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The Norwegian EV policy

A local-level study on the impact of subsidies

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Acronyms and abbreviations

BEV: Battery Electric Vehicle

CIMS: Capital Vintage Model

EEA: European Economic Area

Environmentally Friendly Vehicles: BEVs, E-REVs, PHEVs and HEVs

EPA: Environmental Protection Agency (of the United States of America)

E-REV: Extended-Range Electric Vehicle

EU: European Union

EU-28: Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and the United Kingdom.

EV: Electric Vehicle

HEV: Hybrid Electric Vehicle

ICEV: Internal Combustion Vehicles

MLM: Multinomial Logit Model

NMLM: Nested Multinomial Logit Model

NOK: Norwegian Kroner

Norsk Elbilforening: Norwegian EV Owner Association

PHEV: Plug-in Hybrid Electric Vehicle

REPAC: Respondent-based Preference And Constraints Model

Traditional Vehicles: Internal Combustion Vehicles

U.S.: United States of America

UK: United Kingdom

VAT: Value Added Tax

Executive summary

Norway is the country in the world having the highest percentage of electric vehicles on the roads, with a stunning 31.2% market share in 2018 (Karagiannopoulos and Solsvik, 2019). Part of the reason behind such high numbers can be attributed to the peculiar system of incentives in place, which makes the purchase of a BEV not only environmentally but also financially convenient for the average Norwegian driver. Incentives can be classified into two categories: the ones bearing the same impact nationally, deemed as “national incentives” and the ones bearing different effects depending on the municipality, deemed as “local incentives”. A few studies have studied both the Norwegian and the international markets, suggesting that the importance of subsidies varies greatly, and that some of them are simply more efficient in bringing results than others. The main purpose of this study is therefore to understand how the local incentives helped shaping the market for EVs and which, among them, are the ones bearing the most prominent effect, at least in the Norwegian case. To reach this objective a multiple regression analysis with municipality-level data from 2015, 2016, 2017 and 2018 is performed, and the results show that, among all the variables considered, only two bring a significant impact in explaining the difference in the share of EV among municipalities: the presence of a toll road and the share of energy expenses over total gross expenses. For policymakers this has important implications, as it shows that the most important types of local incentives are the ones granting EVs free access to toll roads and the ones reducing the price of energy for EV charging, the latter one being a type of incentive that it is not yet in place, but that should be considered in a comprehensive EV policy.

1. Introduction

Environmental and sustainability-related issues have, during the last few years, gained particular traction in the political debate all around the world (see, as an example, the section of the OECD website on climate change, or the European Climate Change Programme) as a result of their wide economic, societal and political implications. The world is warming at an alarming rate (Climate Change: Vital Signs on the planet), air pollution is having a distinctive negative impact on the life of humans on earth (Air Pollution), not only in terms of health and quality of life (Matus et al., 2012) but also in terms of economic development (Quah and Boon, 2003 and Kan and Chen, 2004), and the effects on biodiversity caused by these phenomena are predicted to be particularly dire, if not tackled in time in a fast and effective way (Thomas et al, 2004, Harley, 2011).

Transportation and mobility policies play a crucial role in reaching pollution reduction goals: between 19% and 22% of the global share of carbon dioxide emissions comes from transportation alone (Richie and Roser, 2017), with the situation being pretty similar in Europe (27% of the EU-28 share of CO₂ emissions derived from the mobility sector in 2016, according to EEA data) and in the United States (34% in 2018, according to an EPA report). For this reason, governments around the world started to look for possible alternatives to traditional internal combustion-based mobility, and they found out that one of the most promising solutions to mobility derived pollution is represented by electric vehicles (Aasness and Odeck, 2015).

Electric vehicles are, following the definition by Retzvani et al. (2015), vehicles that are either partly or fully powered by electric engines, and therefore do not only include BEVs (Battery Electric Vehicles) but also E-REVs (Extended-Range Electric Vehicles) and PHEVs (Plug-in Hybrid Electric Vehicles). Some studies include also HEVs (Hybrid Electric Vehicles) in the discussion (such as Halveston et al., 2015), treating them as more similar to other electric-powered vehicles rather than to conventional engine vehicles aided by a supplementary battery. Table 1 summarizes the main differences between the types of electric-powered vehicles, while at the same time shedding a light on the reason why there exist such discrepancies in what is included in each study. As a comparison, traditional ICEVs (internal combustion engines vehicles) are included in the table.

Type of vehicle	Acronym	Battery size	Electric range (Km)	Description
Battery Electric Vehicles	BEVs	Large	120-400	Vehicles with an electric motor and a big battery pack. To be recharged they need to be plugged into the electric grid through an outlet.
Extended-Range Electric Vehicles	E-REVs	Medium-large	120-400	Similar to BEVs, but aided by a small traditional engine, acting as an auxiliary energy supply when the one coming from the battery is not available.
Plug-in Hybrid Electric Vehicles	PHEVs	Medium-small	8-65	They have both a traditional and an electric engine. They can be plugged into outlets and uses electricity for short distances and internal combustion for longer ones.
Hybrid Electric Vehicles	HEVs	Small	0	Vehicles using a traditional internal combustion engine aided by a battery pack that improves efficiency through regenerative braking, engine downsizing, engine shutoff at idle and power management.
Internal Combustion Vehicles	ICEVs	Very small	0	Vehicles using an internal combustion engine, aided by a battery that does not function as powertrain, but only as igniter.

Table 1. Sources: Retzvani et al. (2015), Halveston et al. (2015) and Tate et al. (2008)

As the table shows, different types of vehicles are powered by a different mix of energy sources (battery or internal combustion engine), and therefore have a different environmental impact per se, impact that should be taken into consideration when designing appropriate policies aimed at reducing the environmental damage that mobility creates.

To complicate the matter even further, it should be taken into account the fact that the environmental footprint related to plug-in vehicles (so of BEVs, of E-REVs and of PHEVs) does not only depend on how much reliance do they have on the internal combustion engine, but also on how the electricity they use is produced: in case of a non-renewable-leaning electricity mix plug-in vehicles do not represent a marked improvement in terms of environmental protection (in some cases they may even be a deterioration, if the electricity mix is almost entirely derived from non-renewable sources, such as in the case of China, and the damage created by the battery production is taken into account), while in case of a more renewable-oriented production mix BEVs, E-REVs and PHEVs really represent a more sustainable alternative to traditionally powered mobility (Global Energy Statistical Yearbook). Norway and its electricity generation mix represent a clear example of the latter. 96% of all electricity employed by Norwegian users (regardless of them being private, industrial and public) derives from renewable sources (in particular from Hydroelectric, which represents % of all energy production alone), thus making the diffusion of electric-powered vehicles (in particular of BEVs) an efficient way for the transportation in the country to become more environmentally-friendly and sustainable, both in the short and in the long run.

It makes therefore sense that the Norwegian Government has tried, in the last few years, to promote the adoption of electric vehicles by consumers through the mean of subsidies, both direct (for example, by lowering the taxes due when purchasing an electric vehicle or by lowering possession taxes) and indirect (for example, by offering free parking or free tolls for BEVs). The purpose of this study is to, therefore, understand how these subsidies aided the diffusion of electric vehicles in Norway, if they have been a significant factor in the diffusion of them and, in particular, which has proved to be the most efficient type of subsidy in terms of increase in sales.

The paper is structured as follows: section 2 will provide a brief history of the subsidization of electric vehicles in Norway, giving a timeline about when subsidies have been introduced and changed or abolished (if happened), and a general explanation of the different kind of subsidies, section 3 will provide a review of the relevant literature on the topic (with a particular focus on the Norwegian case), section 4 will briefly state which are the theoretical predictions to be expected (basing on previous studies on the topic), section 5 will provide a

description of the database used for this study, section 6 will present the methodological framework followed in this thesis, section 7 will be dedicated to the presentation and analysis of results, section 8 will be dedicated to a discussion of the results and of the following policy implications, and section 9 will close the paper by stating which are the appropriate conclusions that can be taken from this analysis and which are the main limitations of the analysis carried out in this paper.

2. History of incentives and subsidization

Incentives and subsidization of electric vehicles purchase have a long history in Norway, since they trace back to the 1990s, well before the Tesla-age and the subsequent hype that generated afterwards.

The website of the Norwegian EV Owner association (Norsk Elbilforening) provides a complete and comprehensive summary of all the actions that have been taken by the national government and by the different counties to promote the diffusion of electric vehicles in Norway, starting from the first one to be introduced, in 1990, until today.

The first measure to be introduced has been, as mentioned beforehand in 1990, the cancellation of the purchase and import-related taxes on electric vehicles, followed, in 1996, by the abolishment of the annual road tax payment for EV-owners.

Other incentives that have been subsequently introduced include, in chronological order, the exemption from toll roads and ferries payments (from 1997 to 2017), free municipal parking (from 1999 to 2017), a 50% discount of the company car tax (from 2000 onwards), exemption from 25% of VAT payment at the time of purchase (from 2001 onwards), the authorization to use bus-reserved lanes (from 2005 onwards), the exemption from 25% of the VAT payment on leasing (from 2015 onwards), a fiscal compensation given when scrapping fossil fuel-powered vans when converting to a zero-emission van (from 2018 onwards) and, lastly, the possibility for B-class driving license holders to drive C1-class electric vans (from 2019 onwards).

Nevertheless, as a consequence of market developments, some of these subsidies has been modified during the years: from 2016 onwards, for example, local governments have the legal right to grant access to priority bus lane only to vehicles carrying at least two passengers (car-pooling), while from 2018 onwards ferries and parking fees were reintroduced for electric vehicles, even if only on a partial basis (the national law states that the upper limit for charges for electric vehicles is 50% of what ICEVs owners would have to pay for the same leg, in case of ferries fares, or for the same parking time, in the case of parking fees). Moreover, 2019 marks the reintroduction of EV toll road charges, with, as for the ferries and parking charges, an upper limit of 50% of the charge that ICEVs would have to pay to travel the same distance. As can be seen, measures taken are rather different and should be treated as such. A first distinction that should be made is, following Yan (2018), between nationally and locally introduced policies. The difference between the two mainly stems from the different decision-making bodies that are responsible for their determination (the central government versus local

councils) and from the order of magnitude of their effects: local incentives are, in fact, usually both modest in terms of amount and extremely dependent on the driving habits of each single beneficiary, while nation-wide incentives, though being dependent on various factor, such as the car size and on the import price, are much less driver-sensitive, and provide a sizeable amount of the total subsidy.

A second division that could be made is, following Figenbaum (2017), the one among fiscal stimuli, direct subsidies to users and reduction of time costs. Under the first definition fall all the incentives that grant the buyer a reduction of the purchase price or a reduction of the total yearly costs, thus giving BEVs competitive pricing vis-à-vis traditional ICEVs, therefore the exemption from the registration tax, the VAT exemption, the exemption from the annual road tax, the exemption from the annual leasing tax, the reduction on the company car tax and the fiscal compensation when scrapping a traditional engine van to buy an electrically powered one.

The second category comprises instead all that kind of incentives that reduce usage costs and range challenges costs, such as the exemption from toll road fees, the exemption from ferries fees and the financial support for the creation of charging stations, both fast and traditional. Although not considered directly by Figenbaum (2017), the authorization granted to B class driving license holders to drive electric C1 class vans (up to 4250 kg) can also be categorized under this second group, since they indirectly reduce the usage costs of owning an electric class C1 van (instead of a traditionally powered van belonging to the same driving license class) by exempting the driver from having to obtain another class driving license.

