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How Incentives Drive our Future

An Empirical Analysis of Incentives for BEV Adoption

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Abstract
The adoption of electric vehicles (EVs) has only been a matter of time since the first governments proclaimed bans on combustion vehicles in the near future. As a new technology, however, EVs face various adoption barriers that lengthen the process. Governments globally have aimed to mitigate these by offering EV incentives. Even though the adoption of pure battery electric vehicles (BEVs) and not hybrids is the ultimate goal, previous publications on the effect of EV incentives focus on the joint effect on both BEV and hybrid adoption. The purpose and contribution of this paper is to comprehensively evaluate the effect of government incentives on BEV adoption, and to evaluate how that effect changes when considering socio-economic characteristics, in relation to charging infrastructure, and over time. To examine this in an unbalanced panel of 23 European countries between 2013 and 2019, I construct a novel dataset of BEV incentives. I further utilize multilinear ordinary least square panel regressions with a time trend, country fixed effects and various control variables. I identify a significant increase between 17.6% and 19.4% in BEV registrations, per 1000 euros additional incentive, with an indication of a differing effect in small markets. This result is robust to various controls and self-selection into the panel. This paper aims to contribute to the discussion around EV incentives and adoption, as well as reinforcing empirical results on the effects of incentives on BEVs specifically.

Keywords: Electric Vehicles, BEV, Technology Adoption, Incentives, Tax Efficiency

JEL: Q55, Q58, Q48, L98, O38, H21

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1. Introduction

The European Commission has proposed the complete elimination of carbon emissions from cars by 2035. This would effectively constitute a ban on the traditional internal combustion engine vehicles (ICEVs) (Carey and Steitz 2021) and require a significant increase in electric vehicle (EV) adoption (European Environment Agency 2022). Not just the EU, but countries around the world push for EV adoption as part of the effort to reduce emissions and instate incentives towards this goal. On the other hand, Elon Musk, the CEO of Tesla, which currently sells the most popular EV model (Statista 2022a) has spoken up against the implementation of EV incentives, saying "[…] I would just can this whole bill, don't pass it.", in response to a bill by the Biden administration that budgets 7.5 billion USD to incentivize EV adoption (Quartz 2021). This begs the question: *How do government incentives influence the effort of EV adoption*?

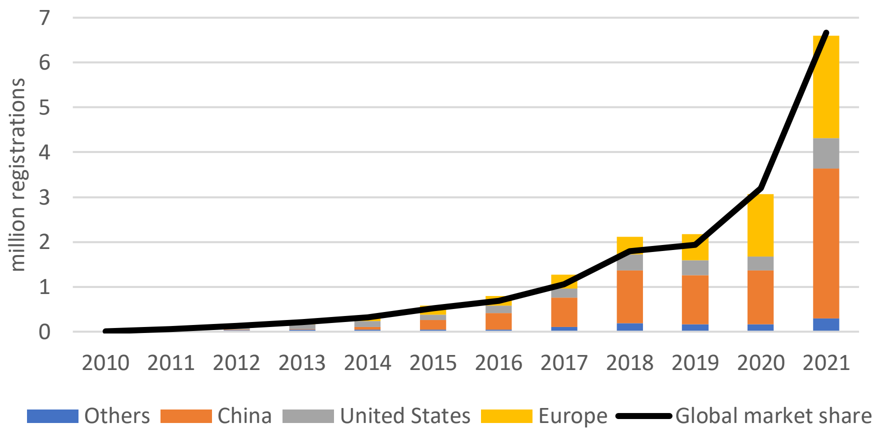
1.1. EV Market

Globally, the need for climate action and a reduction of emissions has been recognized. One major contributor to emissions is the transport sector, which was responsible for 24.6% of greenhouse gas emissions in the EU in 2018 (Ritchie and Roser 2020). Road transport specifically was responsible for 11.9% of global greenhouse gas emissions in 2016 (Eurostat 2021k).

The evident and predominant solution to eliminating this substantial emissions share of cars are emission-free EVs. For instance, US president Biden has announced his policy target that EVs represent 50% of car sales shares by 2030 (The White House 2021). Several cities and countries have even gone so far as to announce explicit bans on ICEVs (IEA 2020), among them the aforementioned indirect ban of ICEVs in the European Union by 2035 (Carey and Steitz 2021). Hence, the adoption of EVs is merely a question of time.

Even without any outright bans on ICEVs, however, EVs have enjoyed staggering popularity in recent years. According to preliminary estimates, while the car industry faced another challenging year in 2021, owing to the global semiconductor shortage, global EV sales more than doubled in 2021, hitting 6.6 million units, up from just over 3 million in 2020 (Richter 2022), as shown in Figure 1 (IEA 2022). In Germany, for instance, the EV share of newly registered vehicles increased by 83% from 2020 to 2021 making up 13.6% of new car registrations (Schmidt 2022). In fact, all net growth in worldwide car sales in 2021 can be attributed to EVs (Richter 2022). Currently, China, Europe, and the United States account for nearly 90% of worldwide EV sales. Additionally, McKinsey & Company (2021) projects for the next decade that while China will remain the largest EV market in total numbers, Europe, as a regulation driven market, will remain a global electrification leader in terms of EV sales shares and therefore especially interesting to study.

Figure 1: Global EV Registrations by Region and EV Market Share (IEA 2022)

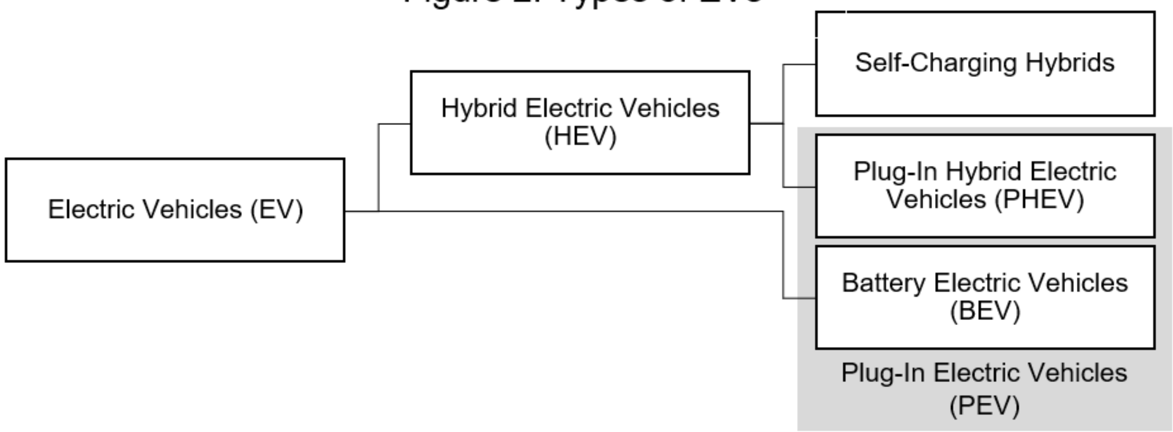


Countries around the world have instituted incentives to further EV adoption. In Europe, all EU member states but Estonia offered monetary EV incentives in 2021 (ACEA 2021b). Norway has the highest EV adoption rates globally and substantially subsidizes EVs, by waiving sales tax, VAT, tolls and parking fees for them. This culminates in annual costs of nearly 19.2 billion NOK (1.9 billion Euros) (Norwegian Ministry of Transport and Communications 2021) for the country. Demonstrating continuous financial commitment to the incentivization of EV adoption, just this February, US president Biden committed 5 billion USD over the next five years to states' EV infrastructure (CNBC 2022).

1.2. The Rise of BEVs

EVs are not a monolith. In literature, a variety of terminology is used to refer to the different types of EVs. ICEVs are traditional internal combustion engine vehicles that use exclusively diesel or fuel. EVs include a variety of car models (Figure 2). Battery electric vehicles (BEVs) are electric vehicles relying solely on electricity as fuel. Hybrid electric vehicles (HEVs) are electric vehicles with either a diesel or gasoline internal combustion engines. They are referred to as plug-in hybrid electric vehicles (PHEVs) if their batteries may be charged externally and self-charging HEVs otherwise. The sum of PHEVs and BEVs is referred to as plug-in electric vehicles (PEVs). For the purposes of comparability and consistency, the above terminology and categorization will be used throughout this paper, regardless of potential differences in terminology in the quoted literature.

Figure 2: Types of EVs



While PHEVs have dominated the market for a long time, there is a shift towards BEVs. Norway, which is ahead of the curve in EV adoption has recently seen a substantial shift towards BEVs. 84% of all newly registered cars in January 2022 in Norway are BEVs, while PHEVs dropped to just 7% of new registrations (Kane 2022).

Furthermore, it is unclear whether the electric driving capabilities of HEVs are actually utilized by drivers. Privately purchased PHEVs appear to electrify the same number of kilometers annually as BEVs, due to BEV owners renting ICEVs for pre-planned long trips (Plötz et al. 2020; Plötz et al. 2017a). On the other hand, a large share of HEVs were purchased by corporations as company cars at the disposal of their employees, commonly due to the favorable taxation of low-emission vehicles in, for instance, Germany (Frahm 2019). It is assumed that a HEV with a 50km electric range drives 75% of all distances using electricity, but since company cars usually cover longer distances, the car emission may be underestimated by 50% to 75%, exacerbated by the weight of the unused but heavy battery (Plötz et al. 2020). Furthermore, German drivers of company car HEVs rarely bother to charge them, since employers can supply fuel charge cards, making gasoline or diesel free while electricity costs of charging have to be paid by the employees themselves.

The United Kingdom and Netherlands ended their incentives for HEVs for these reasons (Frahm 2019). Germany’s government has announced intentions to only grant tax benefits to

PHEV owners if it can be proven that it drives in electric mode at least half the time (SPD et al. 2021).

1.3. Scope and Structure

This paper contributes to the literature on the effect of government incentives on EV adoption in several ways.

