEs), battery electric vehicles (BEVs), and plug-in hybrid electric vehicles (PHEV). An agent’s behavior is restricted by its financial state and the refueling ability of the different technologies.

![Figure 5. Abstract overview of the STECCAR model (Kangur, 2014)](image-url)
Figure 5 shows a simplified overview of the STECCAR model. For every timestep (tick) in the simulation, one week passes in the agent’s world. Hence, every agent has seven possible days to travel a daily distance. The vehicle might need refueling or maintenance due to mechanical failure. Following the week, the agent evaluates the satisfaction of the vehicle’s functionality and costs, while updating its information about the current vehicle and how it influences the agent’s needs. Agents search for new information through inter-agent communication or through media depending on the agent’s state of uncertainty, in line with the Consumat framework. Should the agent be repeatedly unsatisfied, it may decide to buy or lease a new vehicle that is estimated to fulfill the needs. This also happens when the vehicle’s maintenance cost rises above the vehicle’s market value or when the lease contract ends.

4.2.2 Vehicles

The vehicles in the model are defined by their fuel technology, range, price and emissions. Hence, other characteristics of the vehicles such as appearance, size, acceleration and speed performance etc. are left out to reduce the complexity of the model. This is a reasonable omittance for the Norwegian market, as Figenbaum and Kolbenstvedt (2016) found that such qualities, e.g. performance, did not have any significant impact on the purchase decision for neither EV nor ICE buyers.

The three technologies used for fueling the vehicles are gasoline and diesel for ICEs, electricity for BEVs or a combination of both for PHEVs. The refueling methods and maintenance costs differ between these technologies, why agents experience driving differently. The price of a new vehicle in the model is set when it is introduced and the value declines over time with an assumed 15% depreciation per year, in accordance with Hagman et al. (2016) and BNEF(2017). Moreover, the same rate is applied to both EVs and ICEs, as BNEF (2017) found that differences in depreciation are small in the Norwegian market and dependent on the model of the car.

Vehicles have a limited range they can travel. To reduce complexity, a fixed range is chosen for ICEs while BEVs have a specific capacity and energy consumption. Therefore, it is possible to model decreasing battery price per kWh. PHEVs have a fixed range and an electric range due to the dual technologies. Moreover, vehicles have fixed emissions in order to model the tax cost when changing policy stringencies in the scenarios.

4.2.3 Abilities

The agent’s behavior is influenced its abilities. This determines whether an agent is able to satisfy its needs. Driving its personal vehicle is the first ability, followed by access to money, and to charging infrastructure.

Agents own a vehicle at all times and are assigned a car model matching the survey responses regarding fuel type, price class, age and yearly kilometrage. Moreover, the type of ownership is set: lease owner, buyer of new vehicles, or buyer of used vehicles. Depending on ownership type, the available vehicles for the agent differs as well as how the agent assesses costs of separate car models.

The financial ability, access to money, is based on that an agent saves a certain amount of its income every week for the purchase of a new car as well as for maintenance costs. When an agent has sufficient funds and is unsatisfied, it will purchase a new car. The concept of money in the model is useful due to an otherwise high rate of purchases that would occur whenever an agent becomes unsatisfied.
Refueling occurs only on the road for ICE vehicles whereas EVs have three types of locations for this action: at home, at work, and on the road. Having access to a personal parking lot enables the agent to charge at home. Otherwise, public chargers are used as the amount of agents with home charging options are limited. Similarly, certain agents have the ability to charge at work. Road charging is driven by the probability that an agent has access to fast charging opportunities during the drive. This is determined at the start of every drive the agent makes.

4.2.4 Driving and Evaluation

For every tick in the simulation, the agent can do seven trips. The distance traveled corresponds to the respondent’s data from the survey and is initialized again every 52 ticks, corresponding to each year for an agent. The agent evaluates the driving according to the categories finance and functionality which are connected to two of the agent’s needs. These needs, adapted from the Consumat framework incorporate financial, functional, social, and environmental needs where financial and functional are the existence needs relevant for car ownership (Kangur, 2014).

The financial aspect is made up of variable costs and static costs where the first include the energy costs as well as maintenance and the latter consists of taxes. These combined are the basis of the financial satisfaction. An agent’s satisfaction regarding the functionality of the vehicle refers to the ability to travel the desired distance without interruption. Hence, a BEV without the sufficient range and limited access to charging stations affect the overall satisfaction negatively of an agent in a major way if stopping occurs. In addition, agents are sensitive to the time delays occurring when refueling on the road is required. An ICE car refueling on the road is imposed with a time delay which lowers the satisfaction. BEVs require fast charge on the road when energy is depleted, while PHEV owners are assumed to only do so if the gasoline tank needs to be filled.

The agent keeps track of its driving experiences in the memory, while it also updates its beliefs about vehicles. Information regarding vehicles includes price, range, emission and taxes where EV beliefs also concern charge times, energy cost and charging opportunities. This information is gathered from the social network and from media, which later affects the agent’s certainty level with the existence and environmental needs.

4.2.5 Needs and Mentality

The previous section mentions the needs connected to existence in the Consumat framework: functionality and financial, where the other two are needs are social and personality. The social need is reflected in the agent’s network, where agents gain satisfaction by relating their position to other agents, and how a new model would serve this need. Agents desire to conform, anti-conform and have superiority. This means that an agent will adopt the behavior, try to be unique, or seek superior standards in relation to peers. These three components have different weights depending on the agent’s preferences.

The personality need refers to the personal preferences. For the EV market, this need connects to the environmental aspect, being a key preference that influences the purchase decision. In real life, there are of course many personal preferences that affect the purchase and choice of car model but STECCAR considers only the environmental impact in order to reduce complexity. This environmental impact and satisfaction of the agent are correlated to the tailpipe emissions of the vehicle models available, where BEVs have zero emissions, PHEVs low emissions, and ICEs higher emissions. Consequently, a high environmental need is satisfied by purchasing a BEV.
All needs are combined and evaluated which results in the mental state of the agent. The financial and functional needs are derived from the driving experiences while social and personal are derived from the heuristic comparisons. The mental state evaluation results in whether the agent should seek new information on vehicle models. Strategies for information seeking mirrors the ones presented in the Consumat framework, as seen in Figure 4.

4.2.6 Influences

The information seeking strategies are dependent on the level of satisfaction and uncertainty of the agents. They either connect to the influence of the social network of the agents or to the influence of media where agents engage in repetition, imitation, inquiring or optimizing.

Natural for social simulations are the creation of networks where agents are connected. Most often, this communication occurs with similar individuals. The model assigns agents similar to one another as communication partners. Factors determining the similarity are: geographical proximity, age, income, values, ambition, behavior and preferences. The non-trivial factor value refers to the attitudes of the agents. Here, this means that two agents that with a similar ranking of their needs, are more likely to connect. Correspondingly, agents have ambition levels (scaled between 0 and 1) and equally ambitious agents are more likely to interact. Likewise, agents that share behavior and preferences interact which is modeled after the travel distances assuming that agents who travels equal distances are more likely to learn from each other.

The other influencer in STECCAR is media. At every tick, the media publish messages regarding different car models and type of fuel technology that agents can seek information from. In the model, there are four types of messages that occur. Either the media favors a certain fuel technology or are objective. For example, there is a probability EVs will be favored over gasoline, and there is the opposite. However, it is only agents engaging in optimizing that turns outside their social network to media for information about new vehicles.

4.2.7 The Car Market

When an agent has come to the decision to purchase a new vehicle, they turn to the car market. Agents can buy a new or used car, lease or sell a car, depending on the agent’s ownership type. If the agent buys or leases a new vehicle the old one is added to the used car market, where agents who are limited to the used car market buy their car. The purpose of modeling a used car market is to capture the actual market dynamics and account for a "lag" in the diffusion of new models, as not all consumers have the financial possibility to purchase a brand new car. In addition, real-life consumers might not want to buy a brand new car due to the high rate of depreciation or for other reasons.

The decision to purchase a vehicle is based on the satisfaction and the evaluation of the current vehicle (Section 4.2.4) as well as the information seeking that the agent might have engaged in. Also, when a vehicle is at 'total loss' meaning when maintenance costs are higher than the remaining value of the car, the agent always buys a new car chosen by comparing available models. For all agents, the comparison of models is based on the satisfaction and uncertainty of each car model. Hence, the preferred car model is the one expected to be most satisfying and most certain. Agents who privately own their car will make the purchase if they have sufficient funds, while lease agents will swap to the desired model directly.
For the used car market, agents need to perform one more action before they can purchase a vehicle. As the model keeps track of the kilométrages of vehicles, the agent examines the proportional value and kilometrage of every used car. Just as when an agent buys a new car, the old one will be sold to the used car market or sent to scrapping. In order for the used car market to not grow to unproportional, the size is restricted. The proportion of used cars of a specific model can not be more than twice the amount of the owned cars in the population.

4.3 Parametrization

This section presents the parameters used to initialize the STECCAR model that was described in Section 4.2. The parameters are partly based on the model by Kangur (2014), but now updated with the Norwegian data from the COMPETT study (Figenbaum et al., 2014). Furthermore, a description of the sampling procedure is explained.