Lastly, the third category contains all the measures that allow BEVs drivers to save time vis-à-vis ICEVs drivers, thus resulting in an indirect cost-benefit. Examples of the latter can be considered the grant of access to bus lanes and the exemption from parking charges, which also provides at the same time a direct subsidy, thus having a two-sided effect on the savings potential that this measure is able to grant.

Additionally, measures can be further categorized using another method, built upon Levay et al. (2017). On one hand, we have measures that are dependent on the car import price (and thus on the size) while being independent of the driver habits, and on the other, we have measures that are not influenced by the import price, but that are instead affected by the single driver's habits in terms of mileage, daily commute, etc. Examples of the first kind are all the fiscal exemptions, which effect on the total prices of owning a certain type of BEV instead of a comparable ICEV derive from the savings incurred thanks to the avoidance of up-front and recurring tax charges, while under the second category we can find the access to bus lanes as

well as the exemptions from road tolls, from ferries fees and from parking charges, whose effect depends on, for example, how often drivers park their car in pay-to-park areas instead of parking in free parking lots, on how congested is the drivers daily commute (and thus on the time savings granted by the usage of bus lanes instead of the regular ones), etc.

Table 2 provides a brief summary of the types of incentives by combining all these three categorizations in a comprehensive table.

(1): Dependent on the import price (2): Dependent on the driver's habits				Introduction	Status
	Reduction of the purchase price and of the yearly incurred costs	Reduction of usage costs and range challenges costs	Reduction of time costs		
National Policies	Exemption from purchase and import taxes (1)			1990	No changes (expected in 2021)
	Exemption from annual road tax (1)			1996	No changes (expected in 2021)
	50% reduction on the company car tax (1)			2000	After 2018: diminished to 40%
	Exemption from 25% VAT on purchase (1)			2001	No changes (expected in 2021)
		Financial support for building charging stations (2)		2009	No changes
		Financial support for building fast-charging stations (2)		2011	No changes
	Exemption from 25% VAT tax on leasing (1)			2011	No changes (expected in 2021)
	Fiscal compensation when converting from an ICEV to a BEV Van (1)			2018	No changes (expected in 2021)
		Authorization granted to B class driving license holders to drive electric C1 class vans (up to 4250 kg) (2)		2019	No changes
		Exemption from charges on ferries (2)		1997	After 2018: fare capped at 50% of the full price
Local Policies		Exemption from charges on toll roads (2)		1997	After 2019: fare capped at 50% of the full price
			Exemption from parking charges (2)	1999	After 2018: parking charges capped at 50% of the full price
			Access to bus lanes (2)	2005	After 2017: New rules allowing local authorities to only include EV transporting more than one passenger

Table 2: Source: <https://elbil.no/english/norwegian-ev-policy/>, Yan, 2018 and Figenbaum (2017)

3. Literature review

This section of my dissertation focuses on the various studies that have been conducted over the course of the years about the impact of subsidization on the diffusion of BEVs and HEVs in various parts of the world. In particular, building upon Al-Alawi and Bradley (2018), it can be outlined that scholar works employ three main categories of modelling techniques: the consumer choice models, the agent-based ones (with different degrees of complexity) and the ones using sales diffusion rates and their evolution over time (time series).

3.1 Consumer choice models

Consumer choice models have been used in the literature to describe decision-making processes that concern individuals and groups. Two main sub-categories can be defined: logit models, which are used to describe and model probabilistic choices of consumers, and discrete choice models, which calculate the probability of a specific good being chosen among a group of other goods under the influence of the consumers' preferences.

Two different logit models are usually used in the automotive industry, the first one being the multinomial logit model (MLM) and the second one being the nested multinomial logit model (NMLM). The multinomial logit model represents the probability of choosing one specific alternative over the list of all the possible alternatives, while the nested logit model models the probability of choosing one specific alternative over the nest alternatives, which are alternatives that are similar and thus comparable to the main alternative that is considered. In the automotive industry the nest alternatives are, for example, vehicles that are part of the same class k as the main alternative, so vehicles that are comparable in size, brand, price, specifications, etc.

Both of them are based on the utility function of the consumer and on the probability of the consumer of choosing good x over the possible alternatives, keeping in mind that the consumer will always choose the vehicle providing him with the highest utility, which depends on safety, fuel economy, price, range, comfort, general specifications, etc. The main difference in the two models derives from the fact that in the multinomial logit model the choice of the vehicle is done directly by comparing all the vehicles in the market, while in the nested logit model the choice is divided into two steps: the first one entails choosing the class of the vehicle, while the second one entails choosing the vehicle providing the highest utility among the vehicles

of the considered class. Thus, in the nested logit model, the consumer makes two different kinds of decisions subsequently, while in the multinomial logit model the decision is only one.

This implies that the functions underlying the two models are different. The multinomial logit model assumes that the probability that the individual n will choose the alternative i from a set of alternative j in C , set that includes all the possible alternatives, is the following:

$$P_{i,n} = P(U_{i,n} \geq U_{j,n}, \forall j \in C_n, j \neq i) \quad [1]$$

While the general MLM is defined as:

$$P_{i,n} = \frac{e^{U_{i,n}}}{\sum_{j \in C_n} e^{U_{j,n}}} \quad [2]$$

With the sum of all the probabilities being equal to 1:

$$\sum_{i \in C_n} P_{i,n} = 1 \quad [3]$$

$P_{i,n}$ is the probability that individual n will choose alternative i over all the other possible alternatives, while $U_{i,n}$ is the utility function that derives from this choice. In particular, the utility function equation is described as follows:

$$U_i = \sum_n \beta_n X_{i,n} + \varepsilon_i$$

$$\varepsilon_i \sim G(0, \mu) \quad [4]$$

Where $X_{i,n}$ is an explanatory variable for alternative i , β_n is the slope parameter for $X_{i,n}$ and ε_i is the random component. In order to derive β_n , the slope parameter, the elasticity of the probability of an individual n choosing alternative i with respect to a change in $X_{i,n}$ must be derived or estimated from the available data, being the formula used to calculate β_n as follows:

$$\beta_n = \frac{E_{X_{i,n}}^{P_i}}{(1 - P_i)X_{i,n}} \quad [5]$$

Once the slope is known, it is possible to proceed with the calculation of the utility function of each individual n for each alternative i . After that, the final stage of the multinomial logit model entails using function [2] to estimate each individual probability of choosing alternative i .

In the multinomial logit model individuals are assumed to be rational, thus utility maximisers. The utility function, following Greene et al (2004), is defined as:

$$u_{i,j} = b(A_i + \sum_{l=1}^k w_l x_{i,l} + \varepsilon_{i,j}) \quad [6]$$

With

$$\sum_{l=1}^k w_l x_{i,l} \quad [7]$$

being the weighted sum of the attributes considered and $\varepsilon_{i,j}$ being the error term, capturing all the unquantified attributes for every individual. A_i is a constant describing the value of the unmeasured attributes of vehicle i and b is the price coefficient.

The probability of individual n choosing alternative i from k possibilities is then given by the exponential value of the utility of the alternative divided by the sum of all the exponential utilities. Mathematically, the probability that an individual will choose the i th alternative from the k th class can be written as:

$$p_{i|k} = \frac{\exp(bu_i)}{\sum_{l=1}^L \exp(bu_l)} \quad [8]$$

On the other hand, in the nested logit model the utility for an individual that derives from choosing an alternative over all the others belonging to the same class is as follows:

$$U_k = \frac{1}{b} \ln \left(\sum_{i=1}^{n_k} \exp(u_{i,k}) \right) \quad [9]$$

That is, the utility function for each class k is modelled as the probability-weighted average of the utility scores of all the vehicles within that specific class.

The probability that an individual will then choose a specific vehicle from class k is:

$$p_k = \frac{\exp(A_k + BU_{k,i})}{\sum_{K=1}^n \exp(A_k + BU_{k,i})} \quad [10]$$

With K equal to the summation of all the vehicle classes, n being the number of the vehicle classes, A_k being a constant representing the value of the unmeasured attributes of the vehicle class k , and B being a slope parameter capturing the sensitivity of vehicle class choices to changes in their expected value perceived by the consumer.

The probability of the consumer choosing vehicle i from class k is then the product between equation [8] and equation [10], which can be summarized as:

$$p_{ik} = p_{i|k} * p_k \quad [11]$$

3.2 Most important consumer choice modelling studies

The consumer choice modelling technique has been, overall, the most widely employed in studies that investigate the diffusion patterns of BEVs and HEVs. The first study using this modelling technique that should be mentioned is the one done by Lee, Kim and Shin (2016), where choices of Korean consumers with regards to the adoption of HEVs are modelled and analysed using a multinomial logit model, which has been chosen as the appropriate method after consideration of the typical behaviour of the Korean HEV buyer, who tends to consider only cars in the mid-size segment during their purchasing decision. The model used in this study considers three categories of decision-affecting factors: technological, economic and psychological, plus the interactions between couples of already-stated factors. These factors categories can be split into sub-categories, each containing a variable that influences the decision-making process of the consumer. Variables contained in the technological category are the type of fuel, fuel efficiency, displacement and the vehicle power, variables in the economic category are the total acquisition cost and the brands of the car considered and of the possible alternatives multiplied by the promotion programme of the brand in question, while variables pertaining to the psychological category are the size (in this case only the mid-sized segment is considered) and the brands of the car considered and of the possible

alternatives. Interactions considered include power and type of fuel, displacement and type of fuel, total acquisition cost and fuel, fuel efficiency and size, displacement and size, power and size, power and brand, total acquisition costs and brand fuel efficiency. The final model shows that the key determinants in the decision-making process are the vehicle size, the brand, the type of fuel and the fuel efficiency, with the total acquisition cost (thus all the costs that the consumer incur in order to own the car, including both the purchase cost, the tax incentives, maintenance-related costs, taxes due yearly, etc.) and the brand-wide promotion playing a lower role in determining the patterns of consumer choices for HEVs purchases. Of the interactions, the one having the biggest impact on the purchasing decision is the one between the brand the fuel efficiency (that is, the fact that the consumer's favourite brand offers better fuel efficiency increases the market share of the brand more than other interactions), followed by the interaction between the fuel efficiency and the size, this last one having nevertheless a much lower importance in terms of definition of the market share.

Soltani-Sobh et al. (2017) presents another interesting model based on the consumer choice modelling technique, which nevertheless considers different independent variables in the construction of the regression equation. The study uses a macroscopic logit model (that is, it considers aggregate data to model purchasing decisions, and not the choice of the single individual consumer), which employs, as monetary independent variables used in the utility function, the risk tolerance for new technologies (labelled as an income variable, since it is assumed that it is an effective consumer discount rate for future energy costs), gasoline prices, electricity prices and the annual miles travelled. Non-monetary factors included in the equation are the government incentives and the rates of urban roads. The function that is then formed is used to calculate the utility in state i at any given period of time t , equation that is in turn used to calculate the share of BEVs adoption.