First, by being the first to comprehensively evaluate the effect of incentives on BEV adoption in an international sample. The majority of literature on the adoption of EVs examines PEVs, as PHEVs have historically larger adoption rates than BEVs and thus provide more data to exploit. However, since the ultimate goal of EV adoption is carbon neutrality, this can only be achieved by the adoption of BEVs. There is reason to expect that the mechanisms of BEV adoption differ from those of PHEV adoption. PHEVs still possess internal combustion engines and can essentially be used as slightly heavier (due to the battery) and more expensive ICEVs. BEVs, on the other hand, rely solely on electricity as the driving power and are exposed to more adoption barriers, as a completely new technology entirely reliant on novel charging infrastructure.

There is no known comprehensive analysis of the effect of BEV incentives in an international setting. Yan (2018) examine the adoption of BEVs in an international 2 year data set but focus solely on the cost-structure of BEVs compared to ICEVs to explain differences in adoption and do not control for charging infrastructure, socio-economic, socio-demographic or vehicle market controls. The remainder of known literature on the effect of BEV incentives is comprised of just two papers: Mersky et al. (2016) and Clinton and Steinberg (2019). Mersky et al. (2016) examine the effect of only non-monetary incentives on BEV adoption in Norway. Clinton and Steinberg (2019) examine a US data set.

I also analyze the effect of a country sustainability indicator, as a socio-economic variable, on an international BEV panel dataset, which has previously only been analyzed for cross-sectional international PEV data by Sierzchula et al. (2014) and (Wang et al. 2019) both.

Second, I create a new data set on BEV incentives for my sample, to examine my BEV adoption data. For this purpose, I cross-reference several tax indices, EV rebate and incentive data banks, as well as previous publications on EV incentives with overlapping samples to find the exhaustive set of BEV incentive policies. Since these policies typically utilize vehicle characteristics and prices to determine the specific amount granted, I choose a representative

BEV and ICEV, based on their popularity and representativeness of the respective markets as a whole. I then use the representative BEV and ICEV to calculate the incentive value to the average BEV consumer by differencing the government transactions for the two models.

Third, charging infrastructure is generally considered a vital necessity and strong predictor of EV adoption. It stands to reason that charging infrastructure would be expected to influence the effect of government incentives. This has until now only been examined by Rietmann and Lieven (2019) for PEVs. I expand on their results by looking for a similar effect for BEVs with a different methodology.

Fourth, several papers speculate on the temporal development of the effect of incentives on EV adoption as well as the effect of this temporal development on their results (Sierzchula et al. 2014; Wang et al. 2019; Münzel et al. 2019). There does not appear to be an examination of this temporal development, however, which I aim to address.

Fifth, I am the first look for a self-selection bias in EV data by exploiting the unbalanced panel characteristic of my data for a robustness check. I examine whether countries with regular and complete responses to the voluntary BEV adoption questionnaire may be more dedicated to BEV adoption. This is very relevant for external validity and the transferability of results on countries outside of the sample that do not partake in international data collection and documentation efforts for BEVs.

These motivations lead to the following research question:

What effect do government incentives have on the adoption of BEVs?

a. *How important are socio-economic variables and vehicle market characteristics to the adoption of BEVs? Do they influence the effect of government incentives?*
b. *How does the development of charging infrastructure and the effect of government incentives interact to impact the adoption of BEVs?*
c. *How does the effect of government incentives change over time?*

To answer these questions, I utilize the theoretical framework of a purchase decision model in oligopolistic differentiated product markets by Berry et al. (1995) to explain the necessity and mechanism of EV incentives. This understanding, along with further literature on EV adoption factors and previous empirical results on the effect of EV incentives informs my choice of control variables.

I construct a data set for 19 European countries between 2013 and 2019 of BEV registrations shares, estimated BEV incentives, charging infrastructure as well as several more socio-economic, socio-demographic and vehicle market controls. I estimate BEV incentives by cross-referencing various sources to find the exhaustive set of incentives and then calculating the difference in government transactions for a representative BEV and ICEV. After critically comparing alternative methods, I choose multilinear ordinary least square panel regression with country fixed effects and a time trend to estimate the incentive effect. Various checks are performed using alternate controls and different sub samples to ensure the robustness and transferability of results.

I find a statistically significant increase in BEV registrations between 17.6% and 19.4% associated with an additional 1000 euros of monetary incentive. The effect is consistent through the inclusion of various control variables and robust to panel self-selection and EU membership. A robustness check, using only countries with vehicle stocks below 1 million finds a diminished but still significant effect between 9.7% and 11.5% per 1000 euros one-off incentive. A positive, but not statistically significant change in the effect of incentives over time is found. I find the motorization rate, national median income and dwelling types to have a significant effect on BEV adoption. I cannot identify a statistically significant relationship between charging stations and EV adoption or a significant interactive effect of charging stations and incentives.

The remainder of the paper is structured as follows. Next, in Section 2, I will present an overview of EV adoption literature in general and outline recent empirical findings on the effect of EV incentives specifically. Section 3 expounds on the theoretical background of purchase decision models and adoption barriers. Section 4 describes the process of selecting controls, collecting data, as well as the construction of the incentive dataset. Section 5 discusses my choice of empirical method and presents the model specifications used. My results and robustness checks are presented and interpreted in Section 6 and discussed in Section 7. Policy implications, environmental and social considerations are evaluated in Section 8. Section 9 concludes.

2. Literature Review

I will present a short overview of EV adoption literature in general, before moving on to a more in-depth examination of the recent empirical literature on EV adoption and government incentives. These can be categorized by both the region they focus on and the time frame they examine. Finally, I will highlight studies that have examined not just the effect of government incentives but also their interaction with other factors. Fuel price controls, for the sake of brevity, refers to the inclusion of electricity, as well as diesel and/or gasoline prices.

2.1. General Overview

A comprehensive review of the most influential pieces of EV adoption literature is provided by Kumar and Alok (2020), who review and analyze 239 articles, the majority published between 2010 and 2019. Almost a third of the studies focus exclusively on the United States of America (US), while another third is international in nature. They also categorize 5 aspects of EV adoption literature; barriers and motivators for adoption (this includes government incentives), the effect of adoption, the mechanisms through which barriers and motivators influence adoption, the factors influencing the strength of the mechanism, as well as socio-demographic indicators typically related to EV adoption.

This field of research is actively growing (Kumar and Alok 2020) and a variety of effects on EV adoption are examined. In one innovative study, Guo et al. (2020) examine the effect of air pollution on EV adoption, using fixed effects panel regression on a dataset of 20 major Chinese cities in monthly intervals between 2014 and 2018. They find a positive correlation of pollution, measured as PM2.5 concentration, with EVs and BEVs but not HEVs total sales, for different levels of EV model popularity and city-income both.

A majority of EV adoption publications are still survey-based stated-preference studies (Kumar and Alok 2020; Liao et al. 2017; Rezvani et al. 2015), likely due to the yet early stage of adoption and subsequent limited availability of data. Liao et al. (2017) summarize stated-preference studies on consumer preferences involved in EV purchase decisions. They find that while purchase tax and road tax reductions can be concluded to be effective, the consensus on purchase price reductions is inconclusive. Meanwhile, reduced tolls and access to high-occupancy lanes are commonly considered ineffective. It has also been suggested that in the very first years of adoption, the main factors in the purchase decisions are emotional benefits and the symbolism of EV ownership rather than the use of the EV (Rezvani et al. 2015).

Nevertheless, the common attitude-action gap makes empirical studies crucially necessary to gain a better understanding of EV adoption.

2.2. Empirical Findings on Incentive Effect

Empirical papers on EV adoption can be categorized by degree of regionality into international, national and city-based papers. Since incentives for EV adoption are granted on different levels of government and regionality, the chosen degree of regionality typically influences what incentives are examined by a given paper. For instance, free parking granted as an EV incentive by individual cities is difficult to take into consideration in an international comparison.

2.2.1 Cross-Country Results

A growing body of papers examines the adoption of EVs across countries. While studies on a more granular regional level usually work with panel data, international studies use both panel data (Münzel et al. 2019; Yan 2018; Plötz et al. 2017b) and cross-sectional data (Sierzchula et al. 2014; Wang et al. 2019; Rietmann and Lieven 2019). Monetary incentives are the focus of international empirical papers, while non-monetary incentives are less commonly considered, since they are significantly more difficult to standardize across countries. With the exception of Wang et al. (2019) all of these studies identify a significant positive effect of monetary government incentives on EV adoption.

Münzel et al. (2019) analyze the effects of PEV government policy in Europe using country fixed effects and first difference panel regressions. Their models include fuel prices, country fixed effects, a time trend, as well as socio-economic and charging infrastructure controls. They conclude through a variety of robustness checks that the effect of monetary PEV policy is an increase in the PEV share of vehicle registrations by 5-7% per additional 1000 euros in incentives. They find all types of monetary incentives (recurring, one-time, value-added tax, total), their trend estimator, the number of fast chargers per capita and in one specification two controls (Gini coefficient and percentage of people living in houses) to be significant predictors of PEV registration shares.

In a unique approach, Yan (2018) use European data from 2012 to 2014 on 10 specific pairs of popular EVs and their ICEV counterparts to examine the effectiveness of incentives to reduce total ownership costs of BEVs, increase BEV sales, and acquire environmental benefits. They find an average 3% BEV sales increase per 10% increase in total tax incentives. They also find that the price gap between BEVs and their ICEV counterparts is negatively correlated with the BEV price. This price gap is further reduced with increased annual travel distance, in case of strong preferential taxation for BEVs.

Plötz et al. (2017b) use multilinear regression to analyze the effect of monetary and non-monetary incentives on annual PEV sales shares, for 30 European countries from 2010 to 2016, with fuel price and income controls. They estimate 1000 euros in additional incentives to increase PEV sales share by between 4% and 15.9%, depending on the inclusion of country or country-year fixed effects. The total number of non-monetary incentives (e.g. use of special lanes, car registration exemptions, toll exemption), also have a significant positive effect on PEV sales shares. Income and fuel price controls are also significant indicators.