4.3.1 Overview

The parameters used to initialize the agents in the STECCAR model in line with Kangur (2014) is presented below in Table 1 and are categorized in themes for readability. The dataset used to parametrize the model is based on the COMPETT survey by Figenbaum et al. (2014), statistical databases, research institutes, and data from automotive manufacturers. Due to differences in the survey used by Kangur (2014) to initialize the model and the COMPETT study, estimations have been made to several parameters to fit the model. For more detailed information on the estimation of certain parameters, please see Appendix A. Further explanation of the parameters is found in the table below.

4.3.2 Agent Sampling

The Norwegian population was approximately 5.3 million in 2016 (SSB, 2017), at the beginning of the simulation, and was considered fixed throughout the simulation run. To initialize the agents in the model the COMPETT survey, including 3962 respondents, was used. Since the respondents were over-represented by current EV owners, a stratified random sample was derived from the dataset. The 3962 respondents were divided into five subgroups, i.e. strata, depending on their uncertainty tolerance, which correlates with Rogers’ (1962) adopter groups. From each stratum, a random set of agents was taken, in proportion to the stratum’s size to the total data population. This renders a normally distributed sample. The stratified random sample was reduced in size to 1770, to decrease computation time. Even though, there is an inverse relationship between sample size and margin of error, the effect obtained from a reduction of sample size is negligible. This is due to sampling theory which implies that when sampling fraction, i.e. sample size divided by population size, is small there are only insignificant accuracy improvements when increasing the sample size (Krejcie & Morgan, 1970). With a confidence level of 95% and a sample size of 1770, the margin of error was calculated to be 2.3%, and thus sufficed the research requirements.

When investigating the social dimension in the scenario analysis, a different sampling technique was utilized. To allow investigation of more homogeneous agents with certain characteristics, a stratified sample was used. The 3962 respondents were divided into two subgroups depending on their current vehicle type, i.e. EV and non-EV owners. The stratum, only consisting of EV owners, was used to capture social aspects in the scenario analysis.
### Table 1. Parameters used in STECCAR (DS=Dataset; E=Estimated; I=Independent)

<table>
<thead>
<tr>
<th>Agents</th>
<th>Source</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Agents</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>DS</td>
<td>X</td>
</tr>
<tr>
<td>Postal code</td>
<td>X</td>
<td>Used for to obtain spatial coordinates of agents.</td>
</tr>
<tr>
<td>Yearly household income</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Personality</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Need weights</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Ambition</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Uncertainty tolerance</td>
<td>X</td>
<td>Normally distributed in following Roger’s (2010) diffusion of innovation categorization</td>
</tr>
<tr>
<td>Social weights</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Expertise in EVs</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Driving behaviour</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yearly kilometrage</td>
<td>X</td>
<td>Dataset answers assigned to categories, to fit corresponding categories in STECCAR</td>
</tr>
<tr>
<td>Daily driving distances</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Refuel moment</td>
<td>X</td>
<td>Converted from COMPETT</td>
</tr>
<tr>
<td>Access to home charge</td>
<td>X</td>
<td>Derived from COMPETT</td>
</tr>
<tr>
<td>Driving frequency</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Vehicle preferences</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ownership type</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Vehicle price class</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Minimum range</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Maximum charge times</td>
<td>X</td>
<td>Normally distributed around the mean of answers from survey conducted by Kangur (2014). In line with Rogers adopter groups.</td>
</tr>
<tr>
<td><strong>Initial vehicle</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vehicle age</td>
<td>X</td>
<td>Estimated and distributed according to SSB statistics.</td>
</tr>
<tr>
<td>Ownership duration</td>
<td>X</td>
<td>Estimated and distributed according to SSB statistics.</td>
</tr>
<tr>
<td>Fuel technology</td>
<td>X</td>
<td>Derived from COMPETT</td>
</tr>
<tr>
<td><strong>Vehicles</strong></td>
<td>Source</td>
<td></td>
</tr>
<tr>
<td>Car models</td>
<td>BEV</td>
<td>X</td>
</tr>
<tr>
<td>PHEV</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>ICE</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>General aspects</strong></td>
<td>Price per kWh</td>
<td>X</td>
</tr>
<tr>
<td><strong>Infrastructure</strong></td>
<td>Source</td>
<td></td>
</tr>
<tr>
<td>Car market</td>
<td>Initial used cars</td>
<td>X</td>
</tr>
<tr>
<td>Refuel stations</td>
<td>Access to home charge</td>
<td>X</td>
</tr>
<tr>
<td>Access to work charge</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Proximity of road charge</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Refuel time</td>
<td>X</td>
<td>Based on actual time for fast charge up to 80%</td>
</tr>
<tr>
<td>Refuel costs</td>
<td>X</td>
<td>Set on initialization, varies in scenarios</td>
</tr>
<tr>
<td>Maximum recharge capacity</td>
<td>X</td>
<td>Based on fast charge recharge capacity, i.e. 80% of battery capacity.</td>
</tr>
<tr>
<td><strong>Maintenance</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Failure distances</td>
<td>X</td>
<td>Independently determined, based on Kangur (2014)</td>
</tr>
<tr>
<td>Failure probabilities</td>
<td>X</td>
<td>Independently determined, based on Kangur (2014)</td>
</tr>
<tr>
<td>Failure ratios of EVs</td>
<td>X</td>
<td>Independently determined, based on Kangur (2014)</td>
</tr>
<tr>
<td>Battery life</td>
<td>X</td>
<td>Based on manufacture warranty of 8 years or 200 000 km, whichever comes first.</td>
</tr>
<tr>
<td>Maximum battery capacity decrease</td>
<td>X</td>
<td>Based on manufacture warranty.</td>
</tr>
<tr>
<td>Battery warranty</td>
<td>X</td>
<td>Warranty is set fixed according to current setting. 8 Years or 200 000 km.</td>
</tr>
<tr>
<td><strong>Taxes</strong></td>
<td>Road taxes</td>
<td>X</td>
</tr>
<tr>
<td>Emissions tax</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Media</strong></td>
<td>Level of truth</td>
<td>X</td>
</tr>
</tbody>
</table>
5 Method

This chapter provides a description of the methodology of the study. Included is explanations of the research design, data collection methods along with a discussion about the validity and reliability of the investigation.

5.1 Research Design

As the purpose of the study was to investigate the diffusion of electric vehicles in the Norwegian market and assess the effectiveness of factors that affect the adoption rate, an exploratory study with a positivist approach is applicable as the empirical data mainly constitutes quantitative data (Blomkvist & Hallin, 2015).

The research was conducted with an inductive and iterative approach and contained a background study and establishment of a frame of reference, followed by a systematic in-depth literature review that recurrently was revised along with the empirical data gathering, as seen in Figure 6. The underlying data, on which the research and the proposed method for analysis, is based on was mainly collected through secondary sources i.e. statistics from government databases, research notes, and historical sales figures. After the data collection, the proposed method for analysis was implemented. The basic functionality of the model was tested through early simulations to validate the applicability of the model in the new setting. In parallel, scenarios for the Norwegian market were developed. Subsequently, real simulation runs were made for the different scenarios. The results obtained from the simulations were then evaluated, analyzed and discussed. Finally, future work and stakeholder implications were developed.

![Figure 6. Research process and work flow throughout the thesis](image)

5.2 Literature Review Process

In order to understand trends, concepts and compare the study with previous research, a literature review provided a comprehensive overview of EV publications and data from research institutes. At first, the purpose was to gain an overview of the phenomenon and the current state of EV adoption on a global scale and how it compares to Norway. Subsequently, the literature review became more focused and was narrowed down to focus on EV diffusion models, more particularly agent-based models. Research papers on the Norwegian setting including, e.g.
consumer attitudes on EV adoption and political incentives to promote EVs were also reviewed. The findings were used to position the study and locate the area of contribution. Furthermore, it helped us to understand the data that was collected and how to interpret the results of the agent-based model.

The literature review on diffusion of innovations in general, and EVs in particular, gave us a deeper understanding of diffusion theory while presenting different approaches for modeling the rate of adoption, forecasting etc. Hence, after evaluating different models and identifying the knowledge gap, we chose to further investigate the agent-based modeling of vehicle diffusion. Here, we have investigated how an agent-based model should be built along with how agents make decisions, in this case evaluating vehicle purchase. By comparing previous studies using agent-based models in the field of EV diffusion, we combined the key takeaways from these to serve our purpose of using a valid model. Hence, chose to build or study on what we consider the most extensive agent-based model based on the scope of our study, namely the STECCAR model.

Aids and tools for finding literature such as scientific articles, books, journals and reports has been KTH Library, KTHB Primo, Google Scholar, Web of Science and Scopus. Keywords in the area of research are for example: "electric vehicles", "EV", "battery electric vehicles", "plug-in hybrid vehicles", "green transportation", "e-mobility", "diffusion of innovations", "technology adoption", "agent-based modeling".

5.3 Data Collection

In order to collect the data needed for agent creation and vehicle parametrization, several sources of information have been used. The main data source is as previously mentioned the survey results from a Norwegian national survey (COMPETT) that captures the purchase behavior of 3962 Norwegian vehicle owners. This data was collected by the Norwegian Institute of Transport Economics (TØI) where the data was formatted to be anonymous by NSD - Norsk Senter for Research Data AS. Moreover, to validate and further analyze the used car market, market data on used vehicles was provided by FINN (finn.no), which is the largest player on the Norwegian used car market. The data is assumed representative, as the number of car ads on FINN are 7% more than the registered owner transfers (there were about 500 000 ads per year 2011-2016. Owner trades amounted to about 470 000 the same years (OFV, 2017)), which entails that nearly all ads are effective and therefore constituting a sample of the actual transfers.