Another paper that should be mentioned is the one written by Cacere, Corrocher and Guerzoni (2018), which has as main focus the intentions of consumers of six different European nations, namely the UK, Germany, France, Spain, Italy and Poland, to purchase BEVs. The model developed in this study is a rather peculiar one, since it is constructed upon the opportunity given to the respondent to use a predefined sum of money (in this case €3,000 per three times) to improve certain characteristics of the vehicle in question, that are the price, the driving range, the recharging time, the possibility to recharge the battery at home and the top speed reached by the vehicle. Every respondent can choose to place the sum all the three times on improving a given attribute, for example the price, or to switch every time to another one, for

example choosing price-recharging at home-driving range. In this way, the model enables the researchers to at least partly control for endogeneity, as it allows to control unstated biases by providing an environment where the only change in the vehicle characteristics is the one done by the consumer and not, for example, changes in the “greenness” of the vehicle, while at the same time permitting the usage of the intentions to buy instead of the observed behaviours. For each consumer the utility is measured before and after the improvements, and it is assumed that the consumer will purchase a BEV if the utility is above a certain threshold τ and will not purchase a BEV if the utility is below the value of τ , that is, in our case, the utility given by an outside option. Consumer choices are then plotted on a graph, where a particular group of consumers (those with a utility lower than τ before the improvements and higher than τ after the improvement) is extracted. After that, a model focusing on the product improvement choices (respecting the order of the choice) and on the individual characteristics (that are income, age, country and educational attainment) is constructed and tested in the paper. The main results of this study are that the wealthier an individual is and the higher its educational level the more probable it is that she will switch from below to above the threshold, that the distance from the threshold τ is a significant control of the willingness for a consumer to switch from below to above it (that is, the further a consumer is from τ before the switch the less probable it is that she will switch) and that the price is the most important factor that can persuade consumers to purchase BEVs, while the top driving speed has a minimal impact on it.

Axsen, Mountain and Jaccard (2009) developed a model, starting from both the multinomial logit model and the energy-economy model, to describe the impact of the neighbour effect on the sales of HEVs in Canada and California, with the multinomial logit model used to empirically estimate parameters to be used in the energy-economy model (CIMS) by employing both stated and revealed preferences. The energy-economy model uses the lifecycle costs (LCC) to estimate the market share of technology j MS_j by comparing the lifecycle cost of a specific technology with the sum of the lifecycle costs of all the available technologies in the market, subject to market heterogeneity v (that is, how different consumers perceive different lifecycle costs across the economy). The multinomial logit model is used to estimate the v parameter, the parameter r , used to annualize upfront costs that the consumer has to incur when purchasing a vehicle, and i , that is the parameter modelling the neighbouring effect, and to reach this objective both stated and revealed preferences are used in the estimation. This is done mainly because using both kinds of preferences give the possibility to reach a higher

robustness than using just stated or revealed preferences alone. In the stated preferences data collection information about seven different attributes was fetched: capital cost of the ICEV, capital cost of the HEV, subsidy provided by the government for the HEV, horsepower for the HEV, ICEV fuel efficiency, HEV fuel efficiency and gasoline price, summarized in four key attributes included in the respondent set: capital cost, fuel cost, performance and subsidy. Through revealed preference data information about three of the four attributes mentioned for the stated preference was collected, that is information about capital cost, weekly fuel cost and performance. Various models were then tested in the study (both using only stated preferences, revealed preferences, or both in a joint or a subsequent way), and the results reached show that the most effective policy to be introduced in order to improve the diffusion of HEVs, according to the Canadian and Californian collected data, would be to introduce a \$1,000 feebate on HEVs, followed by the introduction of a \$3,000 subsidy (thus decreasing capital costs for HEVs) and by the introduction of a \$100/tonne carbon tax.

The model developed by Chandra, Gulati and Kandlikar (2010) to describe the preferences of Canadian consumers in terms of HEVs adoption is based on the nested multinomial logit model with a particular specification, not common to other NMLM: it does not use the outside option as an alternative, as it is not considered to be a viable solution, as the classical logit model would predict that a large proportion of HEVs would be purchased by people that would not have been purchasing a vehicle without the rebate, which is something that is not empirically true, as the presence of rebates and subsidies does not increase the total number of vehicles sold per year, it changes instead the market composition. Instead of using the outside good, market shares are modelled directly as a function of the rebate and of other attributes, that are the model*generation fixed effect, capturing attributes such as the horsepower, the interior comfort, the fuel efficiency, the brand, the external appearance, the general model perception, general features (both standard and optional) and the time and space invariant components of the price (omitted in the model); the province fixed effect; the year fixed effect, and multiple effects capturing the interactions between the fixed effects mentioned before: the province*segment effect, capturing why a model is appropriate to a specific region in terms of geography, urban density, etc; a segment*year effect, capturing both changes in popularity of a certain segment changing from one year to the other, and a province*year fixed effect, capturing changes in sales in a specific province in a given year. The main findings of the study are that the introduction of a hybrid rebate increases the share of HEVs in the market in a positive and significant way, and that model-generation fixed

effects also explain a large fraction of the variation in vehicle sales across provinces and years. In particular, it is calculated that an increase in the rebate of \$1,000 increases the share of HEVs in the total number of car sold by 34%, and that this replacement mainly affects the intermediate passenger cars, intermediate SUVs and high-performance compact cars segments, while having a negligible impact on all the others.

A further study that needs to be mentioned when introducing the concept of consumer choice model in vehicles adoption patterns is the one by Halveston et al (2015), where a modified version of the classical multinomial logit model, the random coefficient logit model, is used to analyse the impact of subsidies on the diffusion of BEVs in two countries, the U.S. and China. The usage of this modified version is necessary in order to capture variations in the willingness to pay of the individuals, as it allows vectors of the willingness to pay of each consumer to be drawn from a parametric distribution, instead of being equal among all the consumers. The variables that are considered in this specific model are the price paid, dummy variables for HEVs, PHEVs and BEVs, with the baseline (that is, three zeros) being ICEVs, a dummy capturing the possibility to fast charge a vehicle, the operating costs in terms of US cents per mile, the time required for acceleration from 0 to 60 mph, and dummy variables describing if the country of origin of the brand is the U.S., China, Japan or South Korea, with Germany being the baseline (that is, four zeros). Data are obtained through stated preferences by mean of a survey, with controlling mechanisms in place in order to avoid cognitive biases. The experiment is constructed as follows: the respondent chooses a vehicle image, that will be the same for all the kinds of vehicles under comparison, then he will be provided with 15 different choices, each with 3 options, plus a warm-up question mimicking this design, and, lastly, questions on a different set of attributes, such as demographics, experience, knowledge and attitudes, were asked to each participant. The main findings of this study are that lower prices, lower acceleration times, lower operating costs and fast-charging capabilities are preferred by consumers coming from both countries, with Americans being less sensitive than the Chinese on this set of attributes, that brand plays an important role, with nevertheless different perceptions in the two markets (in the United States American, German and Japanese brands are preferred, with Chinese and South Korean brands being not liked, while in China consumers have a strong preference for German brands, while at the same time despising South Korean and Japanese ones), and that the share of BEVs is higher in China than in the U.S., while the share of lower-range PHEVs is higher in the U.S. than in China, subsidies being equal between the two countries.

Lastly, Brand, Cruzel and Anabel (2017) modelled the choice of both UK private buyers and of UK company buyers by using a multinomial logit model, adapted to the specifications of each customer segment. It is in fact assumed that company buyers make their decisions on the basis of different attributes than private buyers, being them more cost-conscious, less infrastructure dependent and having a shorter ownership period than private buyers, thus making more rational cost-driven decisions. The attributes considered for both private and company buyers are the refuelling infrastructure, policy incentives and regulations, the consumer willingness to pay for technology preference (this splits private buyers into four categories and company buyers into two: on one side we have the enthusiast, the aspirers, the mass market and the resistor adopters, while on the other we have the users-choosers and the fleet managers), and socio-economic/demographic characteristics, while the difference in the attributes considered pertains the vehicle characteristics: for private users year 1 costs, annual maintenance costs, access to charging, charging time, driving range, model and brand supply and technology preferences are considered, while for company buyers the total cost of ownership over 4 years, the model and brand supply, the certainty of access to charging and the driving range are considered as the key vehicle attributes that should be considered). The study results show that the UK needs to improve its policies, supply, demand infrastructures in order to reach the targets set for 2030 and 2020, while at the same time giving interesting insights on the most probable new PHEV and BEV buyer, being it a company owner (in particular if she is a fleet manager) rather than a private owner, segment that is itself dominated by enthusiasts and aspirers, with the mass market taking up only after 2030, and resistors not switching at all in the analysed time frame (until 2030).

3.3 Agent-based models

Agent-based models are based on a computer-based simulation creating and developing a virtual environment where the actions of each agent and the interactions among them are simulated. Agents are individuals or entities having control over their actions, and each agent possesses some specific characteristics that dictate their interactions with other agents playing in the same environment.

In the case of vehicle purchases patterns modelling, various kind of agents has been included in the simulations carried out, and these usually include consumers, producers, policymakers and fuel providers. The demand side of the model is represented by consumers, whose

characteristics are defined as their demographical data and their preferences, which include but are not limited to gender, age, income, location, lifestyle, driving needs and patterns, social networks, budget dedicated to transportation, ownership period and vehicle preferences, such as class, type of fuel, reliability, powertrain, safety, performance, etc. This set of characteristics determine the needs and preferences of consumers during the simulation.

On the supply side, the main kind of agent is represented by the automakers, who decide to supply vehicles with, as characteristics, the class, the type of fuel, safety, powertrain, performance and costs. This last one is particularly important, as the main goal of automakers is to bring to the market vehicles that maximize their profits while, at the same time, meeting customer needs and regulatory requests. Policymakers base their actions on factors including the global environmental goals, energy demand oil security, and their main task in the simulation is to lay out the policy playing field where the supply side of the model has to play in. Policymaking players have at their disposal various actions that they can take, typically including subsidies, tax rebates, sales tax exemptions and increasing gasoline taxes.

Lastly, fuel providers have control of the fuel resources in the simulation and base their actions on the consumer demand for fuel, which is mainly driven by price (an increase in fuel price will shift consumers toward more fuel-efficient vehicles), on the policies aimed at regulating the consumption of fuel (such as fuel taxes or clean fuel standards) and on the availability of fuel resources.

3.4 Most important agent-based modelling studies

This section of my dissertation aims at giving a brief overview of the main studies, modelling the adoption patterns of HEV, PHEV or BEV, that employ as method of analysis an agent-based modelling technique.

In Eppstein et al. (2011) the model developed to describe a typical agent decision process during an ICEV vs. HEV vs. PHEV purchasing decision is based on several attributes associated to the agent, attributes that can be split into three different categories: the first one is the one that pertains the agent itself, so her age, her annual salary, her residential location, the miles she travels per year per vehicle, and her typical duration of vehicle ownership, and the second one containing the characteristics that identify the vehicle she currently owns, that are the vehicle age, the kind of fuel and the current fuel efficiency, including both the all-

electric range and the miles per gallon, if the vehicle in question is not a BEV. The last group of features considered describes the agent relationship with external factors, and comprises the agent spatial neighbourhood (that is the radius in which the agent carries out the majority of her activities), the agent social network, the threshold T of perceived PHEV market share over which she is willing to consider adopting a PHEV, the level of rationality R with which she estimates future fuel costs, and the weight that the agent places on heuristically perceived benefits related to saving gasoline that are not dependent from rationally estimated savings. In particular, this last attribute captures both the overestimation of the potential fuel savings over time and the non-financial reasons related to the environment, energy security, and the attraction to newer technologies.