Sierzchula et al. (2014) were the first to examine EV adoption internationally and use fixed effects ordinary least squared regressions to evaluate a cross-sectional data set of 30 European countries in 2012. They use the sales market share of PEVs and control for fuel prices, charging stations per capita, a sustainability index, socio-economic and vehicle market controls. Their analysis finds that monetary incentives, charging infrastructure density and the local presence of a production site or headquarter of an EV producing company are all significant predictors of EV sales market shares. 1000 US dollars of additional monetary incentive are estimated to increase EV sales market share by 0.06%. This is a relatively low estimated effect, which they hypothesize may be explained by its early sample period. The authors similarly suggest that socio-economic controls may not be significant due to EV adoption being limited to a small portion of population and total EV adoption still being low, even if there may be a genuinely strong connection to socio-economic indicators.

Wang et al. (2019) use multilinear regression to examine the effects of monetary and non-monetary incentives on the market shares of PEVs of 30 countries from Europe, Asia and North America in 2015. They use income, fuel price, an environmentalism indicator and charging infrastructure diffusion as controls and find gasoline price, road priority and charging infrastructure diffusion to have a significant positive effect. They cannot find a statistically or economically significant effect of monetary incentives.

Rietmann and Lieven (2019) use a covariance-based structural equation model on a 2017 dataset spanning 20 countries from 5 continents to examine the influence of government incentives and charging infrastructure, measured in stations per highway kilometer, on PEV adoption. They find that charging infrastructure intensity and monetary incentives have a significant, strong, and positive interactive effect. Since charging infrastructure typically accumulates and should have experienced no decline in the first years of EV adoption, this hints towards an increased effect of monetary incentives over time.

2.2.2 National Results

Compared to international studies of EV adoption, national studies allow for a more in-depth analysis of the various factors in play due to limits on data availability and comparability when examining multiple countries. Focusing on one country also allows for analysis of more regional aspects that would be difficult to standardize across countries. Clinton and Steinberg (2019) and Jenn et al. (2018) examine EV adoption in US states and find a significant positive effect of monetary government incentives on adoption. Mersky et al. (2016) examine the effect of government incentives in Norway, where monetary incentives are national and therefore not subject to the regional comparison.

Clinton and Steinberg (2019) use panel regression on an unbalanced panel of model-state data, in quarterly intervals from 2011 to 2015 of BEV registration data in US states. They control for rebates and tax credits separately and in total, fuel prices, charging infrastructure, a green votes index and socio-economic variables (age, gender ratio, education, income). They test pre-trends, do not reject the inherent parallel trends assumption and their application of synthetic controls confirms the existence of a significant positive effect of incentives. Finally, Clinton and Steinberg (2019) find that an increase of 1000 US Dollars in monetary incentives is associated with an 8% increase in EV registrations.

In their study of monthly PEV registration data from US states from 2010 to 2015, Jenn et al. (2018) introduce a novel measure for consumer awareness of the government subsidies in the EV market. Consumer awareness is proxied by the number of newspaper articles discussing the topic, as evaluated with natural language processing. They utilize the total number of newspaper articles in a state less the number of EV articles as an instrumental variable to avoid the endogeneity of a higher number of EV newspaper articles following a high adoption rate of EV. Jenn et al. (2018) find that the 2,6% increase in EV registration per additional 1000 US dollars from their basic model, varies between a 0% and 62% increase under their statistically significant knowledge model.

Mersky et al. (2016) utilize multilinear regression to examine the early stages of BEVs adoption in Norway. They use micro-level data on all Norwegian BEV sales between 2000 and 2013, aggregated on municipal and regional level and qualified by population, to examine the effect of non-monetary incentives (monetary incentives in Norway are national and thereby apply to all sales). Additional controls are selected from the number of EV charging stations, dummies for tolls and bus lanes and socio-economic indicators (dummy indicator for an area bordering on major city, unemployment rate, median household income, average kilometers travelled per vehicle) for each model for the highest predictive power. Due to the micro-level nature of their data, they have the rare chance to differentiate between corporate and private purchases and run separate regressions for all four mutations of corporate and private purchases and short range (range below 121% of average Norwegian commute) and long-range vehicles. They find that corporate purchases are much more dependent on the magnitude of charging infrastructure.

2.2.3 City-based Results

Several types of incentives are often offered on a city level rather than national or regional. It is difficult to integrate these regionally available incentives into an international country-level analysis. Therefore, several papers have also evaluated EV incentives and EV adoption conditions on the city-level, typically using a selection of prominent cities based on data availability and incentive schemes. Ajanovic and Haas (2016) review 10 cities and regions from 7 countries in Asia, Europe and North America, Guo et al. (2020) and Liu et al. (2021) evaluate a selection of Chinese cities.

Liu et al. (2021) examine the impact of EV incentives on the per capita sale of PEVs in 61 Chinese cities from 2009 to 2018 using separate indicators for a city being part of the policy treatment group and a policy being active in that year, as well as their interaction, in a difference-in-difference estimation, which indicates whether a policy is active in a given year and region. The indicator for a policy being active in that year and the policy being active in that year and city, the interaction, are both positive and significant. Further controls are fuel prices, population (density and absolute), presence of EV manufacturers, sulfur dioxide emissions, motor vehicle road space per capita and disposable income, of which diesel prices, local manufacturer presence and air pollution are significant for some models.

2.2.4 Conditional Effect of Incentives

Several previous studies have used interactive models to determine the ways in which incentives may have different effects in the varying circumstances.

In their examination of US car sales by model from 2000 to 2010, Jenn et al. (2013) include interaction terms of a dummy HEV model indicator and an unemployment measure, lagged model sales (their independent variable) and lagged gasoline prices respectively.

Zhou and Li (2018) instrument an interaction term of the number of supermarket stores and 3-month lagged number of charging stations for the charging station network size to avoid potential issues of endogeneity. They also include interaction terms of their socio-demographic controls and their time trend as predictors of PEV adoption.

In her study of PEV adoption in the US, Wang (2020) includes interaction terms both of a dummy indicating whether a state has a goal of 100% Zero Emission Vehicles by 2030 and a dummy indicating whether a state has an emission target with both offered subsidies and an index indicating public awareness of EVs via twitter activity.

To conclude, three of the studies explained in more detail above also considered interaction effects. Clinton and Steinberg (2019) double all regressions with an interaction term of a Tesla dummy indicator with incentives and all other controls. Liu et al. (2021) used an interaction term to analyze the effects of a policy being active in any region at the time, a policy ever being active in the given region and the policy actually being active in a given year and region. Rietmann and Lieven (2019) find that charging infrastructure intensity and monetary incentives have a significant strong positive interactive effect.

In summary, the majority of papers that examine the effect of government incentives find that monetary incentives appear to have a significant positive effect on EV adoption. Results on the various non-monetary incentives are more ambiguous. Due to the larger availability early on and faster adoption of HEVs, there is more literature on PEVs than literature on BEVs.

3. Theoretical Framework

3.1. Purchase Decision Model

To understand the mechanism of EV incentives, I present a stylized model of a vehicle purchase decision. Berry et al. (1995) present a framework to analyze demand in oligopolistic differentiated product markets using the example of the automobile market. They propose that the basis of a purchase decision is the utility of a given model to the consumer as the function of two vectors of model and consumer characteristics, such as this:

$$U(p_k, c_j, m_j)$$

p is the vector of consumer characteristics for consumer k, (c, m) is the vector of vehicle characteristics for model j. Consumer k then purchases model g if

$$U\left(p_k, c_g, m_g\right) \geq U\left(p_k, c_j, m_j\right), \quad for \quad j = 0,1, \dots, J$$

where $j = 0$ represents the choice to not buy a car and $j = 1, \dots, J$ represent the remaining models.

Furthermore, examinations of vehicle demand functions by Gao et al. (2014), Østli et al. (2017) and Gómez Vilchez et al. (2019) help to extend this model for more recent factors affecting vehicle utility and several additional considerations that need to be made when considering vehicles with differing engine types and fuel requirements. Then, personal characteristics of an individual that may influence the vehicle purchase decision include personal values and beliefs, self-image, societal values and perceptions, socio-demographic characteristics, transportation needs (both regular and irregular), availability of alternative transportation, spatial environment (rural or urban, parking space availability, etc). Vehicle characteristics include the cost of ownership (acquisition, maintenance and running costs), applicable governmental regulations (licensing etc., but also the EV incentives at hand), ease of fuel accessibility (charging or fueling infrastructure), technical characteristics (e.g. engine type and power, transmission, emissions), weight and dimensions (including number of seats and doors), visual design characteristics, standard and supplementary equipment, model and brand image and prevalence, magnitude of innovation, reliability.

Occasionally, market characteristics are considered a third dimension (Sierzchula et al. 2014; Plötz et al. 2017b), however, these can typically be expressed as either consumer or vehicle characteristics within the model, as seen above with ease of fuel accessibility or personal spatial environment.

3.2. Adoption Barriers and Incentives

The acceptance of BEVs is impeded by a variety of adoption barriers that decrease the utility of purchasing a BEV. The most important barriers to BEV adoption are technology, the total cost of ownership, the charging infrastructure and general aversion towards change (Kumar and Alok 2020). The technology of BEVs is still being developed and limits the use of BEVs compared to ICEVs, due to limited driving ranges and wait times during charging. The total cost of ownership is higher for BEVs than for ICEVs, their purchase price is significantly higher for similar models and higher maintenance costs can be expected as well. Charging infrastructure is another barrier to adoption as EVs, and especially BEVs are very much reliant on an infrastructure that is only just being built. Consumers are very sensitive to this and a disproportionate worry about a lack of charging infrastructure has been termed “range anxiety”. Further barriers to BEV adoption include, for instance, a limited model selection, lower performance than ICEVs, skepticism regarding the reliability of BEVs to the driver, risk to pedestrian safety (due to lower noise emittance), environmental impact of the built-in batteries as well as electricity load and distribution management.

EV incentives target different consumer and vehicle characteristics to increase the utility of owning an EV over an ICEV and diminish adoption barriers. The vast majority of incentives target the total cost of ownership of EVs, via tax waivers and rebates. Another class of incentives are regulatory benefits such as access to restricted traffic zones or the use of bus lanes on highways, intended to increase the everyday convenience of EV adoption. The government driven installation of charging infrastructure may also be considered an incentive toward EV adoption. However, since intentions to ultimately switch completely to EVs have been announced, this is necessary infrastructure.