Secondary data has also been collected through other databases, i.e. Statistics Norway (SBB), Opplysningsrådet for Veitrafikken (OFV), European Alternative Fuels Observatory (EAFO). Furthermore, market research data from experts at Bloomberg New Energy Finance (BNEF) and Navigant Research among others has been used as secondary sources of information on which the parameter forecasts and scenario analysis were based on. Moreover, vehicle data was gathered from the vehicle manufacturers websites and official publications.

5.4 Quality of the Study

By using peer reviewed literature and data from well known institutes and public databases, we deem the foundation of theory and data which the derivative work is based on, to be of high validity. Moreover, we regard TOI, NSD, and FINN as objective and unbiased actors in the setting. After evaluating various methods for analyzing diffusion of innovations, through the literature review, agent-based modeling was selected due to its ability to capture the heterogeneity
and as other methods tend to form inaccurate results when a limited amount of purchase data is available.

The agent-based STECCAR model, which forms the foundation of our study was chosen based on the literature review, as the most valid model to simulate diffusion of EVs on the Norwegian market. However, as always when forecasting, the validity of the results can be discussed since there are many unknown factors that might have been left out due to either limited knowledge of them or because they would create a too complex model. Therefore, the statistical generalizability of the result is highly dependent on the sampling as argued by Blomkvist and Hallin (2015), and variables, i.e. the factors affecting the diffusion and adoption rate.

As stated in Chapter 4.3.2, the dataset (COMPETT) used to initialize the model is a survey consisting of 3962 unique Norwegian car owners around vehicle preferences and characteristics (Figenbaum & Kolbenstvedt, 2014). By using a stratified random sample, we ensure that we get a more representative sample, as current EV owners were over-represented in the dataset. The decrease in sample size, from the original 3962 to 1770, was made to reduce computation time to reasonable levels. An increase in sample size does not defend the decrease in margin of error, as the sample size is limited to less than a few percent of the entire population. At this point, the return obtained from increased sample size is diminished as changes in margin of error is negligible as the sampling fraction is too small (Krejcie & Morgan, 1970). The literature suggests a confidence level of 95% and margin of error of 5% to suffice most studies, implying a sample size of 384 sufficient. With a sample size of 1770 and confidence level at 95%, we calculate the margin of error to 2.3%, and can, therefore, consider the sample size sufficient for the research. Furthermore, it is important to recognize that, due to the complexity of the phenomenon, the quantitative approach might reduce the intricacy of the problem. However, as discussed by Blomkvist and Hallin (2015), the approach has its strengths when many factors are affecting the phenomena, showing correlations between various variables, which for is true for this study, where different measures to promote EVs are investigated in the scenario analysis.

However, it is important to distinguish the difference between the results from the model simulations and the data used to initialize the model. Even though the data is considered statistically sufficient, the model itself limits the statistical validity due to the impracticability to fully reproduce the real world and its dynamics, especially in a forecast scenario where the results cannot be empirically validated. Therefore, we deem the statistical validity of the results limited, but that it enables analytical capabilities.

To achieve reliability, we have tried to be as thorough as possible in describing the STECCAR model and how we apply our data to fit it. As it is based on a specific survey conducted in the Netherlands, there are a few discrepancies in the survey questions where we either have assigned random values according to either uniform or normal distribution based on the Dutch results, or according to other data obtained in the public Norwegian databases (See Section 4.3). By explaining these aspects of the data mapping, we believe that it would aid others who might want to apply the STECCAR model in a new setting.
6 Results

This chapter provides a description of the scenarios and the respective results derived from the agent-based simulation runs assessing policy, technological, and social factors. The scenarios are categorized according to the level of adjustments, either as isolated or combined. First, isolated and combined factors adjusted in the policy and technology dimension are addressed. Secondly, results derived from the social dimension are demonstrated. Lastly, results from the used car market data is presented.

6.1 Overview

To assess future developments of the automotive market in Norway until 2030, several scenarios have been developed to represent various outcomes. As previously mentioned, Figenbaum and Kolbenstvedt (2015b) identify two main dimensions affecting the diffusion, namely Technology and Policy. Moreover, the Social aspect also play an important role in the diffusion of alternative fuel vehicles (Figenbaum et al., 2015; Figenbaum & Kolbenstvedt, 2016). In order to address research question 1a *"How do policies, technological, and social factors affect the diffusion of electric vehicles?"* different scenarios have been developed to represent these dimensions. Adjustments are made from a control scenario which acts as a reference for the comparative analysis. Furthermore, to answer research question 1b *"What effects on the diffusion emerge when combining several factors simultaneously?"*, two scenario types was constructed; i.e. isolated factors and combination of factors. The former lets us investigate individual effects on factors affecting the diffusion, and the latter illustrate how the combinations of multiple factors affect the diffusion. Figure 7 provides an overview of the policy and technology dimensions. Moreover, the social aspect is applied by changing the agent sample. Further explanation and results for each scenario are found in subsequent sections.

![Figure 7. Overview of scenario dimensions: Control, Policy Alleviation, Technology Development and Combination. The stratified sample represents the Social dimension](image-url)
The adjustments made to the dimensions vary across the scenarios. Listed in Table 3 are the scenarios for the simulation runs, along with the dimensions of which the respective parameters were adjusted in.

**Table 3.** Overview of all scenarios showing in which dimension adjustments are made

<table>
<thead>
<tr>
<th>Scenario Name</th>
<th>Policy</th>
<th>Technology</th>
<th>Social</th>
<th>Combination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Emissions Tax</td>
<td>X</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Emissions Tax: BEV</td>
<td>X</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Battery</td>
<td>-</td>
<td>X</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Fast Charge Probability</td>
<td>-</td>
<td>X</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Fuel Cost</td>
<td>-</td>
<td>X</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Combination Fast Charge</td>
<td>-</td>
<td>X</td>
<td>-</td>
<td>X</td>
</tr>
<tr>
<td>Combination All</td>
<td>X</td>
<td>X</td>
<td>-</td>
<td>X</td>
</tr>
<tr>
<td>Combination All: BEV</td>
<td>X</td>
<td>X</td>
<td>-</td>
<td>X</td>
</tr>
<tr>
<td>Control Social</td>
<td>-</td>
<td>-</td>
<td>X</td>
<td>-</td>
</tr>
<tr>
<td>Combination All: BEV Social</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Each scenario is derived from the *Control* scenario, which is further described below. Table 4 shows all parameters that vary in the scenarios. All scenarios are simulated over 728 ticks, which represent the time frame between 2016 to 2030, where each tick represent 1 week. Since empirical data is only available for the first 52 ticks, i.e. until 2017, future developments past this are hypothetically determined, based on different methods and sources, as described in Table 4.
Table 4. Scenario parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Future developments</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Vehicle</td>
<td>Introduction of new vehicles is first based on manufacturer’s statements of the introduction of new vehicles, after that new vehicles are introduced following the rate at which it has done in the past with better performance according to battery forecast (BNEF, 2016)</td>
</tr>
<tr>
<td>Money</td>
<td>The amount an agent can spend on a new vehicle and maintenance is initially set at 5% of the household income. Due to economic growth it is assumed that agents will have more money to spend on vehicles in the future, therefore, the amount is linearly increased to 10% over the simulation period.</td>
</tr>
<tr>
<td>Emission Upgrade</td>
<td>Until 2018 there is an incremental upgrade by 7% per year, after that there is a 2% upgrade until 2030.</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>The probability that an agent has access to fast charging during their daily travels is initialized at 56% based on survey data from the Norwegian EV Association (Haugneland et al., 2016). Future developments are hypothetical, linear improvements, and is set to reach 95% towards the end of the scenario.</td>
</tr>
<tr>
<td>Fuel Time</td>
<td>Gasoline fuel time is set fixed upon initialization. Adjustments are made on fast charge stations.</td>
</tr>
<tr>
<td>Fuel Cost</td>
<td>Gasoline prices are set to €0.1/km at the start of the simulation, corresponding to an average liter price of €1.66/litre (SSB, 2017). The price then increase linearly by €0.04/km over the simulation period. Resulting in a litre price of €2.33/litre in 2030.</td>
</tr>
<tr>
<td>Battery Cost</td>
<td>The battery cost follows the forecast done by BNEF (2016b). Cost depreciates linearly over the simulation. Baseline price decrease from $273 to $173 in 2030.</td>
</tr>
<tr>
<td>Road Tax</td>
<td>Road tax is based on average monthly cost (€80) for car owners derived from COMPETT, and set fixed over the simulation period.</td>
</tr>
<tr>
<td>Emissions Tax</td>
<td>Emission tax for CO2 emissions are added in some scenarios, as part of policy schemes. The amount of tax is based on the amount car owners in the Netherlands pay.</td>
</tr>
</tbody>
</table>
6.2 Control Scenario

The Control scenario represents the current market setting regarding policies and cautious technology development, following the baseline parameter values, Table 4. It is important to emphasize the Control scenario is mainly used as a baseline for the comparative analysis done when assessing different factors, rather than the most probable development of the market. Figure 8 depicts the diffusion of BEVs and PHEVs for the Control scenario over the simulation period.

Figure 8. Diffusion of EVs in the Control scenario over the years 2016-2030. The solid lines represent the average value, and the faded area standard deviation at the point in time

The result from the simulations in the Control scenario runs, show that the BEVs reaches a diffusion of 21.1% in 2030 where the corresponding number for PHEVs are 63.3%. Hence, in 2030, 84.4% of all vehicles are classified as EVs.