The decision process used in this article can be explained as follows:

1. The first step entails updating the heuristic weight G , which depends on social and media influence on specific issues (such as, oil spills, environmental disasters, sustainability issues, foreign-oil dependency, etc.)
2. Subsequently, the agent has to perform the decision to buy or not a vehicle. If the answer is negative, then the agent decides not to buy a vehicle, otherwise she advances to the next step
3. The agent estimates the relative costs of the vehicle, which include the purchasing costs, the costs of financing, and gasoline and electricity costs. Maintenance costs were not included in the model for insufficiency of data.
4. Relative benefits in terms of gasoline savings other than the financial rational ones are then estimated
5. The total vehicle desirability in terms of heuristic weight, relative costs and relative benefits is then computed, and the vehicle having the highest level of the desirability parameter D is then chosen for purchase by the agent, subject to some conditions
6. The first condition is that the PHEV desirability threshold must be exceeded. If not, the vehicle is deemed to be non-desirable, and no vehicle is purchased for the year
7. The second condition to be met is that the vehicle must be affordable, that is its annual estimated costs must not exceed the 20% threshold of the agent annual salary
8. If no vehicle is deemed affordable by the agent, then no vehicle is purchased for the year
9. If at least one vehicle is deemed to be affordable, then the vehicle associated with the highest desirability parameter is purchased by the agent during the year of the study

This study provides scholars with three main findings. Firstly, rebates are effective to speed up the adoption of PHEVs, but only in the short term (after 15 years the overall market share is in fact the same with and without rebates in place), and that at higher average PHEV threshold T the effectiveness of the rebate is much weaker than at lower thresholds, as the vast majority of the agents is not an early adopter, thus not willing to consider the purchase of a PHEV. In second place, the fleet efficiency increases with the PHEV range, as the projected lifetime fuel costs drop for more agents, thus making more agents purchasing an PHEV, and more agents are willing to purchase longer-range PHEV instead of short-range PHEV, thus resulting in more a fuel-efficient fleet composition. Lastly, at higher battery range the sensitivity of fuel efficiency to PHEV purchase price increases, which means that, with increased fuel prices, cheaper PHEVs are able to provide higher savings as the battery range increases.

Silvia and Krause (2016) employed an agent-based approach to model BEVs diffusion in a simulated environment based on an U.S. city with roughly 300,000 inhabitants and 250,000 vehicles on the road. The main focus of the study is provide an overview of the possible impact of incentives on the diffusion of BEVs across a 35 years period, and not to model all the possible variables that may hinder or incentivize the adoption of a BEV by the average consumer, therefore only the demand side and policymakers are considered in the simulation, keeping the usual supply-side and fuel providers contribution fixed, thus excluding them from the simulation. The environment is defined as a typical American city formed by 4 different areas: a business district area, which has 50% of the BEVs and PHEVs charging stations, an upper-income area, having 40% of the charging stations, a middle-income area, which has 10% of the charging stations on its territory, and a lower-income area, with no charging stations.

Consumers, that are also the agents in the simulation, are modelled following eight attributes:

1. Their income, modelled following the U.S. income distribution
2. Their home location, which is for the vast majority modelled following their income, but with some exceptions in order to better reflect the real-world distribution
3. An attribute that consolidate three different agent characteristics into one: its driving route, the daily miles travelled, and the need to have access to a longer-range car for longer trips that she may take occasionally (10% of the agents are characterized by that)

4. The age of the vehicle that they are driving
5. The current vehicle age at which they decide to purchase a new car, modelled on the average of 6 years, consistent with the U.S. data on vehicle purchases
6. The purchase price threshold, which is 11% of the agent annual income
7. The innovativeness score of the agent, which has an average of 3 and a standard deviation of 1. A value less than 1 is associated with being an innovator and a value greater than 4 is associated with being a laggard
8. The environmental score, which has an average of 3 and a standard deviation of 1. 16% of all the agents are in the highest environmental score.

The decision process unfolds following this procedure: first of all, the agent has to reply to the following question: a) Does the current vehicle age overcome the assigned purchase age? If the answer is no, then no vehicle is purchased for the year, regardless of it being a BEV or an ICEV. Then, the agent is confronted with another set of questions, which include: b) Is the monthly payment required to purchase the BEV less than 11% of the monthly income of the agent? c) Is the BEV driving range greater than at least 120% of the miles currently driven daily by the agent? d) Does the agent have access to other means to take occasional longer trips, should she need it? If the answer to any of these questions is no, then no BEV is purchased, but instead an ICEV is purchased. If the answer to all of these questions is a yes, then the agent needs to reply to the final group of questions, that is: e) Is the BEV cost-effective? f) Does the agent have strong environmental beliefs? g) Does the agent perceive herself as a technological innovator? h) Has the agent seen enough BEV in her community to meet her personal innovation needs? If the answer to any of these questions is a yes, then the agent will purchase a BEV, otherwise a traditional ICEV will be purchased.

The most important result of this simulation derives from the simulated impact of incentives, which are introduced in the model based on the following scenarios:

- a. The first scenario to be considered is a baseline scenario, where no incentive is provided
- b. The second scenario is a scenario where the incentive is represented by 550 \$10,000 discounts on the BEV purchase price
- c. The third scenario entails the usage of the allocated budget of \$5,500,000 to improve the city charging network by building 350 of them

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- d. In the fourth scenario the budget is used by the city government to purchase 250 electric vehicles that will then used in its fleet
 - e. The last scenario is a mix of the previous three, thus comprising a \$10,000 incentive for 183 new BEV purchases, the installation of 116 new charging docks, and the purchase by the city council of 83 BEVs

Under the simulation, on average, the most successful scenario has been the fifth, followed by the second and the fourth, with the third having given even worse results than the baseline scenario. This has important policy implications, as it shows that the most effective policy that policymakers should embrace is rarely a focus on just a peculiar one, but rather a mix of all the available incentives and subsidies available for introduction.

Another study worth mentioning is the one carried out by Shafiei et al. (2012), where an agent-based simulation was employed in order to predict the preference of Icelandic consumers in terms of BEV adoption. Consumer behaviour is modelled according to an MNL consumer choice model, and the results obtained with this step are then inserted into a simulation, where the agents attributes are related to their relationship status, to their living situation (if they live with their parents or not), to their family development (if they have children or not) and to their income, while the vehicle attributes are the purchase price, the type of fuel (electric versus gasoline), the fuel consumption, the length of the vehicle (which is a proxy of the vehicle class), the luggage capacity, the acceleration in seconds, the lower medium and the upper-medium, with the last two being related to the attitude of a consumer towards under-priced or lower-priced vehicles. Some agents may in fact be more willing to buy an over-priced vehicle for status-related reasons, while others may not be interested in buying over fair value, and this is reflected in the upper-medium attribute. An opposite reasoning is applied for the lower medium attribute. The cross preferences between personal and vehicle attributes are obtained based on a study carried out on Danish consumers with, as assumption, cultural similarity between the two countries. From this basic model two modified models are built and tested: in the first one policy intervention is added, in the form of a reduction of the 45% import vehicle tax, while in the second one a world where the agent does not have to worry about recharging her vehicle is. The main results of this simulation are that, first of all, the best scenario for EV adoption would be the one with low EV costs and high gasoline prices, with the negative impact of low gasoline prices on the EV market share being offset by the positive effect of EV lower prices. Therefore, the scenario with low gasoline prices and decreasing EV prices is similar to the scenario with medium gasoline prices and constant EV prices.

Secondarily, the effect of a favourable tax policy, so of a total abolition of import taxes for BEVs, would have an extremely beneficial effect on the adoption of BEV, showing that, without appropriate policy support, the adoption of BEV by Icelandic consumers is not ready to take off. Lastly, the study shows that eliminating agents' concerns about recharging will lead to a situation where more BEV will be adopted from the beginning of the simulation, leading to a much higher BEV market share at the end of the period under scrutiny in this model.

Similarly, Brown (2013) proposes an agent model which is based on a mixed logit model to describe the agent behaviour, which is dependent on the following attributes: the daily gas costs, which is in turn a function of the gasoline price per gallon at the month of purchase, of the vehicle miles per gallon and of the average daily miles travelled, the manufacturer suggested retail price, the class of the vehicle, the horsepower of the vehicle engine, the foot-pound torque of the vehicle (in particular, this last two are consolidated in the logit function as a single attribute called power), the safety rating of the vehicle, the income category of the agent, which is divided into three: low, middle and high, the family situation of the agent, split into five categories: single without children, single with children, married without children, married with children, retired, and the location of the agent, which is assigned following a parametrization according to surveys from Metropolitan Statistical Areas, in order to make the model as similar to reality as possible.

At first, each agent only considers purchasing a vehicle belonging to the same fuel category as the one she already owns, without considering alternative fuels, but will consider other options after their consideration threshold is met through simulated social interactions. The model will then entail various other steps, which, for the sake of brevity, I will not discuss here.

The results of this simulation show that HEV and PHEV market shares are interdependent and going in opposite directions, that is, the higher the market share of PHEV the lower the one of HEV. This is a direct consequence of the fact that, the better PHEVs will be developed, the higher the probability that a consumer will switch from a traditional HEV to a PHEV, lowering the HEV market share. Furthermore, the BEV is the type of vehicle that is proved to be the most influenced by the introduction of incentives based on their retail price, as with the incentives it becomes even more economically convenient to purchase a BEV rather than a PHEV, thus shifting agents towards purchasing more BEVs. Another important result that is shown by the analysis is that, similarly to the result of Shafiei et al. (2012), consumers are

expected to buy more efficient vehicles as gasoline prices increase, thus showing a clear positive correlation between gasoline prices and the diffusion of BEVs. Lastly, the study shows that BEV and PHEV adoption will be favoured in the lowest retail price and sedan categories, as they are favoured by estimates by the logit-model. Nevertheless, as battery characteristics improve and BEVs and PHEVs will become more suitable alternatives to ICEVs, an increasing number of consumers with a lower sensitivity to the retail price but a higher sensitivity to the gasoline prices will buy BEVs and PHEVs, thus increasing the relative market share of more expensive and bigger categories of BEVs and PHEVs.

In De Haan, Mueller and Scholz (2009) a microsimulation agent model is developed to describe the adoption of energy-efficient vehicles in Switzerland, with simulations running both to describe the situations where partial feebates and where full feebates are introduced. Vehicles are each assigned an energy efficiency category from A to G, with A being the highest efficient and G being the lowest efficient. Five different scenarios are explored: the first one, the reference run, uses the same conditions as the ones present in the 2005 market for vehicles in Switzerland; the second one, the partial feebate system with relative policy base, simulates a market where a 3% increase in purchase tax is introduced in the energy efficiency G category in order to introduce incentives to purchase energy-efficient vehicles (therefore the ones belonging to the A category); the third one being the partial feebate system with absolute policy base, which is similar to the previous scenario, but with vehicles being categorized according to their absolute energy-efficient, and not to their energy-efficient relative to the size category they belong to; the fourth one is the full feebate system with relative policy base, where 15.3% of new vehicles having the lowest energy efficiency (those belonging to the G class) pay a €2,000 fee that allows to provide the 14.7% of new vehicles with the highest energy efficiency (those belonging to the A class) with cash incentives; and, lastly, the fifth scenario being the full feebate system with absolute policy base.

The study shows two main results:

1. Feebate policies have high efficacy, meaning that cash incentives outweigh utility losses that consumers may incur from switching to a more energy-efficient vehicle, as in the vast majority of cases the decrease in the utility perceived by the consumers following a decrease of the acceleration time caused by the switch to a less powerful powertrain is compensated by utility gains in sales price, fuel costs and the cash incentive received

2. Feebate policies create low market disturbance, meaning that, if energy-efficient engines are available for vehicles inside a specific class, the total market share of the class will not change, but only the within composition of the market share changes. The only case where this does not hold is the case when no A-rated vehicle is available within a class, such as in the case of SUV and sport/luxury vehicles, which show a decrease in the total market share. Therefore, feebates do not change the total composition of the market, but are able to change the composition of the market sub-categories.