Understanding what factors may influence a consumer’s purchase decision and how incentives interact with these helps to select an appropriate set of controls for my empirical analysis. Furthermore, when considering EVs as a specific subset of models, connected by common characteristics, for which I analyze the demand as a whole, vehicle characteristics are complicated. Individual characteristics of models within the subgroup need to be generalized to the whole group, by using representative sample vehicles, for example. Additional indicators such as the number of models available in the subgroups (Sierzchula et al. 2014) may be included in the analysis as well. Observable consumer characteristics can be included through aggregate socio-economic and socio-demographic indicators.

4. Data

I find my set of control variables by cross-referencing vehicle purchase choice model literature (Gao et al. 2014; Berry et al. 1995; Østli et al. 2017; Gómez Vilchez et al. 2019; Jong 1990) with EV adoption literature (Clinton and Steinberg 2019; Münzel et al. 2019; Mersky et al. 2016; Sierzchula et al. 2014; Wang et al. 2019; Plötz et al. 2017b). First, I compile a list of the control variables used in the EV adoption literature and identify 4 categories: incentives (monetary, non-monetary), charging infrastructure, vehicle market characteristics (e.g. motorization rate, size of vehicle market, presence of car manufacturer), as well as socio-economic controls and socio-demographic controls (e.g. income, education, sustainability, age). I choose the BEV registration share as my measure of BEV adoption, construct my data set on monetary one-off incentives, and collect vehicle market, socio-demographic as well as socio-demographic controls.

4.1. BEV Registrations

While both sales and registration data has been used to analyze EV adoption. registration data is preferable over sales data since a significant part of the incentives tend to be applicable through registration and not sale of the EVs. I use registration data on BEVs only. Previous papers have more commonly used adoption or sales numbers for PEVs, which include BEVs but also PHEVs, (Münzel et al. 2019; Jenn et al. 2018; Plötz et al. 2017b; Sierzchula et al. 2014; Guo et al. 2020; Wang et al. 2019) than just BEVs (Clinton and Steinberg 2019; Mersky et al. 2016), especially so in studies with an international focus. Since HEVs are regularly used as ICEVs only, analyzing them jointly with BEVs could muddle results and not correctly reflect the circumstances and incentives that aid EV adoption with the intention of electric driving. Therefore, I focus on BEV registration data. Additionally, past sales figures show that there is a trend of consumers moving away from HEVs to BEVs (Rietmann and Lieven 2019), making an examination of the driving forces behind BEV adoption even more relevant.

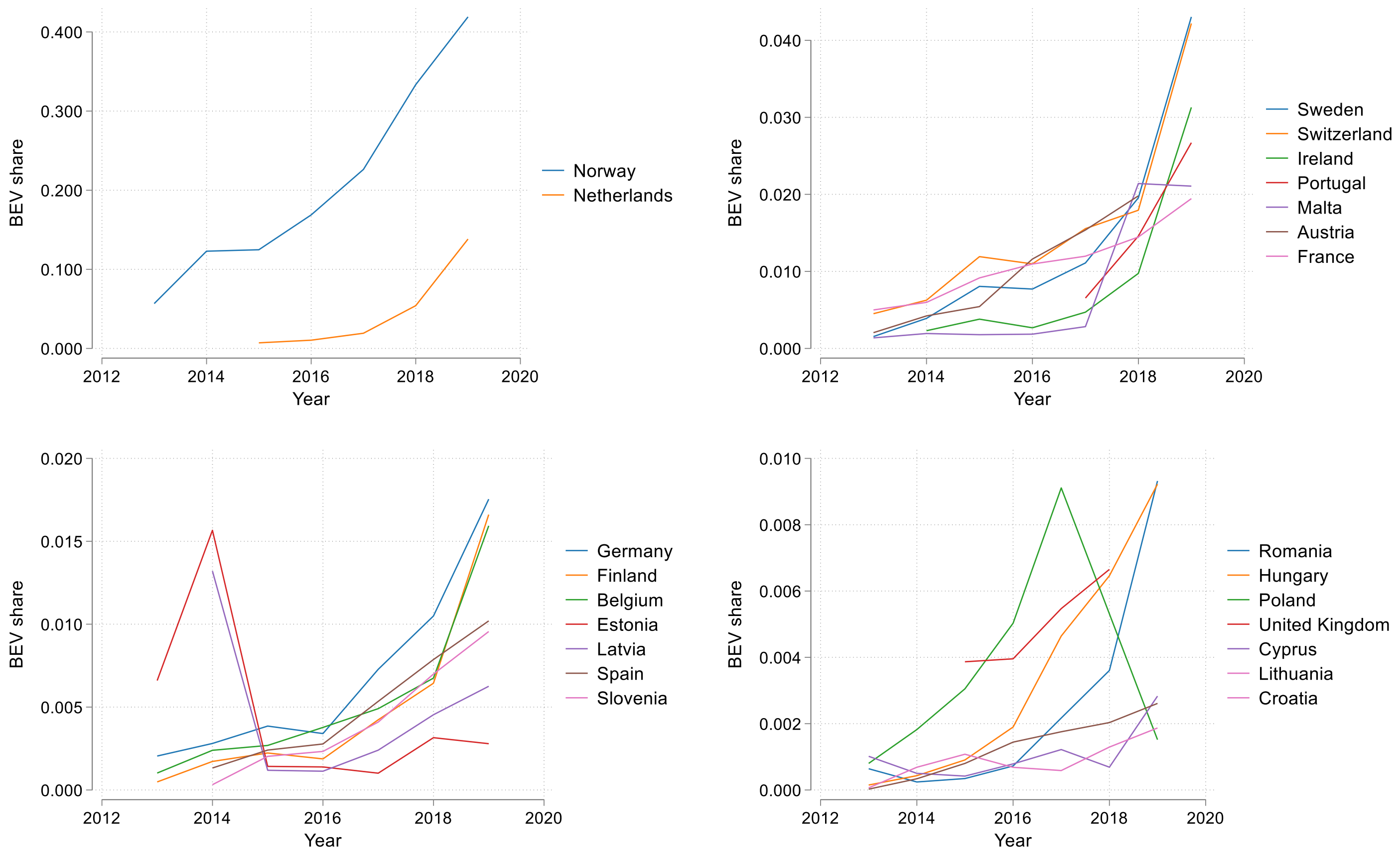
In the previous literature the number of sold or registered EVs has been used as such, scaled per capita, and scaled as the share of total new sales or registrations. However, EVs per capita is dependent on the motorization rate and the total number of EVs on both the motorization rate and the country's total population size. Therefore, I use the BEV share of total registrations.

The data on new BEV registrations is available as an unbalanced panel for 27 countries during the years 2013 to 2019, of which 23 countries were selected for my analysis (Eurostat 2021f; The Society of the Irish Motor Industry 2020). Italy was excluded from the data set, due to only one observation (2019) being available, making it unsuitable for most of my estimations, which include fixed effects. Liechtenstein, Kosovo and Turkey were also excluded due to a significant lack of data availability of control variables. There are 13 countries with complete observations for all 7 years (Belgium, Germany, Estonia, France, Croatia, Cyprus, Lithuania, Hungary, Malta, Romania, Finland, Sweden, Norway and Switzerland) and 11 countries with incomplete sets of observations between 3 and 6 years (Ireland, Spain, Latvia, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, United Kingdom). In total, the dataset contains 146 observations. In line with our definition so far, the data defines EVs as "Battery only EV: road motor vehicle using batteries to feed an electric motor for propulsion." (European Commission et al. 2019).

I calculate the share of BEV registrations as the quotient of BEV registrations per total registrations, *BEV share*. In my empirical analysis, I use the logarithm of BEV registration percentages, *Log(BEV),* due to a right-hand skew in the registration data (Appendix, Figure 7).

Figure 3 presents a timeline of BEV registration shares by country in four groups. Countries are grouped according to their maximum BEV registration share to improve reading comprehension, with scales differing between graphs accordingly. The figure confirms an overall positive growth trend for BEV registration shares in most countries that often seems to be exponential in character. Three exceptions of negative growth rates of the registration share occur either in small countries (Estonia and Latvia) or at relatively low registration shares (Poland), so that this may be the result of singular bulk registrations from a company or institution that caused this spike.

Figure 3: BEV registration shares



4.2. One-off Incentive Estimation

Incentives, across countries, are based on a variety of factors and received during different points in time. I will be focusing on monetary, one-off incentives. I construct my own BEV incentive data set and present the process and assumptions of this approach.

Comprehensive, historical data sets on BEV incentives do not exist, I therefore create my own data set. I use multiple annual reports on European automobile taxation by the European Automobile Manufacturers' Association (refer to Table 1 for a complete list of references) as the basis for a comprehensive list of EV incentives and taxation schemes that favor EVs. I further cross-reference papers covering EV incentives with an overlapping sample that include some indication of the magnitude of their incentive estimations, usually by visual presentation (Münzel et al. 2019; Plötz et al. 2017b; Wang et al. 2019), to capture any further incentives and ensure consistency in the literature. In addition to this, I cross-reference with the European Alternative Fuels Observatory (2022a), which reports current incentives, and Wikipedia (2022), which reports some historical and current incentives for selected countries, to ensure my collection of incentives is as exhaustive as possible. I use the Wayback Machine to access articles and webpages that have been taken offline, since the incentives in question were announced.

EV incentives can be categorized into monetary and non-monetary incentives (Figure 4). Monetary incentives may either be received once, in relation to the registration or purchase of the EV, or recurringly. Recurring incentives include waivers on circulation tax (also referred to as car tax or road tax), company car tax, parking fees and tolls as well as an electricity subsidy. One-off incentives may either be received directly in connection with the purchase and registration of the EV or be claimed in the following tax declaration (income tax reductions and special depreciations for companies). Immediate one-off incentives include rebates, waived taxes (VAT, registration taxes and fees, import tax and pollution tax), scrapping bonuses and charger subsidies. Non-monetary incentives include access to priority lanes (e.g. bus or carpool lanes) and access to restricted traffic zones (e.g. inner cities).

Figure 4: Incentive Categorization

Incentives included in my measure of one-off incentives are presented in bold.