6.3 Isolated Factors

This section provides descriptions of the single factor scenarios, and the results derived from the respective simulations. Adjusting singular factors enables investigation of isolated effects of on the interaction on the diffusion of EVs. The results are compared to the Control scenario which acts as a reference. These scenarios are adjusted in two dimensions, i.e. Policy and Technology development.

6.3.1 Policy - Emissions Tax

High initial cost is identified as one of the major barriers to widespread EV adoption (Adepetu et al., 2016; Boulanger et al., 2011). Due to the rather nascent state of the EV market and technological development, EVs are inherently more expensive than ICEs. To make alternative fuel technology vehicles, i.e. BEVs and PHEVs more price competitive and closer to parity with ICEs, governments can introduce fiscal incentives to assist the diffusion. The current success in Norway is as previously stated, partly due to favorable governmental policies including several fiscal incentives, e.g. VAT exemption, lower registration tax and more. These incentives are included as part of the Control scenario. For simplicity, these have been included by reducing
the list price of EVs. Even though Norway already has favorable incentive schemes in place, scenarios where alternative and additional, incentive schemes have been developed to measure its effect on the diffusion.

### Table 5. Emission tax categories with corresponding tax level

<table>
<thead>
<tr>
<th>Category (End) [gCO₂/km]</th>
<th>Tax [%] of vehicle list price added to annual income for taxation</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;50 (32)</td>
<td>0%</td>
</tr>
<tr>
<td>50-95 (50)</td>
<td>14%</td>
</tr>
<tr>
<td>95-125 (70)</td>
<td>20%</td>
</tr>
<tr>
<td>&gt;125 (&gt;70)</td>
<td>25%</td>
</tr>
</tbody>
</table>

In similarity to the "bonus-malus" memorandum proposed by the Swedish government, and the "Bijtelling" tax in Netherlands, the Emissions tax scenario represents a penalty tax, where a percentage of the vehicle’s list price is added to the agents annual income, and increased road tax on vehicles with CO₂ emissions over 50 gCO₂/km. The penalizing tax is directly correlated with the car’s CO₂ emission, set in categories as seen in Table 5. Due to technology development, the amount of gCO₂/km that is the lower limit for each category decreases as cars emissions standards are upgraded. The number in the parentheses in Table 5 is the lower limit for each tax category at the end of the scenario. Road tax is increased one time by 100% from the Control scenario, from €80 to €160 per month.

Figure 9. Diffusion of EVs in the Emissions Tax scenario over the years 2016-2030. The solid lines represent the average value, and the faded area standard deviation at the point in time

The Emissions Tax scenario simulation results depicted in Figure 9 show small deviations from the Control scenario. PHEV penetration remains within the standard deviation and end at 63%, whereas for BEVs show a slight increase, resulting in a 4.2% increase from the Control scenario at the end of the simulation in 2030 (Control: 21.1%; Emissions Tax: 22%).
6.3.2 Policy - Emissions Tax BEV

The Emissions Tax BEV scenario is almost identical to the Emissions Tax scenario with the difference that only zero emission cars are exempted the penalty tax, instead of cars under 50 gCO₂/km (decreasing to 32 gCO₂/km at the end of the simulation). The diffusion in this scenario is shown in Figure 10.

![Figure 10. Diffusion of EVs in the Emissions Tax:BEV scenario over the years 2016-2030.](image)

The result from the simulation shows a market penetration of 55.8% for PHEVs and 27.5% for BEVs at the end of the simulation run. Hence, the higher tax initiatives contribute to a 30% increase in BEVs in 2030 compared to the Control scenario (Control: 21.1%; Emissions BEV: 27.5%). PHEVs, on the other hand, are diminished by 11.8% (Control: 63.3%; Emissions BEV: 55.9%). The unproportional discrepancy between the BEV increase and PHEV decrease is in this case captured by ICE vehicles, rendering in a 6.8% increase.

6.3.3 Technology - Battery

For EVs, the battery is what currently experience the largest development changes and today accounts for a third of the total production cost. Therefore, the battery plays an imperative role when it comes to EV-ICE parity, both regarding cost and performance. BNEF (2016b), provides an in-depth analysis of battery development and forecast battery price decline until 2030. The battery prices have experienced a strong decline with a 73% price drop since 2010, from $1000 per kWh to $273 in 2016. The forecast adopts the historical learning rate of 19% YoY for future expectations. Hence, the forecast starts at $273/kWh in 2016 and declines to $109/kWh by 2025 and $73/kWh in 2030.

The Battery scenario, as seen in Figure 11, represents this continued decline in battery price, and reaches $73/kWh in 2030 compared to the more pessimistic forecast used in the Control scenario where battery prices only declines to $173/kWh in 2030.
The *Battery* scenario shows a market penetration of 63.0% for PHEVs at the end of the simulation run. As visible in Figure 11, PHEVs reach the same market penetration as in the *Control* scenario, but is during the period from 2020 to 2029 higher than the baseline. Looking at BEV diffusion, it follows the *Control* until 2026 where it starts to deviate and ends at 26.1%, a 24% increase (*Control*: 21.1%; *Battery Cost*: 26.1%).

### 6.3.4 Technology - Fast Charge Probability

Range anxiety often associated with EVs is closely connected to insufficient charging infrastructure. The *Fast Charge Probability* scenario, depicted in Figure 12, illustrates the effect of expanded infrastructure development by increasing the probability that an agent has access to fast charging stations. The probability that agents have access to fast chargers for their daily travels increase linearly from the current 56% to 95% until 2020, compared to the *Control* scenario which reaches 95% first in 2030.
Under the conditions for the Fast Charge Probability scenario, the results indicate a 63.6% market share for PHEVs, and 23.9% for BEVs at the end of the simulation as seen in Figure 12. The PHEV diffusion rate follows the Control scenario, whereas BEVs start to deviate from 2020, with a 12.9% increase compared to the Control scenario at the end of the simulation run (Control: 21.1; Fast Charge Probability: 23.9%).

6.3.5 Technology - Fuel Cost

Over list price and depreciation, operating cost is the third largest cost for owning a vehicle (Hagman et al., 2016), and therefore important for the overall satisfaction with the vehicle and fuel technology. To represent changes in operating cost, alterations in fuel prices have been made in the Fuel Cost scenario. The change is an equal decrease in fast charging cost along with an increase in gasoline cost by €0.005/km per year starting after three years, in 2019.
The Fuel Cost scenario shown in Figure 13 demonstrates a 46.0% penetration for PHEVs and 40.0% for BEVs in 2030. This result is a 27.3% decrease for PHEVs and an 89.1% increase in BEV diffusion from the Control scenario. The PHEV sales start to drop in 2018 under the Control levels, partly captured by ICEs before BEVs, on the other hand, start to deviate and capture market shares in 2022.

6.4 Combination of Factors

This section presents the results derived from scenarios when combining multiple factors, which let us investigate if a combination of factors affect the diffusion more than then summation of isolated factors. The results are like previous subsections compared to the Control scenario and adjusted in two dimensions, i.e. policy and technology development.

6.4.1 Combination - Fast Charge and Fuel Cost

The CombiFastCharge represents a combination of Fast Charge Probability and Fuel Cost reduction scenarios, i.e. 95% probability of an agent having access to fast charge infrastructure in 2020, up from 56% in 2016, and fuel cost reductions by €0.005/kWh for fast charging and €0.005/km per year increase for gasoline.
The result from the Combination Fast Charge scenario depicted in Figure 14 shows a 51.0% market penetration for PHEVs, and 39.8% for BEVs. PHEVs are aligned with the Control scenario until 2023 where it starts to deviate considerably, ending at 19.4% lower than the Control scenario. BEVs start to diverge already in 2019 and increase steadily over the simulation period, ending at 88.2% higher than the Control scenario.

### 6.4.2 Combination - All

The Combination All represents a combination of all factors made in the isolated factor scenarios, including both the policy and technology dimension. This means that the scenario include: penalizing tax on vehicles that have emissions over 50 gCO$_2$/km, fast decline in battery prices, increased fuel cost, and increased fast charge probability.
The Combination All scenario results in a 47.6% penetration for PHEVs and 35.5% in BEVs at the end of the simulation, as seen in Figure 15. This renders a 24.9% decrease in PHEVs and 67.9% increase in BEVs comparing to the Control scenario. The diffusion of BEVs start to pick up in mid-2018 and capturing market shares from ICEs. The PHEV market penetration initially follows the Control scenario but start to decrease in late 2021 captured by the increase in BEVs on the market.

6.4.3 Combination - All:BEV

The Combination All:BEV represents a combination of all factors are made in the isolated factor scenarios, but targeted to favor only BEVs. Here, the scenario is expanded further from the previous, including: penalizing tax on vehicles that have emissions, fast decline in battery prices, increased fast charge probability, decrease in fast charge expenses along with excises on gasoline price.
6 RESULTS

Figure 16. Diffusion of EVs in the Combination All:BEV scenario over the years 2016-2030. The solid lines represent the average value, and the faded area standard deviation at the point in time.

Results from the Combination All:BEV scenario depicted in Figure 16 show a 41.1% market penetration for PHEVs and 51.3% for BEVs in the end of the simulation. Compared to the Control scenario, results differ greatly. PHEVs market penetration drop below the Control scenario by 39.2%, whereas the BEVs capture the market share and reach 142.8% higher penetration than the Control. The BEV penetration surpasses PHEVs mid-2028.