Lastly, Zhuge et al. (2019) developed a model in order to simulate the diffusion and the effects of diffusion in terms of infrastructure development of BEVs and PHEVs in the city of Beijing, classifying agents according to five attributes, reflected as dependent variables in the function describing the BEV adopter behaviour: social influence, driving experience (which includes the usual daily route of the agent), the vehicle purchase price, the environmental awareness of the agent and a random term that captures any effect that may not be properly captured by any of the other variables. The impact of subsidies and incentives is reflected in the purchase price, which is given by the sale price minus subsidies to incentivize the sale of more environmentally friendly vehicles. Agents are considered as possible consumers only if they satisfy three conditions: a. they have a driving license, b. they can afford the vehicle c. they will actually gain a positive utility by buying a BEV. If, for example, an agent will have a longer one way commute than the battery range, then he will gain a strong disutility by purchasing a BEV, making it for him extremely disadvantageous and, therefore, highly improbable.

The simulation demonstrates three important results. First of all, environmental benefits from BEVs adoption are marginal to the total amount of vehicular emissions. This means that the higher the percentage that BEVs take up in the vehicle market share, the more significant the environmental benefits deriving from BEV adoption. Policymakers should therefore adopt policies aimed at supporting the diffusion of BEVs and of PHEVs, which are otherwise slowly adopted by the agents due to their high sales prices. Secondly, BEV adoption will have a low impact on power grid systems, accounting for only 4% of total energy consumption in 2020, with the biggest share of it being taken up by private charging (public charging is going to account for only 10% of the total charging needs). This is partly due to the fact that the BEV adoption rate is going to be low in 2020, meaning that not so many agents will have the need to recharge their BEV, thus keeping the total energy request for BEV recharging low. Lastly, concerning the development of the infrastructure, the study shows that the quantity and the

layout of the vehicle recharging stations almost does not change. What changes is instead the usage of recharging points, with spots occupied more frequently and for longer times in total. For this reason, the development of new charging posts may not be critical at the initial stages of the adoption, but what might be critical is instead their spatial distribution.

3.5 Time series and diffusion rate models

Time series and diffusion rate models are based on the pace of acceptance and adoption by the market of a new technology, which may be already existent or soon to be implemented on the specific market under study. Various internal and external factors have an influence of this pace and on the sales of new products itself, such as communication, time, the social system and, most importantly, innovation, which is also the basis of some of the most important classical theories, such as the concept of classification of adopters, the innovation S-curve, and the role of social influence on diffusion.

The diffusion function of innovative products is usually shaped following a normal distribution, with adopters split into five groups, following the work by Rogers (1995): innovators, early adopters, early majority, late majority and laggards. Innovators are, because of their social and economic status, the first adopters, thus the first ones willing to take up risks associated with the adoption of a new product. Oftentimes innovators are more interested in the new technology itself and on the increase in social status that its adoption will bring rather than on the cost-effectiveness of the purchase, and they will make the decision to purchase and use a new technology even if this does not make sense in financial terms. Early adopters are individuals who are willing to purchase and use an innovation only after the innovators have done that, and they are persuaded in doing that by their social networks and by their relationships with innovators. Early majority and late majority consumers are usually more cost-sensitive than innovators and early adopters and have a lower economic status, therefore they are willing to adopt the new technology at a later stage, when the cost associated to it (so purchase, maintenance and running costs) decreased sufficiently to make the purchase economically viable for them. Laggards are the last group of adopters, and are the ones most resistant to the purchase and utilization of the new technology, and will go on using old technologies until these last ones are available on the market.

There are multiple modelling techniques available to study the diffusion and adoption rate of a new technology, and the ones most widely used are the Bass (1969), the Gompertz (1825) and the Logistic model (see, for an example of use, Bewley and Denzil, 1988).

The Bass model, used in a context to forecast the adoption rate of a new technology, assumes that no competing alternative will exist in the marketplace, and divides the consumers into two different groups: on one side the innovators, which are defined as adopters due to the effect that mass-media has on their willingness to adapt a new technology, and on the other imitators, which are influenced more by word-of-mouth. In order for the Bass model to be effective in being able to forecast long-term sales pattern of new technologies, one of the following two conditions has to be met: either the technology under scrutiny is already present in the market where the time period sales are observed, or the technology is not present in the market where the time period sales are observed but it could induce a market behaviour similar to the one induced by another already existing technology with known adoption parameters.

The main equations defining the Bass model are, for calculating the fraction of the available market that will adopt a product at time t :

$$\frac{f(t)}{[1 - F(t)]} = p + q * F(t) \quad [12]$$

While the adoption at time t is defined by the following equation:

$$a(t) = M * p + (q - p) * A(t) - \left(\frac{q}{M}\right) * [A(t)]^2 \quad [13]$$

With M defined as the market potential (that is, the total number of customers in the adopting target segment), p as the innovation coefficient, q as the imitation coefficient, $f(t)$ as the portion of M adopting the technology at time t , $F(t)$ as the cumulative portion of M that have adopted the technology by the time t , $a(t)$ as the adoption of the new technology at time t and $A(t)$ as the cumulative adoption by the time t .

Existing sales data can be used to fit the generalized Bass model in conjunction with the following equation:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \left(\frac{q}{p}\right) e^{-(p+q)t}} \quad [13]$$

With the following specifications:

$$F(t) = \begin{cases} F(t) & \text{if } t=1 \\ F(t) - F(t-1) & \text{if } t>1 \end{cases} \quad [14]$$

$$A(t) = M * F(t)$$

$$a(t) = M * f(t)$$

The Bass model can be modified to incorporate advertisement and pricing effects by adding the function $x(t)$ to the equation, with this function $x(t)$ defined as:

$$x(t) = 1 + \alpha * \frac{[P(t) - P(t-1)]}{P(t-1)} + \beta * \text{Max}\left\{0, \frac{Ad(t) - Ad(t-1)}{Ad(t-1)}\right\} \quad [15]$$

Where α is a coefficient capturing the percentage increase in diffusion speed resulting from a 1% decrease in price, $P(t)$ is the price at period t , β is the coefficient that captures the percentage increase in diffusion speed resulting from a 1% decrease in advertising, and $Ad(t)$ is the advertising in period t .

The modified Bass model becomes therefore the following:

$$\frac{f(t)}{[1 - F(t)]} = [p + q * F(t)] * x(t) \quad [16]$$

Diffusion models take, as an assumption, the fact that products are redesigned, remanufactured, updated and marketed in successive generations, which are different among themselves but all follow the diffusion process. Therefore, the ultimate product diffusion rate for the product line is nothing but the sum of the diffusion rates of all the generations. As an example, the Bass formula for the first three generation of a product is defined as:

$$G_{1,t} = F(t_1)M_1[1 - F(t_2)] \quad [17]$$

$$G_{2,t} = F(t_2)[M_2 + F(t_1)M_1][1 - F(t_3)]$$

$$G_{3,t} = F(t_3)\{M_3 + F(t_2)[M_2 + F(t_1)M_1]\}$$

Where M_i defines the incremental market potential for generation i , t_i is the time since the introduction on the market of the i th generation and $F(t_i)$ is the Bass model cumulative function, where p and q are the same across all the generations.

M_i , the market potential, is critical in the formulation of the diffusion model, and it needs to be estimated for each technology, as it represents the upper bound of adoption for that technology. Inferring and calculating M_i has proved to be rather complicated, as it is dependent on various factors, such as the market potential for each vehicle class, the market preference for each technology in each of the vehicle classes, and the share of manufacturers who is willing to integrate the given technology in the vehicle class under scrutiny. Moreover, the market potential is not a static measure, but will change over the period of analysis to integrate fleet expansion, the vehicle class volume change, the manufacturer performance and the availability of the vehicle line and of the technology. The formula to calculate the market potential can be exemplified using the following equation:

$$M_i = S * P_{rf} * S_t \quad [18]$$

Where M_i is the market potential of the technology during year i , S is the total number of new vehicles class in a given country in a given class, P_{rf} is the consumer preference towards the technology vis à vis its incremental cost, and S_t is the market share of the manufacturers selling vehicles using a specific technology or that have announced their plans to do so in the near future.

The frameworks for using the Gompertz and the Logistic models are similar to the ones that are employed in the Bass model, in the sense that they also require the fitting of pre-existing data, the concept of product generations, and an estimation of the market potential M as detailed as possible.

The only factor differentiating the three models is the underlying equation which, in the case of the Gompertz model, is described by:

$$f(t) = M e^{-bt} e^{-l e^{-bt}} \quad [19]$$

Where

$$F(t_n) = \sum_{i=1}^n f(t_i) \quad [20]$$

$$A(t) = M * F(t)$$

$$a(t) = M * f(t)$$

With M defined as the long-term market potential, b as the delay factor and I as the inflection point, that is the point in time where 36.8% of the market potential is expected to be reached.

The logistical model used to model the diffusion of innovation is instead defined by the following equations:

$$f(t) = \frac{M}{1 + B * \exp(-A * t)} \quad [21]$$

$$B = \exp(I * A) \quad [22]$$

Where M is the long-term market potential, t is the time index, A is a delay factor comprised between 0 and 1, and I is the inflection point, that is the point in time where 50% of the market potential is reached.

3.6 Most important time series and diffusion rate modelling studies

Time series and diffusion rate models have been employed various time in the literature regarding BEV, PHEV and HEV adoption, oftentimes in conjunction with another model used to estimate the market potential, in order to overcome possible difficulties that can arise in its estimation. An example of a study where a time series model is used in combination with a cross-sectional modelling technique to estimate the market potential is given by Diamond (2009), study that has as main focus the impact of incentives and subsidization on the diffusion of HEVs in the United States. The author notes that one of the main problems arising when using time series data in the analysis of hybrid adoption is the generalized increase of some of the predicting variables, which makes isolating the effect due to subsidies difficult. Market

share curves appear to follow the fuel price curve, but the latter is itself an unreliable indicator, as it exhibits seasonality and is subject to sharp short-term market fluctuations. Moreover, market share is also an unreliable indicator, as it does not take into consideration supply constraints that may arise during periods of high demand, where the waiting time can exceed six months. For this reason, market share is computed by using a cross-sectional model that compares data from the 50 US states in terms of variance in hybrid adoption. The model developed is then used to study the effect of various policies introduced at a state level. The study main result is that, at an aggregate level, monetary incentives provided to consumers in order to induce them to adopt HEVs do not bear significant results, while, at the same time, exposing significant effectiveness differences depending on the State where they are implemented in, with changes in policy incentives in Connecticut, Florida, Maryland Virginia being consistent with sustained significant changes in market share compared to the US monthly average and New York, California and Utah not showing a statistical significant difference even if they implemented more than one incentive policy change during the period analysed in the study (thus from the year of introduction of selected HEVs, that are the Honda Civic Hybrid, the Toyota Prius and the Ford Escape Hybrid, throughout 2006).

Secondarily, another important study that should be mentioned among the ones using time series data to model the adoption of environmentally friendly vehicles is the one carried out by Münzel et al. (2019), in which the authors explore the impact of subsidization and incentives policies on the diffusion of PHEVs and BEVs in selected European countries. Also in this case the sales data are modelled on the basis of a time series, while at the same time considering differences that arise from different subsidization policies in different countries. The analysis is therefore performed using a panel data methodology by comparing registrations of two sets of vehicles, one BEV or PHEV and one ICEV, representing the ones with the highest registration data in their respective category (Nissan Leaf vs. Volkswagen Golf VII 1.2 TSI and Mitsubishi Highlander PHEV vs. Volkswagen Tiguan 2.0 TSI). The results show that recurring incentives have an effect on registration of environmentally friendly six times larger than one time incentives, thus revealing the preference of consumers towards incentives that are available for a longer period of time, rather than for incentives that are introduced *una tantum* to induce the adoption of BEVs, PHEVs and HEVs. More specifically, the most effective types of subsidies are, apart from recurring incentives, rebates and PoS tax benefits, with estimates for other kinds of incentives (income tax reduction and

VAT benefits) showing reliability issues that make results on the effects that they are able to create very difficult to be taken.