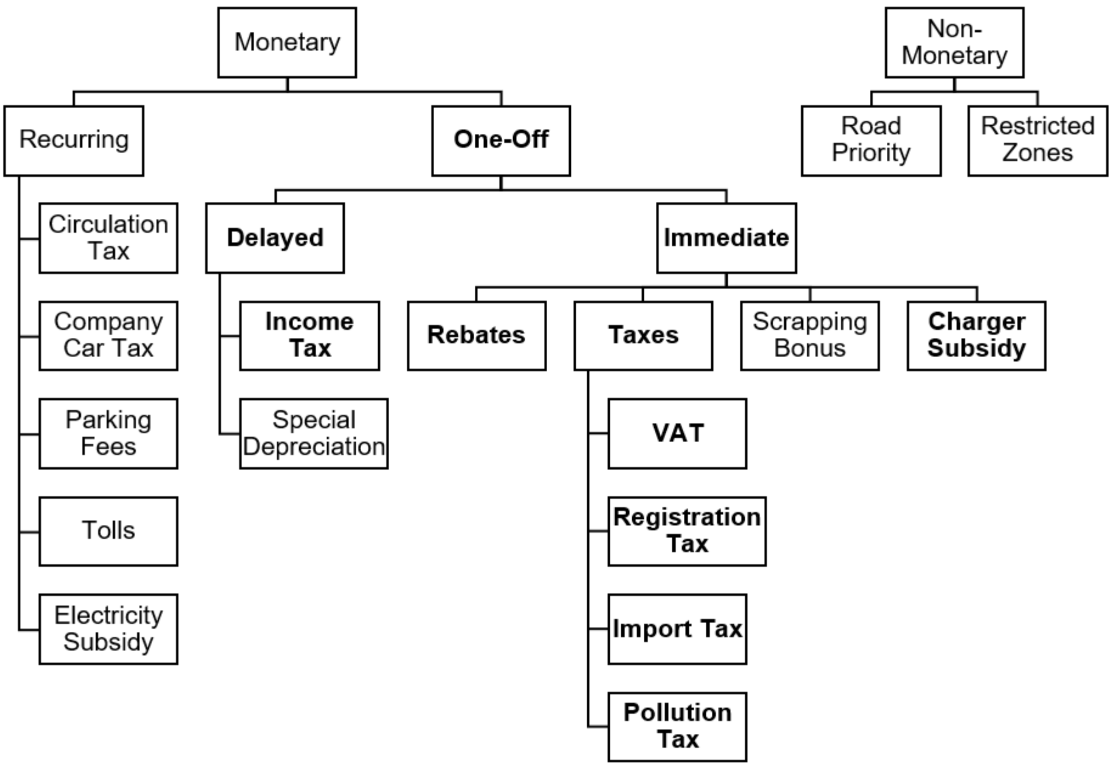


Table 1: Data Sources

	Data	Sources
Incentives	Incentives and Tax Rates	Indices (ACEA 2013, 2014a, 2014b, 2015a, 2015b, 2016a, 2016b, 2017a, 2017b, 2018a, 2018b, 2019a, 2019b, 2021a; CMS 2022; European Alternative Fuels Observatory 2022a) Supplementary Material (partially accessed through the Wayback Machine) Belgium (Statista 2022d; European Commission 2013b), Croatia (European Commission 2013a), Netherlands (Automotive World 2014), Germany (Bundesamt für Wirtschaft und Ausfuhrkontrolle 2016), Cyprus (Burke Bros 2020), United Kingdom (Guardian 2015; Next Green Car 2015), Hungary (Hungarian Ministry of Finance 2016; HungaryToday 2020), Estonia (IEA 2019; Kredex 2014), Spain (International Council on Clean Transportation 2019; Ministry of the Presidency, Spain 2011), Romania (Romania Insider 2016), Finland (The Association of Automobile Importer in Finland 2018), Malta (Times of Malta 2016; Transport Malta 2014, 2018), Austria (Wirtschaftskammer Österreich 2021)
	Harmonized Index of Consumer Prices	(Eurostat 2022a)
Other Variables	Number of charging stations	(European Alternative Fuels Observatory 2022b)
	Gasoline and Diesel Prices	(European Commission, Directorate-General for Energy 2021; European Commission, Directorate-General for Energy. 2013; European Commission. Directorate General for Energy. 2018; European Commission. Directorate-General for Energy. 2016) Croatia (Statista 2021a); Switzerland (Statista 2022b); Norway (Trading Economics 2021);Turkey (Statista 2022c)
	Electricity Prices	(Eurostat 2021b); Switzerland (Statista 2021b)
	Vehicle Stock	(Eurostat 2021g); United Kingdom 2015 (Department for Transport 2016)
	Population	(Eurostat 2021h)
	Gender Ratio	(Eurostat 2021j)
	Gini	(Eurostat 2021c)
	Median Income in Cities	(Eurostat 2021d)
	National Median Income	(Eurostat 2021e)
	Education	(Eurostat 2021i)
	Median Age	(Eurostat 2022b)
	Dwelling House	(Eurostat 2021a)
	Environmental Performance Index	(Wendling et al. 2020; Wendling et al. 2018; Hsu et al. 2016; Hsu et al. 2014)
	Exchange Rates	(OzForex 2022)

It is difficult to construct a comprehensive measure that combines immediate and recurring incentives, since the holding period as well as the discount rate of private and corporate consumers is likely to differ and there is no comprehensive data available on the consumer group proportions. Considering immediate and recurring incentives separately should therefore allow for consistent estimators. This does however assume that recurring incentives that are nominally equal are equally meaningful in all countries, which is not self-evident, since consumers' expected benefit from recurring incentives depend on their expected holding period of the vehicle and discount rate. While reliable data for all countries and years of the sample on vehicle holding periods are not available, it is however clear that the holding period may vary between countries in the sample as well, by as much as 80% (Autoalan Tiedotuskeskus 2021). Furthermore, it is unclear how the holding period of EVs may differ from that of ICEVs, which currently provide the basis for holding period estimates. Furthermore, the value of certain recurring incentives such as waivers on parking fees or road tolls can be very difficult to estimate annually, even if all necessary data were available. This is however typically not the case, as these are commonly applied at local levels, similar to non-monetary incentives. Therefore, I will be focusing my analysis on one-time incentives, received within a year of registration.

The estimated incentive, *One-off Incentive*, for a given country and year is the difference in one-off government transactions (taxes, fees, rebates, etc) for a BEV vs ICEV within the first year, based on their difference in engine type and emissions.

Car characteristics such as prize, weight, engine size, engine power, length, etc. are commonly required to compute the difference in transactions based on engine type and emissions. Due to limited data availability, it is unfortunately not feasible to construct a comprehensive dataset of EV model market shares across countries and years. Instead, I select a representative BEV and ICEV counterpart to use as reference for technical characteristics (CO2 emissions, fuel consumption, vehicle weight, battery capacity, battery range, electricity consumption) and prices. The reference vehicles are chosen based on their popularity, representativeness of the vehicle market as a whole and in the case of the ICEV counterpart, characteristics of likely EV substitutes. The chosen representative vehicle models based on these criteria are the Nissan Leaf and the Volkswagen Golf (refer to Table 2 for vehicle characteristics).

During my sample period, the Renault Zoe and Nissan Leaf are typically the most popular BEVs, claiming large shares of the market, in Europe (CarSalesBase 2022), with the Renault Zoe being slightly more popular overall. Since the Nissan Leaf is a 4-door car and in a higher price segment than the 2-door Renault Zoe, it is more representative of the remaining EV market as a whole. The original Nissan Leaf was replaced by the second generation of Nissan Leaf in 2017, with a standard model and a plus model introduced in 2019 with larger battery and engine power. The basic Nissan Leaf of the second generation (Nissan 2022) was chosen as an overall representative, more specifically the Nissan Leaf Acenta, the second cheapest option, for price data collection due to its widespread availability. Meanwhile, the most popular ICEV in Europe has been the Volkswagen Golf since 2008 (JATO Dynamics 2022), the Volkswagen Golf 7 was produced from 2012 to 2019. More specifically, I choose the 'Golf 7 Comfortline 1,4l 110 kW', a model that best matches the Nissan Leaf for direct comparison (Volkswagen 2022; Dynamic Works 2022), with equal engine power, equipment level and a gasoline engine, since Gasoline vehicles are most likely substitutes for EVs, if they are not available (Xing et al. 2021). Since Volkswagen offers a variety of cars and the Golf 7 has since been discontinued, I use the closest successor available in a given country for price data, most commonly the 'Golf 8 Style 1.5 TSI 110kW'.

Table 2: Comparison of Sample BEV and ICEV Characteristics

	Nissan Leaf	**VW Golf**
Engine Type	Electric	Gasoline
CO_2 Emission in g/km	0	122
Fuel consumption in l/km	0	6,8
Engine Power	150	150
Battery Size	39kWh	n/a
Engine Size	n/a	1.395l

I source list prices for both models directly from the manufacturers' national websites, preferably from price lists and alternatively from the sales websites, by manually excluding any promotions to avoid biasing the prices with short term promotions. Prices for the sample time period are then constructed using the Harmonized Index of Consumer Prices (HICP) for motor cars, following the established example of Berry et al. (1995). Volkswagen price data was unavailable for 5 smaller countries, due to supply chain interruptions and thus constructed as the average of the geographic neighbor countries' prices, with weights according to BEV prices.

Some countries posed specific restrictions on what models were eligible for rebates. Since these always included the most common models and typically only excluded higher priced segments, I consider these incentives in full. The German rebate introduced in 2016 is subject to manufacturer participation, but all major EV manufacturers participated.

There are several more assumptions underlying the incentive calculation. In cases where VAT is payable on waived taxes, the VAT amount is included in the calculated incentive. Incentives were added in full, if available for at least 6 months of the year. As taxation often differs for newly registered and second-hand EVs, another implicit assumption is that all registered EVs are newly bought. This is reasonable since secondary markets for BEVs have largely not been established or are still quite small due to the market yet being in the early stages of adoption (Turrentine et al. 2018).