6.5 Social Dimension

As seen in Figenbaum and Kolbenstvedt (2015b), social interactions between agents have a strong effect on agents propensity to purchase an EV. Considering that the Consumat framework builds on the premise that the agents’ social network consists of similar others in terms of for instance age, income, and opinions; and that emergent behavior arise through agent-to-agent interactions, creating network externalities, changes in the social dimensions will thus affect the diffusion process. By initializing the model with a stratified sample only including current EV owners, we ensure certain characteristics and a more homogeneous sample, which changes the normative pressures and thus affecting the later adopter groups categorized by Rogers (1962). Changes enable investigation of network effects, result sensitivities on individual data, and elasticities inherent with agent-based models as discussed by Al-Alawi and Bradley (2013).

6.5.1 Social - Control Scenario

The Control Social scenario builds on the exact same conditions as in the Control case, with the only exception that the agents are initialized with a stratified sample. These agents, are more homogeneous than the stratified random sample used in the other scenarios that are representative of the Norwegian population. Since the stratified sample of agents already own, or live in a household that owns an EV, they have attributes which imply an increased propensity to buy an EV in the future as well.
Under the conditions of the Control Social scenario, the results depicted in Figure 17 show a large deviation from the Control scenario both for BEVs and PHEVs. The market penetration for PHEVs are 36.0%, and BEVs 40.1% at the end of the simulation run, i.e. respectively 66.5% lower and and 89.5% higher than the outcome in the Control scenario.

6.5.2 Social - Combination All:BEV

The Combination All:BEV Social scenario, is like the Control Social scenario, initialized with a pro-EV stratified sample. The scenario represents a combination of all factors, targeted to favor BEVs. ImPLYing the scenario include: penalizing tax on vehicles that have emissions, fast decline in battery prices, increased fast charging probability, and a decrease in fast charging expenses along with excise on gasoline.
Figure 18. Diffusion of EVs in the Combination ALL:BEV Social scenario over the years 2016-2030. The solid lines represent the average value, and the faded area standard deviation at the point in time.

The results shown in Figure 18 illustrate large discrepancies from the Control scenario, and widespread EV diffusion already instantly. PHEVs only reach a 26.7% penetration at the end of the simulation, which is 57.9% less than the Control scenario. The difference is captured by BEVs which increase steadily and ends with a 66.6% market share in 2030, a 215.1% increase from the Control scenario.

6.6 Results Overview

This section provides an overview of the results derived from the simulations, for easier comparative analysis. Furthermore, average fleet emissions [gCO₂/km] from the scenarios are depicted, showing the environmental impact for each scenario.

6.6.1 Fuel Type Partition In 2030

In order to easily compare the outcome of all scenario simulations, the diffusion and fuel type partition in 2030 were compiled.
By comparing the different scenarios shown in Figure 19, we see that the diffusion of BEVs varies from 21% in the Control scenario to 67% in the Combination ALL:BEV Social scenario. The PHEV diffusion is relatively similar ranging from 51-64% in all scenarios except the CombiBEV and both Social scenarios, where it is as low as 27% in favor of BEVs.

### 6.6.2 Average Emissions

In addition to the different partitions of EVs, a comparison of the tailpipe emissions was made to demonstrate the environmental impact for each respective scenario. We can see from Figure 20 how the emissions of the fleet vary depending on the different fuel type partition. The figure depicts the average emissions for the entire vehicle fleet at three different points in time: 2016, 2020 and 2030.

---

**Figure 19.** Diffusion in the different scenarios sorted on BEV diffusion in the end of the simulation, year 2030
Emissions vary considerably between the different scenarios. The average emissions in 2016 are initially approximately 114 gCO$_2$/km. In 2020, depending on the scenario the emissions vary between 91-105 gCO$_2$/km. At the end of the simulation, in 2030, emissions ranges 35-73 gCO$_2$/km. This implicates that a combination of factors will be needed to reach the emissions target of 85 gCO$_2$/km in 2020. Changes between scenarios might seem modest, but considering the cumulative decrease when extrapolating on fleet level, where passenger cars travel approximately 34.5 billion km per year (SSB, 2017), we see that a decrease of 5 gCO$_2$/km, renders in savings of 172 500 tons CO$_2$ per year.

### 6.7 Used Car Market

The simulation results show that the used car market for EVs experiences an increase of BEVs and PHEVs approximately three years after the start of the simulation in the Control scenario, as seen in Figure 21. At the introduction of BEVs on the used car market, there is a higher proportional rate of diffusion among buyers of used vehicles than the overall diffusion in the Control scenario, ending at 44.8% diffusion of used BEVs. Meanwhile, PHEVs achieve only 33.5% of the used market. In order to gain more knowledge regarding this aspect, statistics on the used car market in Norway are calculated from data obtained from Statistics Norway (SSB) and from the sales platform provider FINN. The data from SSB contains information on the number of registered vehicles by fuel type. The largest marketplaces for used cars, FINN, has provided us with data on the used car ads including quantities, price, mileage, and fuel type. By combining the results of the simulation and real world data, we can achieve better insight into the market dynamics of the used car market. However, due to inconsistencies in the data, PHEVs are omitted from this part of the study.
6.7.1 Market Size Changes

During the years 2011 to 2016 the total amount of registered cars experienced a growth of 11.7%, where BEVs, PHEVs, and diesel cars had a positive contribution, as shown in Figure 22.

Diesel cars constituted a large part with an increase by 40.3%, where the year-on-year (YoY) increase have gone from 14.9% in 2011 to 5.0% in 2016. The largest change in YoY, ΔYoY, occurred between 2011-2012 where the YoY went down from 14.9% to 11.3% for diesels. Moreover, the total number of registered gasoline cars have been declining during the period by 17.9%
with a $\Delta$ YoY ranging from -3.6% to -7.3%, where the larger final year decrease is related to the increase in hybrids (which previously were categorized as gasoline cars), amounting to nearly 80 000 at the end of 2016. During the same period, BEVs have increased by 2396.4%, going from 3849 to 96086 cars, passing 100 000 in February 2017. BEVs had the largest $\Delta$ YoY 2011-2012 amounting to 17.7%.

Just as the number of registered vehicles, the used car market experienced a similar growth of 13.0% in trades (2011-2016). This is lower than the increase in advertised vehicles on FINN, as seen in Figure 23, which was 34% in the same period of time.

![Figure 23. Number of used car ads on FINN, 2011-2016](image)

Like the total amount of registered vehicles, the number of used diesel cars ads increased by 37.9%. As for gasoline cars on the used car market, the number increased by 9.2%. Like the overall registers, the used car ads for BEVs and hybrids increased by respectively 1657.3% and 1179.8%.

### 6.7.2 Median Price

An indicator for how the depreciation of used vehicles occurs is the median price change of the car ads by fuel type and year model as seen in Figure 24 and Figure 25. Note that the newest models each year is the "next years model", e.g. for 2011 the 2012 year models are the latest, as it is common to release coming year models in advance.

![Figure 24](image)

![Figure 25](image)
Figure 24. Median price development of used cars by fuel type and year model on FINN. Year models 2011-2013

Figure 25. Median price development of used cars by fuel type and year model on FINN. Year models 2014-2016

The median prices of diesel and gasoline cars 2011-2016, follow general car depreciation curves, matching logarithmic, or exponential depreciation. As such, a car loses its value most the first year which is apparent from Figure 24 and Figure 25. The first year depreciation is larger for newer models from the years 2014-2016, BEVs exempted. To shed more insight into the area of depreciation, Figure 26 shows the first year median depreciation with linear and logarithmic forecasting for the coming five years.
Figure 26. First year depreciation of cars by fuel type and year model. Numbers for year 2017 and forward are linearly forecasted together with logarithmic trend

Of the non-forecasted values, diesel cars lost most the first year in 2014 (-21%), closely followed by 2013 (-19%) and 2016 (-17%). The linear trend as well as the logarithmic shows that the depreciation is expected to increase. The same goes for gasoline cars, although the first year depreciation does not amount to the loss diesel cars experienced. However, in terms of percentages, gasoline cars lost 20% in 2015, 18% in 2016, and 16% in 2011. BEVs had a median price depreciation of 18% in 2011, which turned positive with 1% for models 2012. The second largest decrease in price for BEVs occurred in 2015 with a loss of 11%. The trend for BEV depreciation is also that value losses will be higher coming years, although being more stable than for ICE vehicles.
7 Analysis

This chapter will present an analysis of the results presented in Chapter 6. First, the isolated effects of policies and technological development are analyzed. Secondly, how combinations of different factors affect the diffusion. Thirdly, the social aspect is covered. Lastly, the results obtained regarding the used car market are assessed.

7.1 Isolated Effects

When comparing isolated effects in the single-adjustment scenarios, there are only a slight deviations from the Control scenario. Looking at the different policy stringencies which are represented in Emissions Tax and Emissions Tax BEV, we see the results vary considerably between the two. The Emissions Tax BEV scenario, where only zero emission vehicles are exempted from the penalizing tax, show a much higher BEV adoption penetration. This is explained by a decreased cost satisfaction that arises due to increased operating costs for agents owning vehicles emitting CO\textsubscript{2}. The increase in ICEs in the Emissions Tax BEV scenario is related to the fact that the small difference in operating cost between PHEVs and ICEs does not outweigh the difference in list price, where the former is more expensive than the latter.