Lastly, In Jenn, Azevedo and Ferreira (2013) the impact of a specific policy (the Energy Policy Act, implemented in 2005) on the sales of HEVs in the U.S. is explored through a panel data regression. Sales data from January 2000 to December 2010 by month, make and model are used in the analysis, controlling for the introduction of the Tax Relief Act, implemented in 2004, the introduction of the Cash for Clunkers programme, implemented in 2009, advertising campaigns carried out by Toyota (as the most sold HEV sold during the period is, by far, the Toyota Prius, it makes sense to control only for advertising campaigns carried out by the specific brand not by advertising campaigns carried out by other brands active in the market), for model discontinued by manufacturers and by vehicles imported or produced domestically (which is an important control, as imported vehicles are sold in different quantities than their domestic counterparts). The results of the paper show that the Energy Policy Act of 2005 had a remarkable and positive effect on the diffusion of HEVs in the U.S. market, with an incentive amount of \$3,150 leading to a 15% increase on the sale of HEVs. Moreover, two other interesting effects are noted in the analysis: firstly, unemployment and sales of vehicles show an important negative correlation, with a 1% increase in unemployment meaning an 8% decrease in sales, and secondarily that gas prices do not bear an influence on the sale of ICEVs, but instead have a positive impact on the sales of HEVs, meaning that increasing gas prices may not dissuade consumers from purchasing ICEVs, but at the same time increase the sales of HEVs in the months following high gas prices.

3.7 Other methods

In addition to what is outlined in the previous sections, other studies regarding the adoption of non-traditional vehicles should be mentioned, as they used other methods of analysis, used a combination of 2 or more methods, or used no method at all, and focused on a more qualitative type of analysis. To the latter category belong articles that either present a literature review of the most important pieces on the adoption and diffusion of electric-powered vehicles, such as Rezvani, Jansson and Bodin (2015) or Gnann et al. (2018), or which describe the history of subsidization in a particular country in a comprehensive and detailed way, such as Holtmark and Skonhoft (2014), who focused on the Norwegian case and on its transferability to other markets.

Other methods used in the analysis of the adoption of BEVs, PHEVs and HEVs include the total cost of ownership model, the spatial model and the cross-sectional modelling technique, considering mainly the geographical differentiation (so differences in the adoption rate in different regions of the same country or in different countries) and the vehicle differentiation (so by comparing vehicles that can be considered similar among themselves but having a single different attribute, for example by comparing two vehicles belonging to the sub-compact segment being one electric-powered and one powered by a traditional engine). To the first group, the total cost of ownership one, belong studies such as Lévy, Drossinos and Thiel (2017), Taefi, Stütz and Fink (2017) and Yan (2018), which include in their calculation costs related to purchase, day-to-day operation and maintenance. The second category comprises instead articles such as Mirhedayatian and Yan (2018), who developed a model for the resolution of the optimization problem for a logistic company owning both BEVs and ICEVs in its fleet, which is operating in an urban area divided into two different zones, internal and external. Both areas are defined as entailing different costs to be active in, such as the external cost of congestion, climate change charges and costs associated to local pollution. In the third batch of studies we can find, as an example, Genn, Springel and Gopal (2018), who developed a model to describe the development of sales of environmental vehicles in the U.S. with, as a starting point, the geographical differentiation of sales in a given year, Mersky et al. (2016), who performed a similar analysis for Norwegian counties and municipalities, and Gallagher and Muehlegger (2011), who carried out an analysis on the geographical distribution of HEV adoption in the U.S..

Furthermore, other studies that should be mentioned are:

- Wee, Coffman and La Croix (2018), which is based on a high-dimensional fixed-effect regression model and analyses U.S. data
- Vergis and Chen (2015), where a regression model based on geographical differentiation in the U.S. is built and implemented
- Sierzchula et al. (2014), employing an OLS regression to estimate the influence of financial incentives on electric vehicles adoption using data from the following countries: Australia; Austria; Belgium; Canada; China; Croatia; the Czech Republic; Denmark; Estonia; Finland; France; Greece; Germany; Iceland; Ireland; Israel; Italy; Japan; the Netherlands; New Zealand; Norway; Poland; Portugal; Slovenia; Spain; Sweden; Switzerland; Turkey; the U.K., and the U.S..

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- Figenbaum (2017), which uses a multilevel perspective to describe the Norwegian case and the impact of subsidization in the country
 - Bjerkan, Nørbech and Nordtømme (2016), where survey data and a regression model are used to analyse the Norwegian market and the propensity of the consumers to purchase a BEV, giving insights also on which is the most effective type of subsidy that has been introduced
 - Krupa et al. (2014), article that analyses survey data to derive conclusions about the diffusion of PHEVs in the U.S. market
 - Mau et al. (2008), which employs a CIMS (Capital Vintage Model), for which the main parameters are obtained through a discrete choice model based on data obtained from a survey carried out in Canada
 - Priessner, Sposato and Hampl (2018), who used a multinomial logistic regression to process data regarding the propensity of Austrian drivers to purchase and adopt as their vehicle
 - Wolinetz and Axsen (2017), where a REPAC (Respondent-based Preference And Constraints) model is employed using data derived from the Canadian Plug-In Electric Vehicle Study

Lastly, various studies combined two or more models in the same analysis, mainly to overcome possible deficiencies and inaccuracies derived from employing just one of them. Examples include Bilotkach and Mills (2012), where a combination of a consumer choice model and a spatial modelling technique is used, Beresteanu and Li (2011), where a consumer choice and a supply-side model are simultaneously employed, and Li, Jiao and Tang (2019), where a consumer choice model and a small world model are utilized.

3.8 Summary of the literature review

The studies concerning the adoption and diffusion of environmentally friendly vehicles can be split into four main categories, each employing different methodologies and analyses: the ones based on consumer choice models, the ones based on agent-based models, the ones based on time series and diffusion models, and the ones based on other models.

In the consumer choice category studies can be further divided into two distinct sub-categories: on one side we have analyses carried out employing the multinomial logit model (MLM), where it is assumed that the decision process involves just one step, and therefore the consumer

will consider together all the vehicles which respect certain characteristics in terms of affordability, driving range, power, etc, while on the other side we have paper based on the nested multinomial logit model (NMLM), in which decision making is considered to be a two-step process: first of all the consumer chooses a specific class of vehicle (e.g.: compact, sedan, SUV, etc) and, later, compares vehicles belonging to this class in order to make her final choice. Notable examples of consumer choice models are Soltani-Sobh et al. (2017), Aksen, Mountain and Jaccard (2009) and Chandra, Gulati and Kandlikar (2010).

Agent-based models employ a computer simulation that creates an environment where agents interact among themselves and, by that, are persuaded to take decisions that lead to the adoption or to the lack of adoption of a particular good. In the case of vehicles diffusion there are four main actors considered in the simulation: the demand side, which is formed by drivers, the supply side, which comprises vehicle manufacturer, fuel providers and policymakers, which have the task of regulating the environment in which the simulation is taking place. The list of most important agent-based model studies on vehicle diffusion includes Eppstein et al. (2011), Silvia and Krause (2016) and Shafiei et al. (2012).

Time series analysis and diffusion rates model are used to describe the speed of acceptance of new technologies, which may or may not be already present in the market under study. Three different methodologies are used in these kinds of studies: the Bass model, the Gompertz model and the Logistic model. All the three of them are based on the division of consumers between innovators, influenced by mass media and imitators, influenced by the word of mouth. Consumers can then be split further into five categories, following Rogers (1995): innovators, early adopters, early majority, late majority and laggards. Among the studies based on diffusion rates and time series models are Münzel et al. (2019), Jenn, Azevedo and Ferreira (2013) and Diamond (2009).

Lastly, the others section comprises studies that do not use any model, but instead provide a qualitative overview of the main incentives provided by policymakers and of the studies investigating their effects, such as Rezvani, Jansson and Bodin (2015) and Holtsmark and Skonhoft (2014), articles combining two or more models, such as Bilotkach and Mills (2012) and Beresteanu and Li (2011) and, lastly, articles using other models not mentioned beforehand, such as the total cost of ownership (see, for example, Taefi, Stütz and Fink, 2017), the CIMS (Capital Vintage Model) (see, for example, Mau et al., 2008), geographical based models (see, for example, Sierzchula et al., 2014 and Mersky et al., 2016) and the REPAC

(Respondent-based Preference And Constraints) model (see, for example, Wolinetz and Axsen, 2017).

4. Methodology, data and approach

Based on the list of articles and theories outlined in the previous literature section, the following theoretical predictions about the model can be made:

1. Variables associated with the environmental consciousness of the individual, such as her propensity to save energy, to recycle, or to employ energy coming from cleaner sources, will have a positive impact on the probability of adoption of a BEV by that specific individual consumer. This is coherent with the idea that more environmentally conscious people are more attracted to environmentally friendly technologies, even if they are costlier at the beginning, and will therefore be more adoption-prone, all else equal.
2. Consumers will, among a given set of alternatives, choose the one granting them the highest possible level of utility. In particular, if consumers are rational, they will prefer the lowest total-cost alternative, thus adopting the technology that will maximize their saving potentials both at the time of purchase and during the whole vehicle life. Therefore, consumers will prefer BEVs over ICEVs if, for example, the first will provide them with free parking, free ferries and free access to toll roads, thus variables related to this particular factors will show a positive relationship with the share of BEVs over the total market for vehicles. This theoretical prediction is coherent with the theory of the rationality of consumers as outlined, for example, in Hall (1990).

The data used in my analysis has been obtained from the Statistisk Sentralbyrå (The Norwegian Central Statistics Bureau) via their website and the queries that the above-mentioned institution put at the user disposal. Various type of information has been downloaded, among which:

1. Vehicle sales data by municipality, by fuel (petrol, diesel, electric and other) and by vehicle type (vehicle on own account, bus, taxi, coach, learner car, hotel car and hired car) for the period 2008-2018
2. Population data by municipality for the timeframe 2008-2018
3. Data about the road traffic volumes in millions of kilometres and about the average road traffic volume per vehicle in kilometres by municipality for the timeframe 2008-2018

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4. Data about the number of ferries by county for the period 2015-2018
 5. Data about the yearly energy expenses per square meter in NOK in the timeframe 2015-2018 in each municipality
 6. Municipality-level data about the yearly energy expenses as a share of gross expenses for the period 2015 to 2018
 7. Data about the renewable energy used yearly in the municipality as a share of the total yearly energy usage for the 2015-2018 timeframe
 8. Municipal-level data about the yearly CO₂ emissions (expressed in grams per kilowatt-hour) deriving from energy use for the period 2015-2018
 9. Data about the amount of waste produced yearly by each inhabitant of each municipality in the timeframe 2015-2018
 10. Data on the share of household waste sent to material recovery (including biological treatment) for each municipality for the period 2015-2018
 11. Data about the number of km designed for cycling per 10,000 inhabitants at a municipal level for 2015 to 2018
 12. Data about the number of charging parking spaces present in the municipality for the period 2015-2018
 13. Data about the number of public parking spaces present in the municipality for the period 2015-2018

In addition to that, two other pieces of information have been retrieved from different websites:

1. Data about the number of public charging facilities in each municipality in 2019 (List of Charging Stations).
2. Data about the spatial disposition of toll ring roads in 2019, constructed as a dummy variable taking value 1 if the city possesses a toll ring road and 0 otherwise (Toll Roads).