Incentives are often offered for both private and corporate purchases. This is commonly an issue in the estimation of incentives, as there is no data available for what proportion of EVs in a given country and year can be assumed to have been purchased from these parties for most countries. It has been argued that private consumers will benefit from corporate incentives when corporate EVs are sold on the second-hand market, since they will factor benefits to corporate consumers into their willingness-to-pay and thus reduce their own purchase price, spreading the corporate incentives to all consumer groups (Münzel et al. 2019). Since I focus on one-off incentives, this is not much of an issue, as these are mostly applied to all consumer groups. Recurring incentives differ much more drastically across consumer groups. In my data set, there were only two cases of consumer group incentive differences.

First, private consumers in Belgium receive income tax benefits. For these I follow the joint collection approach of Münzel et al. (2019). Since a personal income and marginal personal income tax rate need to be referenced, I use 146% of Belgium's median income, based on 2019 data on socio-economic characteristics of EV owners from the US (Fuels Institute 2021; U.S. Census Bureau 2021).

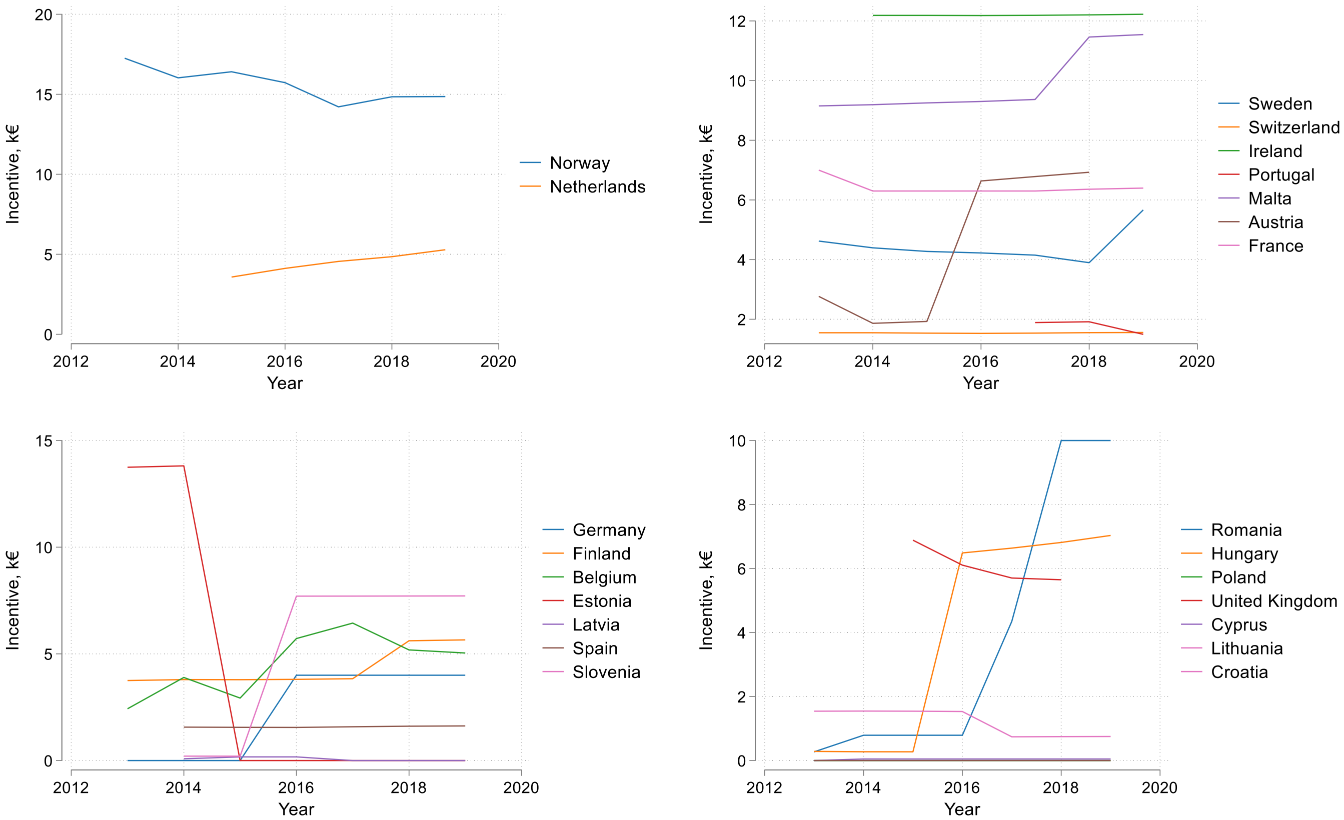
Second, Portugal and the United Kingdom offered special VAT deductions for corporate consumers of BEV during the sample period. Instead of the common 18-25% first year depreciation, both countries allowed for BEVs to be written off wholly in the year of acquisition. This deduction represents a slight financial advantage since the corporate tax burden is moved into the future. Since the tax burden is only shifted and interest rates have been low in Europe in the past decade, I have chosen not to include an estimation of the value of this benefit.

During the sample period France, Malta, Romania and Spain offered scrapping bonuses for the decommission of old ICEVs in connection with the purchase of an EV. The scrapping bonuses were always offered in connection with and lower than BEV or EV purchase bonuses. They are conditional on the age of the decommissioned vehicle, requiring a minimum age of typically 12 to 15 years. The lowest minimum age is 7 years for a Spanish scrappage scheme. Since these minimum ages are well above the respective average vehicle ages and EV consumers are typically high-income (Fuels Institute 2021; Autoalan Tiedotuskeskus 2021), I assume that these bonuses are not available to the majority of EV interested consumers and exclude them from the analysis.

Figure 5 shows the development of the estimated incentive value by country in the same groups as the BEV registration share in Figure 3. Note that scales differ in the individual graphs. Different types of incentive developments can be observed. First, some countries, such as Sweden or Spain, maintain nearly constant levels of estimated incentive throughout the entire observation period. Second, countries, such as Norway or Belgium, maintain relatively constant levels of incentives with slight variations that are typically the result of a consistent incentive or tax break that is calculated via a tax or incentive formula with slight annual corrections. Thirdly, big jumps in the estimated incentive are typically the result of the introduction or abolishment of lump sum rebates or tax breaks, such as in Estonia in 2015 and Hungary in 2016.

Due to the international scope of my data, I focus on monetary incentives which have better comparability across countries. Non-monetary incentives include the use of priority lanes (e.g. bus lanes or carpool lanes) and access to otherwise restricted areas. The first two are excluded from the analysis for two reasons: data availability and data reliability. Non-monetary incentives are commonly offered at regional or city level and therefore subject to variation within countries (Wang et al. 2019; Münzel et al. 2019). In order to reliably include non-monetary incentives in the analysis, one would either have to limit themselves to only those offered at the national level or have to determine the fraction of the population the incentive was offered to. The data for the latter is unfortunately not reliably available for the majority of our sample, due to the time span analyzed, with a 10-year gap between the sample beginning and the start of the analysis and the data available on municipal, regional level or city level for this.

Figure 5: Estimated One-off Incentives



4.3. Controls

In addition to the BEV registration shares and the constructed data set of one-off incentives, I collect and control for a number of vehicle market, socio-economic and socio-demographic variables. I select these using purchase decision theory and previously published empirical studies. In addition, I use the Yale Environmental Performance Indicator to construct my own country sustainability dummy.

I control for charging infrastructure in all of my models, as it is considered a main decision factor in EV purchases, correlated with EV incentives and bears omitted variable risk. Heuristically, it is logical to suspect that countries that offer larger one-off incentives would also invest more money in improving charging infrastructure. Table 4 also shows a positive correlation of the two variables. Accordingly, not controlling for charging infrastructure risks an upwards bias in the estimated effect of one-off incentives. However, the inclusion of charging infrastructure bears inherent issues of endogeneity, as a spike in EV sales or registrations may lead to a spike in installed charging infrastructure, due to higher demand for the same. This is especially a concern due to the yearly frequency of observations. I avoid this by lagging charging infrastructure by one year. I consider both population and area as options to scale the number of charging stations and ultimately settle for charging stations per capita, since charging stations per area could be misleading due to very different population densities within countries. For instance, in a country like Sweden, larger areas with low population density and therefore presumably lower charging infrastructure may significantly skew this measure. Hence, I select charging stations scaled by population and lagged by one year, *Lagged Charge*. After examining a scatterplot of BEV registrations and lagged charging infrastructure per capita, to ensure linearity (Appendix, Figure 8), I take the logarithm of the lagged charging stations per capita, *Log(Lagged Charge)*. Since 18 observations (12%) have zero charging stations, I add one charging station before scaling by population to ensure that no observations are lost.

The vehicle market indicators are the *Motorization Rate* (vehicles per capita), and an indicator of fuel prices. Due to the high correlation of gasoline and diesel price data, including both indicators in a regression would lead to collinearity. A variety of approaches have been taken in the literature to include either of these indicators or a combination of them in the analysis. If either is chosen, it is typically argued to be the one more likely to influence the purchase decision of an EV based on the most likely replacement ICEV, were EVs not available. Fuel price controls may also be summarized in one electricity and combustion fuel price ratio (Münzel et al. 2019), calculated per mile driven (Clinton and Steinberg 2019) or calculated as a weighted average based on gasoline and diesel use (Sierzchula et al. 2014).

I use annual gasoline price points in my estimation, as Xing et al. (2021) find, via the application of a discreet choice model and market simulations without EVs available for purchase, that EVs mainly substitute gasoline vehicles (79%) and typically with high fuel efficiency. Electricity prices are the annual average by country for consumption between 2,500 kWh and 5,000 kWh, as the average annual EU electricity household consumption is 3,700kWh (Odyssee Mure 2021).

Furthermore, to save a degree of freedom in the regression, electricity prices and gasoline prices are combined into a *Fuel Price Ratio*, as the ratio of this should be relevant to consumers.

Socio-economic controls include the Gini coefficient of equivalized disposable income (indicator of the equality of the income distribution), *Gini*, and an education indicator (percentage of the population between 15 and 64 with tertiary education), *Education.*

I consider controlling for both the median net equivalized national income in euros, *National Income*, and the median net equivalized urban income in euros, *Urban Income,* as there might be differences in BEV adoptions depending on degree or urbanization. Ultimately, I control for the national income only, and not for the median net equivalized urban income, since the correlation coefficient with urban median income is 0.99 (Table 4) and the inclusion of both variables would lead to collinearity as well as data on city income not being available for parts of the sample. Furthermore, I use the logarithm of the national median income, *Log(Income)*, due to indications of non-linearity in a scatter plot with BEV registrations (Appendix, Figure 8).