Interestingly, even though the penalizing tax is introduced in mid 2017, we do not see the effect on the diffusion until March 2019. As previously mentioned, Figenbaum and Kolbenstvedt (2015a) identified similar dynamics when comparing Norway with the UK market with regard to fiscal incentive schemes, and argue that the discrepancy in effectiveness could be explained by the time frame of the incentive scheme, due to the rather slow turnover rate of the vehicle fleet. This illuminates to why incentive schemes need to be upheld for a long period of time to give visible effect on an aggregated level. Even though new sales, which often acts as a proxy for diffusion, shows significant increases, changes on a fleet level is a slow process due to its excessive size. This delayed effect is also apparent in the Battery scenario. Under the conditions of the Battery scenario, BEV diffusion first starts to diverge in 2026, when battery prices reach $130/kWh. However, considering the inertia of the system, i.e. vehicle turnover rate, it indicates that the actual BEV adoption threshold is reached before battery cost hit $130/kWh. For PHEVs on the other hand, we start to see a positive deviation already in 2020. This could be explained by the fact that the reduced battery cost initially favors PHEVs as the reduction in price does not outweigh the perceived negative surplus BEVs have in comparison at the point in time.

Access to sufficient charging infrastructure is, as previous studies (see e.g. Adepetu et al. 2016; Shafiei et al., 2012) and the results from the Fast Charge Probability scenario indicate, necessary for consumers to start considering buying an electric vehicle. If agents are able to drive their daily distances without the trouble of charging, their overall perceived and experienced satisfaction to the fuel technology increases. As in the other single-adjustment scenarios, there is a lag before we can identify changes on fleet level. As previously contended, the threshold is likely reached before reaching 95% probability in 2020 due to the delay, caused by the inertia of the system. Since PHEVs do not use fast chargers, there is no identifiable difference from the Control scenario.

Looking at the results from the Fuel Cost scenario which affects the operating cost by altering the fuel cost, and thus the total cost, we see that with easings on fast charging and excise on gasoline, agents turn toward the more economically viable BEVs in 2022. However, this does not indicate that agents start to consider total cost of ownership. Seeing how the model is built, the agents form their decisions based on historical experience of satisfaction rather than preventive rational
reasoning around total cost of ownership. Therefore we lack the ability to capture this aspect in the simulation. However, even though total cost of ownership would be a better indication and proxy for vehicle purchase, it is often overseen by consumers due to the challenge to estimate cumulative driving distances, fuel usage, and maintenance cost; thus have difficulties weighing the tradeoffs between different alternatives (Eppstein et al., 2011; Hagman et al., 2016). Furthermore, as contended by Turrentine and Kurani (2007), consumers who purchase eco-innovations have a tendency to use non-rational reasoning, i.e. perceived greenness, over financial reasons.

7.2 Combination of Factors
In comparison to the single-adjustment scenarios, we observe positive synergetic effects on the diffusion rates when factors are combined. The underlying reason for this added effect could be explained by a combination of reaching a certain threshold and the positive feedback loops that emerge as a result of the social interactions between agents, i.e. the homophily tendencies between individuals, meaning that individuals have an inclination to associate and bond with similar others. This implies that the agents will converge towards a mutual interpretation and therefore increase the rate at which a specific technology diffuses in line with Rogers diffusion of innovations theory.

Looking at the results from the combination of the Fast Charge Probability and Fuel Cost scenarios, the synergy effect is very apparent for BEVs, where the sales start to take off in 2019 and continue to diffuse in a stable pace throughout the simulation period. When comparing to the single-adjustment scenarios, we see that with a combination of measures, it is possible to both expedite and increase the diffusion of BEVs on the market. On the contrary, PHEVs naturally decrease from the Control scenario, captured by the increase in BEVs. This is a consequence of the BEV targeted measures which are enough to offset the negative effects otherwise associated with BEVs.

When combining all factors in the Combination All and Combination All:BEV scenarios, the highest overall EV diffusion is reached at 92% in 2030. What differs is the BEV diffusion depending on how the easings are targeted. In both cases, BEV penetration increases over the Control scenario, however, as seen when comparing the cases we see that when easings are made for both PHEVs and BEV there is a decrease in market penetration for BEVs from 51% to 35%. This consequently results in, on average, 20 gCO₂/km higher emissions at the end of the simulation period than if easings only targeted BEVs.

During the Combination All:BEV scenario, we observe a discrepancy in the diffusion in 2019, where BEVs suddenly increase with a consequent drop in PHEV. This sudden change is due to a large portion of BEV lease contracts expiring which renders an influx on the used car market. This subsequently leads to more models and price competitive alternatives for the agents that purchase these vehicles on the used car market.

7.3 Social Aspect of Diffusion
Changes in the social dimension, or in other words changes to a stratified, more homogeneous and pro-EV, set of agents, illustrate result sensitivities toward individual data and elasticities that are inherent with agent-based models, as discussed by Al-Alawi and Bradley (2013). The difference in individual data from the stratified random sample used for the other scenarios renders in overall lower thresholds for adopting to BEVs. Consequently, more consumers adopt to the technology. In turn, alters the normative pressure on the market as consumers consolidate
towards a mutual understanding, making EVs a viable option for later adopter groups that put more value to normative influences (Rogers, 1962).

The Combination All:BEV Social scenario diffusion rates for BEVs imply that a majority of the agents surpass the threshold for buying an electric vehicle, which consequently renders positive feedback from interactions between agents. In addition, we can categorize the stratified sample as innovators and early adopters according to Rogers (1962). The behavior displayed is consistent with the theories of the Consumat framework (Jager, 2000), which suggests that these type of agents are more heavily relying on the needs for social belonging and personal preference, i.e. taking risks and being innovative.

Another interesting aspect we can derive from the Social scenarios is that if uncertainties around EVs, e.g. range anxiety and future technology developments are reduced, we might expect a faster adoption rate as EVs will become a viable option for larger adopter groups, as the uncertainty tolerance of agents correlates with Rogers (1962) adopter groups. Instead, other factors will become the "new" uncertainties, such as e.g. autonomous driving which needs to be adopted by a set of people, i.e. early adopter groups, before it gets on a normative basis and accepted by the majority.

7.4 Used Car Market

In order to answer research question 2b, ‘How is the used car market affected by the diffusion of electric vehicles?’ data from Statistics Norway and from the online marketplace FINN were analyzed as a complement to the agent-based model, thereby gaining more insight into the dynamics of the Norwegian used car market. The results presented in Chapter 6.7, show that the used car market experiences approximately the same development as the overall fleet in Norway. The reason for this is mainly that the used car market is nearly three times as large as the new sales market. This implicates that the used car market registrations will affect the overall fuel type partition in Norway more than new sales. However, the exception is apparent in EVs. The growth is initiated from new sales, as the technology is relatively novel and characterized by a high development rate. The new sales are currently driven by early adopter groups, but as EVs enter the used car market, later adopter groups will perceive EVs as a viable option, due to price depreciation and the technology maturity, thus becoming more accepted by the society. Therefore, an accelerated increase in EV penetration is expected. Moreover, as lease agents replace their car when the lease period is over, growth is accelerated at a higher pace than if everyone privately purchased their vehicle. It is a contributing factor to EV diffusion in the simulated results, particularly in the Combination All:BEV scenario, where used car agents favor BEVs over other fuel types when many vehicles are introduced on the used market when lease agents upgrade their vehicles after the lease contracts expire.

As the demand on the Norwegian market for BEVs have been running high, the relatively low depreciation can be explained. Also, what can be seen in the number of registered vehicles is that the largest absolute value in change for diesel ($\Delta$YoY of $\{-3.6\%\}$), corresponding to 60 800 cars, occurred in 2011-2012. The same years, BEVs experienced the largest $\Delta$YoY increase of 17.7% and consequently the BEV fleet grew with 4112 cars. Here, we can assume that a small portion of the consumers considering the purchase of a diesel car, an otherwise increasing fleet, instead chose a BEV. In addition, the depreciation numbers and fluctuations as seen in Figure 26, especially the “positive” depreciation in 2012 model BEVs, can be partially explained by the small number of advertised cars, ranging from 8 ads of 2012 models in 2011 to 3413 ads of the newest model in
2016. Hence, in the lower range there is a higher uncertainty, and extremes are statistically more occurring (Kahneman, 2011). Nevertheless, BNEF (2017) found that the initial value retention of Norway’s most popular models, Nissan Leaf and Tesla Model S, is comparatively high and range from 75% to 90% respectively, which is relatively consistent with the first year median depreciation we found ranging from (+)1% to -18%. Moreover, as more lease cars of these two popular models enters the used market in 2017, one can expect a growing interest by consumers in switching to electric as the supply is increased and the experiences of previous owners become well-known, which corresponds to the agents in our simulations. Still, uncertainties about the technology and the quickly changing performance of EVs, might affect the purchase decisions on the used car market. This aspect coincides with the mindset of the more hesitant adopter groups, i.e. late majority and laggards, that want to wait out the uncertainties.