All the data downloaded has then been organized in a single excel file through the usage of the power query functionality and analysed with the help of the software “STATA” following the methodology outlined in the next section.

The choice of using past share data instead of other kinds of data, such as stated future preferences collected through a survey, mainly derives from the focus of this analysis, which is to describe how the Norwegian BEV market developed through the year (and how the incentives already in place helped to shape it), rather than to forecast how the future demand

behaviour will be. The uniqueness of the Norwegian EV landscape, where BEVs are not considered to be the privilege of just a few drivers (generally wealthier than average and with a strong sense of environmental friendliness) but are already taking up a considerable share of the total vehicle market, makes the analysis of past data feasible in terms of availability and comprehensiveness and the results deriving from it possibly trustworthy.

The methodology employed in the study is relatively uncomplicated, and it is based on the packages provided by the software “STATA” for statistical analysis. A multiple linear regression analysis is performed having, as dependent variable, the share of EV as a percentage of total sales in any given municipality and, as independent variables, the population of the municipality, the average road traffic volumes in the municipality, the toll ring dummy variable, the number of charging station present in the municipality, the number of ferries in the respective county where the municipality is located, the energy expenses as a share of gross expenses, the share of renewable energy used in any given municipality as a percentage of total energy usage, CO₂ emissions from energy usage expressed in grams per kilowatt-hour, the kilograms of household waste produced by inhabitant in each municipality, the number of kilometres designed for cycling in any given municipality per 10,000 inhabitants and, lastly, the share of charged parking spots available in the municipality as a percentage of the public parking spaces available. Relative data, such as shares and amounts per population has been chosen in order to, on one side, relativize the impact of the policies, and capture how they change the market composition and not the market size itself, and on the other side to avoid overestimations or underestimations of variable coefficients due to differences in the scale of measurement.

The model here outlined is therefore built on geographical differentiation, developed following Sierzchula et al. (2014) but with a peculiar focus on municipality-level differences, and not on bigger-region differences, and on studying the impact of incentives that show differences at a municipal level, rather than on subsidies that are provided at a national or regional level. The following equation describes the model that I constructed:

$$y = \sum_{i=1}^N \beta_i x_i + \varepsilon_i \quad [23]$$

With y being the independent variable, β_i being the coefficient describing the effect of each dependent variable, x_i being the dependent variables itself, and ε_i being the error term, which

captures the variance not explained by the model itself. As it is possible to see the summation is performed from i to N , with N being set equal to 12, so that, in this way, all the 12 different variables under scrutiny are captured and accounted for in the model.

To perform the analysis data from 2018 are used and, in order to test the accuracy of the model predictions, runs using 2015, 2016 and 2017 data (where available, so for every variable apart from the toll road dummy variable and the number of charging stations present in each municipality, for which 2019 data are used) are tested and presented in the following section of this dissertation.

5. Results, discussion and policy implications

This section has been developed with, as aim, the outline and presentation of the main results deriving both from the 2018 main model run and from the 2015, 2016 and 2017 test runs.

As shown in table 3, 4, 5 and 6, it should be specified that the model does not seem to have a high level of explanatory power, accounting for slightly more than 20% of the variability of the observations between different municipalities, with adjusted-R² comprised between 0.2479 in the main 2018 run and 0.2188 in the 2017 test run. This is partly due to the peculiar design of the model, which is only aimed at capturing differences arising from policies that have an impact locally, rather than on the general drivers of EV adoption. Therefore, the effects of national policies, which may be recognized differently by different consumers, are not included in the model specifications.

Moreover, the model should not be considered as exhaustive: it captures in fact only a selected fraction of the total amount of drivers that induce EV diffusion, being them the average road traffic volumes, which can be used as a proxy of the average distance that each resident in the municipality travels in a year, and some of the characteristics related to environmental friendliness that may or may not induce the driver to purchase a BEV instead of an ICEV, such as energy expenses as a share of gross expenses, the share of renewable energy used in any given municipality as a percentage of total energy usage, CO₂ emissions from energy usage expressed in grams per kilowatt-hour, the kilograms of household waste produced by inhabitant in each municipality, the number of kilometres designed for cycling in any given municipality per 10,000 inhabitants. Other important factors are not accounted for in the model, such as economic characteristics, among which it is possible to mention the average savings propensity of each municipality, the average wealth owned by each individual residing in the municipality, and the share on monthly expenses that it is dedicated to transportation; or other personal preferences, which may induce a consumer to purchase or not to purchase a BEV, such as the prestige factor, the driving range anxiety or the model availability on the market.

	Coefficient	Standard Error	t-value
Population	8.20*10 ^{-8*}	4.51*10 ⁻⁸	1.82
Average road traffic volumes (per vehicle)	1.71*10 ^{-6*}	8.75*10 ⁻⁷	1.95
Presence of toll rings (dummy)	0.0529921***	0.0101085	5.24
Number of charging stations	0.0006866	0.0005417	1.27
Number of ferries in the county	-0.0000259	0.0002697	-0.1
Energy expenses/total gross expenses	-0.0322868***	0.0063872	-5.05
Renewable energy as a share of total energy usage	0.000463	0.0003751	1.23
CO ₂ emissions from energy usage (in Kwh)	0.0002416	0.000188	1.29
Household waste per inhabitants	-0.0000243	0.0000226	-1.07
Share of household waste sent to material regeneration	0.0001	0.0001582	0.63
Kilometres designed for cycling for 10,000 inhabitants	-0.0000283	0.000074	-0.38
Charged parking/total public parking	-0.0025804	0.0068335	-0.38
Constant	-0.0266386	0.0473646	-0.56
Number of observations	345		
F (12, 332)	10.45		
P-value	0.0000		
R ²	0.2741		
Adjusted-R ²	0.2479		
Root mean squared error	0.02868		

Table 3: Results from the 2018 run. Note: *** significant at 0.01, ** significant at 0.05, * significant at 0.1

	Coefficient	Standard Error	t-value
Population	$2.31 \cdot 10^{-8}$	$1.99 \cdot 10^{-8}$	1.16
Average road traffic volumes (per vehicle)	$6.16 \cdot 10^{-7*}$	$3.45 \cdot 10^{-7}$	1.79
Presence of toll rings (dummy)	0.0188363***	0.0044264	4.26
Number of charging stations	0.0004246*	0.000237	1.79
Number of ferries in the county	0.0001308	0.000119	1.1
Energy expenses/total gross expenses	-0.0150203***	0.0032034	-4.69
Renewable energy as a share of total energy usage	0.0001586	0.0001995	0.8
CO ₂ emissions from energy usage (in Kwh)	0.0001114	0.0000831	1.34
Household waste per inhabitants	$-1.04 \cdot 10^{-6}$	$8.73 \cdot 10^{-6}$	-0.12
Share of household waste sent to material regeneration	0.000083	0.000068	1.22
Kilometres designed for cycling for 10,000 inhabitants	0.0000466*	0.0000258	1.8
Charged parking/total public parking	0.0014494**	0.0005803	2.5
Constant	-0.014277	0.0235385	-0.61
Number of observations	305		
F (12, 292)	8.71		
P-value	0.0000		
R ²	0.2635		
Adjusted-R ²	0.2333		
Root mean squared error	0.0124		

Table 4: Results from the 2015 run. Note: *** significant at 0.01, ** significant at 0.05, * significant at 0.1

	Coefficient	Standard Error	t-value
Population	$4.56 \cdot 10^{-8}$	$2.78 \cdot 10^{-8}$	1.64
Average road traffic volumes (per vehicle)	$5.14 \cdot 10^{-7}$	$5.02 \cdot 10^{-7}$	1.02
Presence of toll rings (dummy)	0.0246328***	0.006135	4.02
Number of charging stations	0.0005364	0.0003745	1.43
Number of ferries in the county	0.0001752	0.0001573	1.11
Energy expenses/total gross expenses	-0.0236099***	0.0045117	-5.23
Renewable energy as a share of total energy usage	-0.0001548	0.000212	-0.73
CO ₂ emissions from energy usage (in KwH)	0.0001779	0.0001092	1.63
Household waste per inhabitants	0.0000119	0.0000135	0.88
Share of household waste sent to material regeneration	0.0000399	0.0000921	0.43
Kilometres designed for cycling for 10,000 inhabitants	0.0000134	0.0000502	0.27
Charged parking/total public parking	-0.002918	0.0043995	-0.66
Constant	0.261931	0.0278623	0.94
Number of observations	322		
F (12, 309)	8.8		
P-value	0.0000		
R ²	0.2546		
Adjusted-R ²	0.2257		
Root mean squared error	0.01724		

Table 5: Results from the 2016 run. Note: *** significant at 0.01, ** significant at 0.05, * significant at 0.1

	Coefficient	Standard Error	t-value
Population	7.22*10 ^{-8***}	3.6*10 ⁻⁸	2.01
Average road traffic volumes (per vehicle)	1.13*10 ^{-6*}	6.51*10 ⁻⁷	1.74
Presence of toll rings (dummy)	0.035041***	0.0079876	4.39
Number of charging stations	0.0007191	0.0004753	1.51
Number of ferries in the county	0.000202	0.0002114	0.96
Energy expenses/total gross expenses	-0.026749***	0.0057146	-4.68
Renewable energy as a share of total energy usage	0.0001403	0.0001833	0.77
CO ₂ emissions from energy usage (in Kwh)	0.0001831	0.0001117	1.64
Household waste per inhabitants	0.0000243	0.0000176	1.38
Share of household waste sent to material regeneration	0.0001968	0.0001262	1.56
Kilometres designed for cycling for 10,000 inhabitants	-0.0000252	0.0000598	-0.42
Charged parking/total public parking	-0.0026536	0.0054904	-0.48
Constant	-0.205702	0.029031	-0.71
Number of observations	332		
F (12, 319)	8.73		
P-value	0.0000		
R ²	0.2471		
Adjusted-R ²	0.2188		
Root mean squared error	0.02254		

Table 6: Results from the 2017 run. Note: *** significant at 0.01, ** significant at 0.05, * significant at 0.1

Even if, as mentioned in the section before, the model presents a quite low level of explanatory power, it is nevertheless possible to draw some conclusions about the effects of incentivization of BEV adoption at a local level and, possibly, provide recommendations to policymakers about the possible way to follow in order to incentivize the diffusion of more eco-friendly types of vehicles.

First of all, it must be mentioned that some of the independent variables under scrutiny do not show a coherent effect on the dependent variable through the years, but instead seem to have a fluctuating effect, thus reducing their effectiveness in inducing consumers to purchase BEVs, PHEVs and HEVs. The most relevant one belonging to this group is the share of charged parking spots as a share of public parking available in the municipality, which has a negative effect on the share of BEVs in the market in 2016, 2017 and 2018, but at the same time a positive one in 2015. This contradicts the theoretical predictions as, according to them, the relationship between the EV share and the share of charged parking over the total number of public parking should be positive (a higher share of charged parking spaces over total public parking spots means that the saving potentials are higher if the individual driver decides to adopt a BEV instead of an ICEV, as the probability that, by purchasing a BEV, he will not have to pay for a spot that he would have nevertheless had to is higher as the share of charged parking spaces over total public parking spots increases).

There are mainly two reasons behind this contradiction: on one hand, cost-conscious drivers may not be fully aware of the benefits that BEVs bring in terms of parking access and, everything else equal, they may decide completely not to purchase a vehicle and use public transportation instead if the share of charged parking over public parking is higher in their municipality, rather than adopt a different kind of vehicle. Therefore, the remaining vehicles adopters may be less interested in the savings potential of the car they are purchasing and more on other characteristics of the vehicle (brand image, prestige, driving range, etc.), and may therefore be more induced to purchase an ICEV instead of a BEV, thus lowering the EV share in that particular municipality.