Additionally, a dwelling type indicator, *Dwelling House*, representing the percentage of the population living in houses, as opposed to flats or other arrangements, is used to proxy the ability of people to charge their EVs at home, to supplement the official charging station count.

Socio-demographic controls are the ratio of women to men, *Gender Ratio*, and the median population age, *Median Age*.

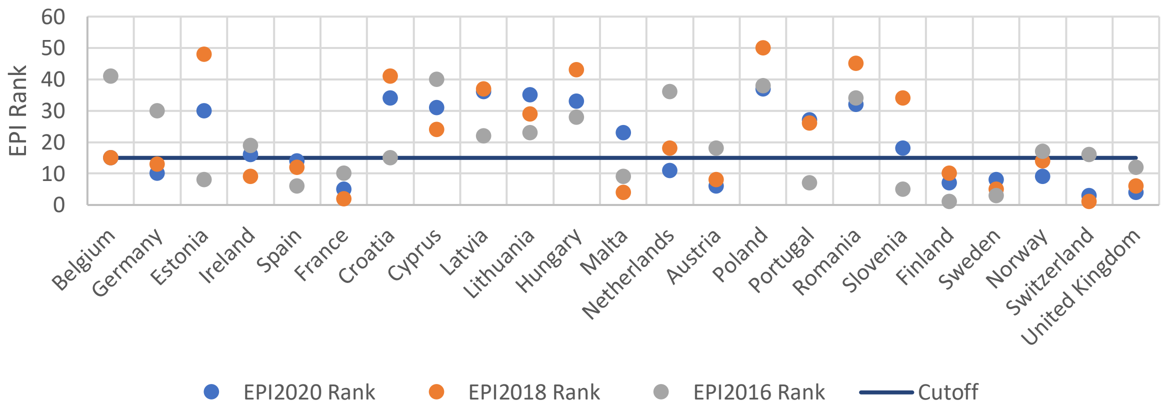
In order to examine the interactive effect of one-off incentives with charging infrastructure and time respectively, I construct two interaction variables, the product of one-off incentives with the time trend, *Incentive*Time,* and the logarithm of charging stations per capita, lagged by one year, *Incentive*Log(Lagged Charge)*.

A new country sustainability indicator, *Sustainability*, is created from the Yale Environmental Performance Index to indicate the relatively most sustainable countries. While environmental performance indices have been included in cross-section sample estimations to gauge the sustainability of regions (Sierzchula et al. 2014; Clinton and Steinberg 2019; Wang et al. 2019), no appropriate international measure could be found that is recommended for use across time periods by the publishers.

The Yale Environmental Performance Index, commonly used to gauge countries' sustainability is published biennially with the most recent data for each indicator, typically up to two years before the publication date. The country scores cannot be used as a time series since the construction of the measure varies between years. I therefore construct my own country sustainability indicator from the Environmental Performance Indices 2016, 2018 and 2020. I rank countries according to their Environmental Performance Score in each report and use the individual rankings for the time periods up to two years (one year for the 2020 ranking, since the 2022 report is not yet published) before publication, due to the lag of incorporated data. Hence, the 2016 performance index is used for the period 2013 to 2014, the 2018 performance index is used for the period 2015 to 2016 and the 2020 performance index for the period 2017 to 2019. The top 15 countries in each report are then considered sustainable. This measure considers 9 countries to be sustainable at some point, leading to 54 country-year combinations (37% of observations) to be sustainable (Figure 6).

The construction of a time-invariant country sustainability indicator (i.e. a country has to rank consistently above a certain threshold to be considered sustainable), but time-invariant variables are not possible in the fixed effects specifications used in this paper.

Figure 6: Countries' Environmental Performance Index (EPI) Ranking



Finally, Table 3 provides an overview of the basic summary statistics for untransformed incentives and regressors. Table 4 shows the correlations (ρ) between transformed incentives and regressors. Notably a lot of the control variables have a strong linear correlation with the BEV registration share, especially one-off incentives, charging station density, income and Gini coefficient ($|\rho|>0.4$). The only candidates for multicollinearity are the national and city focused median net equivalized incomes, which I adjust for by controlling only for national median equivalized income.

Summary Statistics for untransformed Incentives and Regressors

	Mean	Median	Std. Dev.	Min	Max
BEV share	.0172252	.0039316	.0520169	.0000257	.4190657
Incentive, k€	4.300527	3.770237	4.443381	0	17.2546
Charge	.5001545	.1417613	1.464179	0	13.41796
Lagged Charge	.359021	.1045548	.9615196	0	8.604535
Fuel Price Ratio	8.051503	8.16203	1.806539	4.406324	11.32879
Motorization Rate	.4829427	.4925746	.0890505	.2244769	.6285329
Education, %	.3002945	.316	.0697287	.138	.407
National Income, k€	19.49999	18	11.93091	2.327	50.961
Gini	29.75479	29.35	3.525025	22.7	37.9
Dwelling House, %	.6016507	.625	.1736087	.331	.952
Sustainability	.4246575	0	.4959924	0	1
Median Age	41.59863	41.95	2.11223	35.8	46
Gender Ratio	1.057096	1.043	.050927	.986	1.189
Observations	146				

Table 4: Correlation Matrix

	Log(BEV)	Incentive, k€	Log(Charge)	Fuel Price Ratio	Motorization Rate	Education, %	Log(Income)	National Income, k€	Urban Income, k€	Gini	Dwelling House, %	Sustainability	Median Age	Gender Ratio
Log(BEV)	1													
Incentive, k€	0.582***	1												
Log(Charge)	0.729***	0.430***	1											
Fuel Price Ratio	-0.143	0.0869	-0.258**	1										
Motorization Rate	0.216**	0.0735	0.355***	-0.233**	1									
Education, %	0.379***	0.179*	0.455***	-0.307***	0.450***	1								
Log(Income)	0.597***	0.378***	0.659***	-0.380***	0.608***	0.678***	1							
National Income, k€	0.627***	0.391***	0.594***	-0.253**	0.440***	0.594***	0.934***	1						
Urban Income, k€	0.606***	0.396***	0.658***	-0.358***	0.586***	0.677***	0.996***	0.946***	1					
Gini	-0.373***	-0.430***	-0.410***	-0.0312	-0.373***	-0.125	-0.544***	-0.504***	-0.556***	1				
Dwelling House, %	0.0666	0.414***	0.0423	0.00836	-0.163*	0.113	0.138	0.127	0.155	-0.451***	1			
Sustainability	0.429***	0.336***	0.394***	-0.134	0.307***	0.327***	0.577***	0.552***	0.587***	-0.240**	-0.0791	1		
Median Age	0.0212	-0.349***	0.138	-0.00642	-0.0292	-0.362***	-0.130	-0.148	-0.146	0.0521	-0.489***	0.0449	1	
Gender Ratio	-0.396***	-0.483***	-0.317***	0.221**	-0.315***	-0.131	-0.592***	-0.602***	-0.617***	0.642***	-0.417***	-0.441***	0.277***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.0$

5. Empirical Method

The previous section showed that the estimated one-off government incentives per vehicle and other individual controls share a positive correlation with the registration share of BEVs. To better approximate the true effect, I utilize multilinear ordinary least square panel regressions with country fixed effects, a time trend and four different sets of control variables.

Two-way fixed effects, controlling for both fixed effects within subjects or groups and time periods are a very common method to evaluate treatment effects (Chaisemartin and d'Haultfoeuille 2020). Fixed effects or two-way fixed effects are also very commonly used for the analysis of EV adoption, depending on the data-set dimensions (Sierzchula et al. 2014; Plötz et al. 2017b). Two-way fixed effects are equivalent to the difference-in-difference estimator in a setting with two subjects and two periods, with the same underlying assumptions of parallel trends. However, two-way fixed effects in settings with more subjects and time periods also require treatments effects to be constant between subjects and time periods for being unbiased (Chaisemartin and d'Haultfoeuille 2021).

Alternative methods to fixed effects specifically, that are robust to heterogeneity, have so far mostly been developed for cases with binary treatment and staggered adoption (Chaisemartin and d'Haultfoeuille 2021). Due to the high variety in monetary, one-off incentives between countries, it would not be appropriate to reduce the incentives to a binary treatment/non-treatment classification.

Alternatives to time fixed effects, used in the literature, are for instance the inclusion of a lagged independent variable (Jenn et al. 2018) or a trend variable (Münzel et al. 2019). A lot of the empirical studies are also cross-sectional, which does not allow controlling for country fixed effects, even though this would be better suited for policy analysis (Münzel et al. 2019; Kumar and Alok 2020).

The time trend variable models a constant growth factor rather than the time fixed effects' independent shocks over the years. The use of a lagged dependent variable is not recommended within fixed effects estimations (Angrist and Pischke 2009). Since EVs are a growing market, I consider a time trend to be more appropriate. Therefore, I use country fixed effects in combination with a linear time trend variable.

Finally, I use the following five empirical models to answer my research questions.

(1) Basic Model

$$Log(BEV)_{kt} = (\beta_0 + u_k) + \beta_1\, Incentive_{kt} + \beta_2\, Log(Lagged\ Charge)_{kt} + \beta_3\, Timetrend_t + \varepsilon_{kt}$$

The basic model includes one-off incentives, charging infrastructure as the main control and a time trend. k represents the country and t represents the time period ranging from 1 through 7 (representing each year 2013 through 2019). $Log(BEV)_{kt}$ is the natural logarithm of the registration share of BEVs of all car registrations. β_0 stands for the intercept, while u_k is a vector of unobserved country specific time constant fixed effects. $Incentive_{kt}$ represents the estimated monetary one-off incentives in thousand euros by country and year and $Log(Lagged\ Charge)_{kt}$ signifies the logarithm of the yearly number of charging stations per capita for each country, lagged by one year. $Timetrend_{kt}$ is the linear trend over time, constant across countries. Finally, ε_{it} indicates the unobserved error term.