Another interesting aspect of the median prices is that they have increased, where the median introduction price for 2016 diesel cars was as high as 654 000 NOK. That is nearly 180 000 more than the equivalent for 2012 diesel cars introduced in 2011. This could be an effect of the combination of increased tax on ICE vehicles and technology developments of both engine efficiency, emission levels, safety, and electronic equipment in the cars, adding to higher resale prices. The automotive market have only experienced comparatively incremental changes up until now, where new trends such as connected car technologies, advanced electronic control systems and autonomous driving technology are replacing preceding solutions at a fast pace. As a result, vehicles not possessing these solutions might experience a lower value retention on the used car market. Consequently, the increasingly higher first year depreciations presented in Figure 26 might be connected to this aspect. The other part, tax policy and regulations implying higher costs for owning an ICE car compared to an EV might also have an effect on the depreciation amount. Also, the benefits in place for foremost BEVs such as bus lane access, gives consumer further incentives to switch fuel type. Such benefits are however harder to estimate the value of, as they satisfy the consumer more variably depending on living location, driving frequency, work hours etc.

The linear forecast implicates that an increased depreciation rate is expected over the following years for ICEs, diesel cars in particular. Since this is based on historical data, we might expect an accelerated depreciation as EVs start to capture more market share, as seen in the simulations. However, it is also important to consider that if prices decline on ICE vehicles on the used car market they become more economically viable and thus the demand increase, which stabilizes the price, despite the environmental benefits the consumer otherwise would get with an EV. This will consequently impede EV adoption on the second hand market. What could have larger consequences on ICE value is external legislation and regulations which prohibit or excise vehicles with emissions, similar to the diesel bans in large cities in 2025 (Harvey, 2016). In the case of a highly regulated market, it is important to consider the ramifications the strict regulations have on the economy and its consumers, and consequently the diffusion of more environmental alternatives. If ICEs, that can be considered a relatively large investment for most consumers, would become obsolete instantly due to the regulations, their residual value would be no more than the scrap value of the vehicle. This would affect the consumers negatively, as they then would not have the same economic possibilities when buying a new vehicle.

7.5 Validation of Results
As previously mentioned, this study puts emphasis on analytical assessment of factors, rather than to yield quantitatively accurate future predictions. Therefore, it is the change different factors cause, rather than exact figures in each scenario that is of importance.
Looking at the simulation results indicate a very sudden increase of EVs in the beginning for all scenarios. When comparing to empirical data this sudden change could be considered irregular and implicate some instability in the simulation during the first 52 ticks before it stabilizes. This may be explained by agents having enough funds for purchasing a new vehicle, in addition to initially being unsatisfied with their current one. If we look at the average duration at which agents own their current vehicle in the simulation runs, we see that the duration initially is 5.2 years, dropping rapidly to 3.3 years during the first 52 ticks, before it stabilizes and starts to increase back up again and end at 6.4 years in 2030, as seen in Figure 27. Comparing this with the data from FINN, we see that is is a plausible length of ownership as the weighted average age of vehicles advertised were six years. In addition, the most frequent ages of advertised vehicles were three, four and five years old. Hence, with a large amount of lease vehicles being put on the market after three years along with continuous replacement of ICE vehicles to new EVs, the suggested ownership age of 5.2 years is justified. However, not the sudden decrease in ownership duration. The decrease renders growth in turnover of the vehicle fleet, and therefore affects the diffusion of new technology positively, posed that consumers are willing to adopt to it.

When ownership duration starts to stabilize, the diffusion rate returns to reasonable levels, compared to empirical data. In recent years, there has been an upsurge of EVs on leading markets, especially in Norway. Due to the low total number of EVs, changes in fleet size have been very large in recent years, with increases between 60-115% per year. In contrast to recent years development, our results show more moderate changes in fleet size, which is to be expected as it grows. This effect is already seen in the empirical data, where the change in fleet size was 115% between 2013-2014 and only 38% between 2015-2016. Why we deem the diffusion rate as reasonable, as of the inertia of the system, i.e. the automotive market.

Prices on the used car market have not yet been stabilized for EVs and are still a bit volatile. This, in addition to the small number of data points available renders in that extremes are more common (Kahneman, 2011) and thus we lose validity when analyzing the first year depreciations. Thus, there is a need more data points to present valid results regarding the used market for EVs,
for example positive median price depreciation for BEVs in 2012 is unlikely to have occurred for any model.

In contrast, the number of ICEs, gasoline and diesel cars, that make up the median price data from FINN are more representative samples why it should give an indication of the most common depreciations of these vehicles. Of course, further analysis should be made looking at specific car models as the data used here aggregates all vehicles regardless of type and style, e.g. luxury, sedan, combi. This lies beyond the scope of this study.
8 Discussion and Conclusions

This chapter provides a discussion of the results and analysis made, where we present the conclusions of the study. Moreover, we look back at the purpose and how the research questions have been answered. We end by summarizing the most important findings.

8.1 Review of Purpose

The purpose of this thesis was to investigate the diffusion of electric vehicles in the Norwegian market and assess the factors that affect the adoption rate. In order to fulfill this purpose, two main research questions were formulated:

1. How does an agent-based model describe the diffusion of electric vehicles?
2. What can we learn about future developments in the Norwegian car market?

These two research questions (RQs) are answered in the following sections, subsequent to their respective sub-questions.

8.2 Diffusion Factors and Their Combination

RQ 1a. How do policies, technological, and social factors affect the diffusion of electric vehicles?

Through the literature review and research institute report readings, we identified that what affects the diffusion of electric vehicles were policy and technology developments together with social interaction. These were subsequently investigated by comparing different scenario simulations in the agent-based model. We found that policy stringencies have a considerable influence on EV adoption as taxation of emissions results in lower cost satisfaction for agents that drive vehicles with high emissions. As a result, the zero-emission BEVs are favored when the strict taxes are implemented. Moreover, the operating cost of PHEVs are quite similar to those of ICEs, which in the case of incentives targeted to only BEVs, render that some might not buy a PHEV as the list prices generally are higher than ICE prices. Consequently, the simulation for the scenario where only BEVs are exempted, generated a higher ICE number. In addition, the diffusion pattern for EVs when penalizing taxes are implemented shows that there is a lag in diffusion of the aggregated fleet, as the excessive size of the system entails certain inertia. Hence, political incentives need to have extended time frames in order to sustain diffusion.

Besides the policy effects on diffusion we investigated the technological aspect. Political incentives and plans are as well-known, permeated by certain inertia, as bureaucracy and thorough investigation often take part in the decision-making process. Once incentives are in place, they span several years before they are revised or removed. Technology on the other hand is developing at a much higher pace, which leads us to the conclusion that the technology scenarios are prone to change more over time than the policy scenarios. It is however apparent that technological developments of EVs and charging infrastructure are essential for widespread adoption. Looking at recent years developments of EVs, the battery capacity and range improvements together with faster charging times are factors that play a vital role if consumers are to adopt the innovation. Similarly, these factors correlate with the satisfaction of the agents in the simulations. We saw that BEV adoption have a higher correlation with reduced battery prices and improved performance, which is natural as PHEVs total ranges are not purely relying on the battery. Furthermore, as PHEVs do not require charging while on the road for longer distances, they are not affected by charging infrastructure developments and locations in the same way of BEVs.
Discussion and Conclusions

Social interaction has a large impact on the diffusion. Through the initiated change in the sample of agents, we saw that by aligning consumer sentiment about EVs there is a possibility to achieve faster diffusion. Looking at Rogers (2003) definition of diffusion 'the process by which an innovation is communicated through certain channels over time among members of a social system', it implies that when consumer sentiment is aligned, the communication will converge faster towards a mutual perception. Consequently, changing the normative pressure on the market, making later adopter groups more likely to overcome the initial uncertainties they might have. However, technology development and policies still have a large impact as they change and create new uncertainties. More so, as automakers are widely reinventing their product portfolios, adding EVs to the product mix.

RQ 1b. What effects on the diffusion emerge when combining several factors simultaneously?
The results indicate that under the condition of isolated adjustments the positive effects are not generally enough to outweigh the negative surplus of BEVs compared to PHEVs, and thus have small impact on the overall diffusion. An interesting finding derived from the single adjustment scenarios is that even though changes are made instantly there is a delay before its effectiveness is seen on the market, which could partially explain the advantage Norway has over other markets, as incentive schemes have been in place since 1990 (Figenbaum, 2015a). Of the single measures in the simulation, we saw that the technology driven scenarios feature slightly higher diffusion rates than pure political incentives.

Combined measures, on the other hand, create synergetic effects that both expedite and increase EV adoption. Looking into the previous five years’ considerable growth in EVs, it shows that the previously dubious technology is catching up to the incentives in place in Norway, creating a combined measure. The reinforcing effect arises from the combination of more agents passing the adoption threshold along with the positive feedback loops and network externalities that emerge as a result of the increased adoption.

Furthermore, we found that when easings are targeted towards both PHEVs or BEVs, the former tend to benefit more, than if the BEVs are targeted exclusively. Consequently, the result is overall higher emissions, thus impeding the emission goal to reach 85 gCO\textsubscript{2}/km in 2020. It is thus in the interest of policymakers to consider how the incentives are directed. However, targeting both types impacts the overall diffusion of EVs more, meaning less ICEs on the road. In that case PHEVs could act as a stepping stone towards buying a BEV.

RQ 1. How does an agent-based model describe the diffusion of electric vehicles?
The answers to the two sub-questions combined allows us to address the first main research question, which shows that in the agent-based model, the impact of the political and technology dimensions of EV diffusion are reciprocally interdependent, for widespread EV diffusion.