On the other one, it should be taken into account that in 2018 the municipalities were given permission to cap the total charge for parking for BEVs at 50% of the ICEVs fare, thus making charged parking effectively no longer free for BEV owners all over the country. The debate

about this increase in prices started in 2016 (see, for example, Bjerkenes, 2016 and Rasmussen and Tiller, 2016), and the decrease of the savings potential deriving from adopting a BEV vis à vis adopting and ICEV that this policy change introduced in the Norwegian BEV subsidization landscape may have been a factor that induced cost-conscious individuals to purchase a traditional ICEV instead of a BEV.

Of the variables showing a positive relationship with the share of BEV sold, the presence of a toll ring in the municipality is the one having the biggest impact, thus meaning that the presence of a toll road is one of the most important factors considered by consumers during their vehicle purchasing decision. Moreover, the t-statistic shows that the estimation is reliable. This means that, from a policy perspective, one of the most efficient policies to implement at a local level to foster the diffusion of BEVs would be the introduction of toll rings around major cities and the exemption from the payment of the associated fare granted to environmentally friendly vehicles.

On the other side, the presence and the diffusion of charging stations may not seem to be a decisive and significant factor influencing BEV adoption. This may stem from the fact that the majority of Norwegian BEV drivers have access to their own charging facilities at home, and prefer to charge through this channel, as shown in Lorentzen et al. (2017), making the construction of a publicly available charging merely a plus, but not a “make or break” decisional component. Similarly, also the presence of ferries may not seem to be a driver of adoption, not having a significant effect on the EV share during all the four years. This means that, from a policy perspective, investing in a public network of charging stations available to all BEV drivers may not be the best choice, and may not lead to the forecasted results in terms of adoption.

Of the other variables under scrutiny, the only one showing a significant negative relationship with the share of BEVs in a specific municipality is the share of energy expenses over all gross expenses. This shows that drivers may be less willing to adopt BEVs if their energy expenses are already high compared to the sum of all their expenses, as their forecasted savings potential over the vehicle lifetime may be perceived as lower than by drivers having a lower share of energy expenses over total expenses. From a policy perspective, this has important implications, as it shows that one effective way to accelerate the diffusion of environmentally friendly vehicles would be to provide consumers with either a general lower level of electricity

prices or with peculiar discounts on the cost of energy when the latter is used to recharge the battery of a BEV.

6. Summary and conclusion

The Norwegian EV landscape represents, as of today, a unique situation in the whole world, and for this reason this dissertation deemed appropriate to investigate why it is so and what other countries can learn from that. In particular, the focus of this study is to understand how incentives having an impact at a local level (thus whose importance and effect changes from municipality to municipality) fostered the adoption of BEVs by an always growing number of drivers spotted all around Norway. An attentive review of the literature splits previous studies concerning EV adoption in four main categories: the ones based on consumer choice models, the ones based on agent models, the ones based on time series and diffusion rate based and others.

The methodology employed is a relatively uncomplicated multiple linear regression, built on geographical differentiation, developed following Sierchula et al. (2014) but with a peculiar focus on municipality-level differences, which uses publicly available data both related to the incentives and to the environmental friendliness of the various municipalities under scrutiny. The model is then run four times, using data from 2015, 2016, 2017 and 2018, with the exception of data related to the presence of toll roads and to the number of public charging stations, which are to be considered as of 2019. The results show that the two most important predictors of EV adoption are the presence of toll roads around the municipality and the share of energy expenses over total expenses, each of them having respectively a significant positive and negative effect. The number of charging stations available in the municipality has a negligible positive effect on the EV share rates, while the share of charged parking over total public parking and the number of ferries present in the municipality's county do not show coherent effects in the four runs, making predictions on their effect on EV adoption difficult to be taken and not always reliable. Other variables related to environmental friendliness do not seem to have a particularly strong effect, thus dismissing the claim, at least at a Norwegian level, that BEVs are purchased mainly by enthusiastic environmentalists.

The main limitations of the study derive both from its limited geographical focus and to the relatively low explanatory power of it. Being focused on the Norwegian case, the analysis does not provide any hint on how subsidization may work in other countries, and there is nothing that tells us that the same drivers that facilitate BEV adoption in one country are the same as in any different country. Moreover, countries are different in terms of consumer mentality, environmental friendliness and driving patterns, thus complicating the matter even further. For

example, it could be argued that in a country where electricity prices are lower than the Norwegian level the share of energy expenses over total gross expenses may not be a good predictor of BEV adoption, while at the same time the availability of a public network of charging stations may be. Furthermore, the relatively low explanatory power of the model shows that a large part of the difference in BEV adoption present between municipalities is still unexplained, thus making deduction difficult to be taken in some cases, in particular when the effect of a particular variable is fluctuating over time.

Further research on the topic should therefore, on one hand, focus on broadening the geographical scope of the analysis by comparing similar countries in terms of customer mentality but with a different set of policy incentives in place, in order to check if the results are transferable to a different setup or if they are dependent on the Norwegian case, while on the other hand ensuring that more variables, representing different policy instruments, are introduced in the analysis, so that the explanatory power of the model can be improved and the results be more reliable and effective in helping policymakers in their decisions.

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Appendix

Source	SS	df	MS	Number of obs	=	305
Model	.016069703	12	.001339142	F(12, 292)	=	8.71
Residual	.044909838	292	.000153801	Prob > F	=	0.0000
				R-squared	=	0.2635
				Adj R-squared	=	0.2333
Total	.060979542	304	.000200591	Root MSE	=	.0124

evshare2015	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
population2015	2.31e-08	1.99e-08	1.16	0.246	-1.60e-08	6.22e-08
sum2015artv	6.16e-07	3.45e-07	1.79	0.075	-6.30e-08	1.30e-06
tollring	.0188363	.0044264	4.26	0.000	.0101245	.027548
numberofchargingstations	.0004246	.000237	1.79	0.074	-.0000419	.0008911
numberofferries	.0001308	.000119	1.10	0.273	-.0001034	.0003649
energyexpensesasshareofgrossexpe	-.0150203	.0032034	-4.69	0.000	-.0213249	-.0087157
renewableenergyasshareoftotalene	.0001586	.0001995	0.80	0.427	-.000234	.0005512
co2emissionsfromenergyusegkwh201	.0001114	.0000831	1.34	0.181	-.0000521	.0002748
householdwasteperinhabitantkg201	-1.04e-06	8.73e-06	-0.12	0.906	-.0000182	.0000161
shareofhouseholdwastesenttomater	.000083	.000068	1.22	0.223	-.0000508	.0002169
numberofkmdesignedforcyclingperl	.0000466	.0000258	1.80	0.072	-4.24e-06	.0000974
sharechargedparking2015	.0014494	.0005803	2.50	0.013	.0003073	.0025915
_cons	-.014277	.0235385	-0.61	0.545	-.0606037	.0320498

Table 7: Results from the STATA software of the 2015 run

Source	SS	df	MS	Number of obs	=	322
Model	.031377567	12	.002614797	F(12, 309)	=	8.80
Residual	.091849884	309	.000297249	Prob > F	=	0.0000
				R-squared	=	0.2546
				Adj R-squared	=	0.2257
Total	.123227451	321	.000383886	Root MSE	=	.01724

evshare2016	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
population2016	4.56e-08	2.78e-08	1.64	0.103	-9.21e-09	1.00e-07
sum2016artv	5.14e-07	5.02e-07	1.02	0.307	-4.73e-07	1.50e-06
tollring	.0246328	.006135	4.02	0.000	.0125611	.0367045
numberofchargingstations	.0005364	.0003745	1.43	0.153	-.0002004	.0012732
v53	.0001752	.0001573	1.11	0.266	-.0001342	.0004847
v61	-.0236099	.0045117	-5.23	0.000	-.0324875	-.0147324
v65	-.0001548	.000212	-0.73	0.466	-.000572	.0002624
v69	.0001779	.0001092	1.63	0.104	-.0000369	.0003927
v73	.0000119	.0000135	0.88	0.380	-.0000147	.0000386
v77	.0000399	.0000921	0.43	0.666	-.0001414	.0002211
v81	.0000134	.0000502	0.27	0.790	-.0000854	.0001121
sharechargedparking2016	-.002918	.0043995	-0.66	0.508	-.0115747	.0057387
_cons	.0261931	.0278623	0.94	0.348	-.0286306	.0810169

Table 8: Results from the STATA software of the 2016 run

Source	SS	df	MS	Number of obs	=	332
				F(12, 319)	=	8.73
Model	.053225139	12	.004435428	Prob > F	=	0.0000
Residual	.162133514	319	.000508256	R-squared	=	0.2471
				Adj R-squared	=	0.2188
Total	.215358653	331	.00065063	Root MSE	=	.02254

evshare2017	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
population2017	7.22e-08	3.60e-08	2.01	0.046	1.38e-09	1.43e-07
sum2017artv	1.13e-06	6.51e-07	1.74	0.082	-1.46e-07	2.42e-06
tollring	.035041	.0079876	4.39	0.000	.019326	.0507559
numberofchargingstations	.0007191	.0004753	1.51	0.131	-.000216	.0016543
v54	.000202	.0002114	0.96	0.340	-.0002139	.0006179
v62	-.026749	.0057146	-4.68	0.000	-.037992	-.015506
v66	.0001403	.0001833	0.77	0.445	-.0002203	.000501
v70	.0001831	.0001117	1.64	0.102	-.0000367	.0004029
v74	.0000243	.0000176	1.38	0.167	-.0000102	.0000589
v78	.0001968	.0001262	1.56	0.120	-.0000515	.0004451
v82	-.0000252	.0000598	-0.42	0.674	-.0001428	.0000925
sharechargedparking2017	-.0026536	.0054904	-0.48	0.629	-.0134555	.0081483
_cons	-.0205702	.029031	-0.71	0.479	-.0776866	.0365463

Table 9: Results from the STATA software of the 2017 run

Source	SS	df	MS	Number of obs	=	345
				F(12, 332)	=	10.45
Model	.103115088	12	.008592924	Prob > F	=	0.0000
Residual	.273045346	332	.000822426	R-squared	=	0.2741
				Adj R-squared	=	0.2479
Total	.376160434	344	.00109349	Root MSE	=	.02868

evshare2018	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
population2018	8.20e-08	4.51e-08	1.82	0.070	-6.67e-09	1.71e-07
sum2018artv	1.71e-06	8.75e-07	1.95	0.052	-1.19e-08	3.43e-06
tollring	.0529921	.0101085	5.24	0.000	.0331074	.0728769
numberofchargingstations	.0006866	.0005417	1.27	0.206	-.000379	.0017521
numberofferriesintheirrespective	-.0000259	.0002697	-0.10	0.924	-.0005565	.0005047
v63	-.0322868	.0063872	-5.05	0.000	-.0448513	-.0197224
v67	.000463	.0003751	1.23	0.218	-.0002749	.001201
v71	.0002416	.000188	1.29	0.200	-.0001282	.0006115
v75	-.0000243	.0000226	-1.07	0.284	-.0000688	.0000202
v79	.0001	.0001582	0.63	0.528	-.0002111	.0004112
v83	-.0000283	.000074	-0.38	0.702	-.0001738	.0001172
sharechargedparking2018	-.0025804	.0068335	-0.38	0.706	-.0160227	.0108619
_cons	-.0266386	.0473646	-0.56	0.574	-.1198113	.066534

Table 10: Results from the STATA software of the 2018 run