The results from the simulations showed us that political incentives alone do not hold the power to make consumers rapidly switch to new technology if it is deemed un-superior or unable to satisfy the needs of the individual. Technology developments are more likely to impact the diffusion significantly alone, although only reaching innovators and early adopters as the adoption threshold is not surpassed without political incentives. Moreover, diffusion of EVs is more prone to occur in societies where individuals hold similar needs, personality, status, and income which we can conclude from the scenario variations where a stratified, homogeneous, sample was used. The positive feedback loops in the social networks allows for an increased willingness to adopt new technology, as it forms a normative behavior in the population.
8.3 Automotive Market Expectations

RQ 2a. What will the diffusion of electric vehicles look like until 2030?
The simulations of agents representative of the Norwegian car buyer allowed us to investigate how the automotive market may evolve until 2030 considering various impact of factors. Chapter 6 presented the simulated results in each scenario. What can be concluded is that in the span of all scenarios, EV diffusion in the car fleet 2030 span ranges from 76% to 93% where BEVs constitute 21% to 67%, while PHEVs constitute 27% to 64% of the total fleet (Figure 19). In other words, in the best case scenario for EVs (not counting the Combination All:BEV Social scenario with the unrepresentative, stratified, agent sample), they will make up 92% while ICEs hold 8%. In the worst case scenario, EVs make up 76% while ICEs hold 24%. We saw that the higher ranges of diffusion are achieved when measures are combined, while the lower ranges occur when only limited political incentives are in place.

As the simulations were running on a constant quota of new car buyers, lease holders, and used car buyers based on the current setting in Norway, one can point out that if these structures were to change due to developments in the various scenarios, the outcomes would differ. A higher proportion of lease agents would mean shorter ownership times or vice versa. Consequently, the rate in which the fleet could be turned over would be higher respectively lower, and thus enable a faster transition towards new technologies as the system becomes more agile.

RQ 2b. How is the used car market affected by the diffusion of electric vehicles?
What can be seen from our results is that the diffusion of EVs on the used car market follows the diffusion of the overall market. However, due to a high demand for BEVs, the median prices and depreciation of this type of used cars have been kept relatively high compared to diesel and gasoline cars, which have shown increased first year depreciations since 2011. Nevertheless, as more EVs will enter the used car market, prices are expected to move towards those of ICEs, allowing a new segment of customers to consider an EV when purchasing a vehicle. Especially if new BEV models have significant range improvements, pressuring older BEVs with short ranges to lower residual values. Regardless of fuel technology, vehicles in the near future are going to experience a technological revolution featured by collision sensor systems, autonomous driving, and connected car technologies for example allowing software updates wirelessly. EVs that have advanced battery control systems are well positioned to gain advantage from the latter.

Moreover, as lease car contract usually span three years and private owners average ownership exceeds this, we expect that the used car market will experience an influx of the most popular BEV models sold in 2013 and 2014, the Nissan Leaf and Tesla Model S which according to our findings in the simulation and agent behavior, should contribute to an increase in fleet penetration of EVs. In line with the Rogers’ diffusion of innovation theories and the Consumat framework, a growing EV fleet including these models, could allow later adopter groups to switch to an electric vehicle as they become more normative and diffused in the prospective buyer’s social network. What is more, sustained and increased incentives along with technology developments as shown in the scenario simulations will naturally affect the uptake on the used market just like the new sales.

RQ 2. What can we learn about future developments in the Norwegian car market?
By answering the two sub-questions above, the second main research question could be evaluated. We found that continued incentives along with technology developments will affect the Norwegian market most as shown in the combination scenario where all factors are in favor of EV adoption, resulting in a maximum diffusion of EVs reaching 92% in 2030 consisting mainly by BEVs (51%).
In that scenario, the average emission levels were at 76.8 gCO$_2$/km, below the Norwegian target of 85 gCO$_2$/km in 2020, reaching 48.8 gCO$_2$/km in 2030.

From our analysis of the simulation results, we have concluded that policy and foremost technology advancements are encouraging innovators and early adopters to replace their vehicles, creating an influx of EVs on the used car market together with lease cars. This will allow the early and late majority to consider an EV, as sentiment is improved and driver experiences are communicated in the social networks.

Compared to today’s values of used EVs, an increased supply together with updated battery technology and range are expected to make depreciation curves of used EVs approach those of ICEs. We found that the first year depreciations are expected to increase for ICEs, but should be stabilized by the market, due to the law of supply and demand if not regulations prohibit ICEs on the roads.

### 8.4 Conclusions

Although new sales of EVs are increasing, the market is still coupled with uncertainty and is strongly dependent on policy schemes and technology advancements to challenge and disrupt the dominance of conventional vehicles. Using an agent-based model, we have investigated how different factors and the interplay between combined sets of factors affect the diffusion rate of EVs. Additionally, retention values of used vehicles have been analyzed and forecasted which were used in conjunction with the results derived from simulation runs.

To conclude, the purpose of this thesis was to investigate the diffusion of electric vehicles in the Norwegian market and assess the factors that affect the adoption rate. The most important findings we derive from the study are:

- Single factors have limited effect on the diffusion, whereas a combination of factors create synergetic effects that both expedite and increase EV adoption rate. While policy incentives and technology development, isolated and combined, can affect the adoption, social interaction between consumers can expedite diffusion even further.

- By 2030, the most progressive scenario shows that up to 92% of the Norwegian car fleet could be electric, where 51% would be pure battery electric vehicles.

- If the Norwegian 2020 emissions target is to be reached, a combination of factors is necessary. Furthermore, if easings are exclusively targeted towards BEVs, overall emissions can be reduced compared to if both PHEVs and BEVs are alleviated.

- The used car market have experienced an influx of electric vehicles recent years which is expected to increase further as more lease cars become available. Median prices of diesel and gasoline vehicles on the used market have experienced increased first year depreciation. Accelerated first year value depreciation is expected in coming years, although stabilized by the market.
9 Future Work and Stakeholder Implications

This chapter presents future research areas and recommendations for stakeholders. These are based on the experiences we have gained during the research process as well as on the results and analysis.

9.1 Future Work

The nonlinear and multi-level interactions between consumers and the myriad of exogenous factors that affect the outcome of the automotive industry renders in a complex environment which has to be simplified in order to derive insights from it. The continuous updates of consumer sentiment, policy, and technology solutions allows for frequently updated data inputs, modifications of scenarios and forecast models in order to reflect reality as close as possible.

- Further research using agent-based modeling could try to capture more accurate consumer preferences in the Consumat framework, and develop the model to include these advancements. There are numerous needs and wants that could be taken into account, that are not included here due to the complexity and scope of the thesis. Such preferences could be appearance, safety features, brand preference, etc. Moreover, adding a dimension representing the fact that most households in Norway own more than one vehicle, could further be used to achieve insight into the purchase behavior.

- For the used car market, more detailed data on specific models could be investigated if included in the model and the compared to similar historic data, such as ours from FINN. As previously mentioned, there are possibilities to deep-dive into data on specific features of car models and their respective states when sold on the used market. Even more so when additional EVs are present without existing battery warranties, which may change the used car buyers view on how cars, especially BEVs, should be priced.

9.2 Stakeholder Implications

The stakeholder implications refer to the practical use of the findings from this study. As agent-based modeling is performed to give indications at foremost a macro-level, the conclusions made can be used as guidelines toward where the market is heading. This has implications for stakeholders such as consumer organizations, automakers, policy makers and infrastructure providers. Based on the results of the simulations and conclusions, these stakeholders can form active strategies to be responsive to the suggested market changes.

For consumer organizations, this could entail informing members on the implied rise in demand and supply of EVs as a whole and on the new and used car market, the residual values of vehicles, policy, and technology developments. Automakers should acknowledge the rise in demand and could accordingly form strategic production plans. For marketing purposes, they could also if needed and possible try to target consumers in the existing customers social network, as we have seen that influences in the social network have a large effect on the purchase decision. However, this statement somewhat contradicts itself as it suggests that these potential customers would seek out the product themselves, if for example recommended by a friend.

Policy makers can use our findings as an indicator of how emissions levels would differ if incentives were to be removed or expanded. On a basis for incentive cost calculations, rough estimates can be made by looking at the market penetration of EVs and thus the aggregated fees, taxes, or
costs that correlate with the number of registered vehicles. Similarly, the increase in vehicles that need charging would put pressure on infrastructure and energy providers to expand charging networks, plan electricity capacity to be sufficient at peak hours, and maintain electric mains hardware to realize further diffusion of EVs.
References


Bloomberg New Energy Finance, (2016a), The first 1% is the hardest, Q4 2016 Global Electrified Transport Market Outlook.


References


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A Conversion of Survey Responses & Estimation of Data

This appendix describes how the conversion between the Norwegian survey COMPETT and the parameters in the STECCAR model was undertaken.

A1 Need Weights

Need weights in the STECCAR were mapped to questions holding similar properties in the COMPETT survey. If a need weight did not correspond, it was normally distributed following the means and standard deviations of the original Dutch sample in STECCAR, as one can assume there were similarities between the respondents.

A2 Ambition

Ambition need was estimated from COMPETT answers to several questions, where the response in household income combined with the highest completed education was assumed to give an indication of ambition level. E.g. if both of these questions had a high response value, a high ambition value was assigned.

A3 Social Weights

Just as the need weights, the social weights were normally distributed according to the mean and standard deviation of the original STECCAR sample.

A4 Expertise in EVs

Corresponding to two questions in COMPETT regarding the interest in cars as well as perceived technology competence of the respondent.