(2) Additional Controls Model

$$Log(BEV)_{kt} = (\beta_0 + u_k) + \beta_1\, Incentive_{kt} + \beta_2\, Log(Lagged\ Charge)_{kt} + \beta_3\, Timetrend_t + \gamma\, Controls_{kt} + \varepsilon_{kt}$$

The additional controls model extends the basic model with a set of vehicle market, socio-economic and socio-demographic controls. $Controls_{kt}$ stands for the vector of additional vehicle market and socio-economic controls by country and year, including Fuel Price Ratio, Motorization Rate, Education (the percentage of the population between 15 and 64 with tertiary education), Income (the logarithmized national median equivalized income), the Gini Coefficient, Dwelling House (dwelling type indicator in percent), Sustainability, Median Age and Gender Ratio.

(3) Additional Controls Model without Fixed Effects

$$Log(BEV)_{kt} = \beta_0 + \beta_1\, Incentive_{kt} + \beta_2\, Log(Lagged\ Charge)_{kt} + \beta_3\, Timetrend_t + \gamma\, Controls_{kt} + \varepsilon_{kt}$$

The majority of variation in the vehicle market, socio-economic and socio-demographic indicators is between and not within countries. In a specification with country fixed effects, a lot of this variation is absorbed by them. Therefore, I present this model specifically without fixed effects as well, to better understand the effect of vehicle market, socio-economic and socio-demographic indicators on EV adoption.

(4) Charging Infrastructure Model

$$Log(BEV)_{kt} = (\beta_0 + u_k) + \beta_1\, Incentive_{kt} + \beta_2\, Log(Lagged\ Charge)_{kt} + \beta_3\, Timetrend_t + \beta_4\, (Incentives \times Log(Lagged\ Charge))_{kt} + \varepsilon_{kt}$$

The charging model extends the basic model with the interaction term $(Incentives \times Log(Lagged\ Charge))_{kt}$ of one-off incentives and the logarithm of per capita charging stations, by country and year.

(5) Temporal Development Model

$$Log(BEV)_{kt} = (\beta_0 + u_k) + \beta_1\, Incentive_{kt} + \beta_2\, Log(Lagged\ Charge)_{kt} + \beta_3\, Timetrend_t + \delta\, (Incentives \times Time)_{kt} + \varepsilon_{kt}$$

The temporal development model extends the basic model with interaction terms to examine the temporal development of the effect of one-off incentives. $(Incentives \times Time)_{kt}$ is the interaction term of the one-off incentives and the linear time trend.

6. Results

Table 5 shows the main regression results from the five models presented in the last section. I examine Q-Q-plots for normality and residual scatterplots for nonlinearities, outliers, unbalanced residuals and heteroskedasticity. A modified Wald (1943) statistic for groupwise heteroskedasticity in the residuals of a fixed effects regression, following Greene (2000), indicates heteroskedasticity, which is already accommodated by using robust standard errors clustered at the country level. Linearity is confirmed visually, as shown in Section 4.3.

All four regression models present statistically significant results. They explain between 70% and 74% (adjusted R^2) of the variance in BEV registrations, with the second model explaining the most variance. The estimated time trend is positive and significant at the 1% level for all five models, speaking to an endogenous EV market growth.

Table 5: Empirical Results

	(1) Basic	(2) Add. Controls	(3) Add. Controls	(4) Charging	(5) Time
One-off Incentive, k€	0.169***	0.177***	0.162***	0.169***	0.145***
	(0.0279)	(0.0219)	(0.0216)	(0.0280)	(0.0348)
Log(Lagged Charge)	-0.00628	-0.0135	0.0116	-0.00630	0.0140
	(0.0560)	(0.0492)	(0.0454)	(0.0559)	(0.0564)
Time Trend	0.343***	0.376**	0.290***	0.343***	0.298***
	(0.0433)	(0.116)	(0.0424)	(0.0438)	(0.0723)
Fuel Price Ratio		0.0717	0.0423		
		(0.135)	(0.0904)		
Motorization Rate		-7.471**	-5.669***		
		(2.394)	(1.382)		
Education, %		5.996	3.561		
		(4.745)	(3.069)		
Log(Income)		-0.657	0.874*		
		(1.110)	(0.369)		
Gini Coefficient		0.0811	0.0356		
		(0.0645)	(0.0488)		
Dwelling House, %		8.721	-1.791+		
		(5.587)	(1.044)		
Sustainability		-0.191	-0.0638		
		(0.124)	(0.118)		
Median Age		0.118	0.118		
		(0.254)	(0.107)		
Gender Ratio		-2.697	-5.218		
		(22.08)	(3.314)		
Incentive* Log(Lagged Charge)				-0.0000628	
				(0.00507)	
Incentive*Time					0.00692
					(0.00671)
Fixed Effects	YES	YES	NO	YES	YES
R-Squared	0.708	0.758	0.758	0.708	0.711
Adj. R-Squared	0.702	0.737	0.736	0.700	0.703
Observations	146	146	146	146	146

Standard errors in parentheses
Standard errors are clustered by country.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A 1000 euro increase in one-off incentives, is associated with a stable 17.6% ($e^{0.162}$-1) to 19.4% increase in the BEV registration share, significant at the 0.1% level, in models 1 to 4. The inclusion of various control variables does not materially affect the one-off incentive effect estimate. The average one-time incentive offered of 4220 euros would therefore be associated with an increase in the BEV registration share between 74.3% and 81.9%, ceteris paribus, compared to no incentive being offered. Model 5 estimates a slightly lower effect of one-off incentives, but also a positive, albeit insignificant, change in the effect of one-off incentives over time. The estimated effect, significant at the 0.1% level, is 15.6% and the estimated total effect lies between 16.4% in 2013 and 21.3% in 2019. This total effect size is once again consistent with the estimated effects in models 1 to 4.

The estimated effect of charging infrastructure is surprising. Across models, charging infrastructure has an insignificant effect oscillating around zero. The interactive effect of charging stations and incentives is negative, but insignificant in model 4. To examine whether this may be a result of using the number of charging stations lagged by one year, I reevaluate all models without the lag on charging stations. (Appendix, Table 6) The coefficients of charging stations (including the interaction term of model 4) are then all positive, although still very much insignificant.

Considering that charging infrastructure is considered to be an important barrier of BEV adoption, it is surprising that no effect can be identified. I propose four possible reasons for this effect. First, it is possible, that due to the early stage of adoption and technological development in the BEV market, consumers were sufficiently served with their charging opportunities at home and at their workplace. Essentially, since the driving range of BEVs was still quite low, BEVs were mainly used to cover short distances and therefore, the number of public charging stations is not as important. McKinsey & Company (2021) also finds that 80% of EV buyers in 2020 had access to private charging stations. Second, there is an observable threshold of minimum number of charging stations that needs to be fulfilled in order for most people to purchase a BEV. An increase in the number of charging stations per capita beyond that is then irrelevant to BEV adoption. Third, since the number of charging stations is a self-reported measure to the European Alternative Fuels Observatory (2022b), that is then cross-checked by the European Alternative Fuels Observatory for accuracy and completeness, it is possible that there are inconsistencies in the data. Fourth, charging infrastructure may be distributed differently within the countries, and therefore have different effects in different countries.

Unfortunately, a measure of the efficacy of the charging infrastructure distribution is very difficult to construct.

In the model 2 and 3, with additional vehicle market and sociodemographic controls, the significant estimators are the motorization rate, median net equivalized income, and the share of people living in houses. The motorization rate is estimated to have a negative and significant effect both with and without specification of country fixed effects. A possible mechanism behind this is that BEV adoption is more common in countries with a lower reliance on cars as the sole transportation option (and thus lower motorization rate). As expected, the use of fixed effects soaks up between-country variation, leading to more significant estimators in model 3, with no fixed effects. The logarithm of the median net equivalized income is then positively associated with the BEV share. Due to the increased total cost of ownership of BEV compared to ICEV it is unsurprising that high-income countries have higher BEV adoption rates. The share of people living in houses is estimated to have a negative association with the BEV registration share. This is surprising, since this indicator was used to proxy the ability to charge at home and thus expected to be positively associated with BEV adoption. However, it is possible it functions instead as an indicator of degree of urbanization, with urban areas having fewer houses and higher BEV adoption.

6.1. Robustness Testing

In addition to the inclusion of further controls and the switch to non-lagged charging infrastructure in the regression models, as described above, all models are rerun on three different reduced samples to examine potential sources of biases and confirm the robustness of regression results against them. First, I examine the nature of the sample as an unbalanced panel and whether the differences in self-reporting between countries influence estimated effects and suggest a self-selection bias in my sample. Second, I test whether vehicle markets exert a leverage effect on estimated effects. Third, I test whether EU membership influences the estimated effects, due to shared international carbon and climate legislature.

First, countries with incomplete observations are excluded from the sample to examine whether voluntary international self-reporting of BEV adoption figures is associated with any systematic differences in the countries. Essentially, I examine the possibility that countries with regular and complete responses to the voluntary BEV adoption questionnaire may be more dedicated to BEV adoption. This is very relevant for external validity and the inference of these results on countries that do not record BEV registration data or do not partake in international data collection and documentation efforts for BEVs. Since only BEV registration data and almost no other indicator was of limited availability, this is not a general bias in the recording and sharing of data. The countries with incomplete time series that are dropped are Ireland, Spain, Latvia, Netherlands, Austria, Poland, Portugal, Slovenia and the United Kingdom. The one-off incentive effect estimates are not materially altered, although slightly higher between 18.1% and 21.2%, compared to the full sample (Appendix, Table 7). Notably, the effect of tertiary education on BEV adoption is positive and significant in both model 2 and 3. Hence, the differences in voluntary, international BEV adoption self-reporting do not seem to affect the effect of one-off incentives.

Second, small vehicle markets are excluded from the sample, to examine whether they exert an undue leverage effect on the regression results of average incentive effect, since all countries are weighed equally. Small vehicle markets are defined as countries with a stock of registered vehicles below 1 million, including Cyprus, Estonia, Latvia and Malta. This modification reduces the estimated coefficients of one-off incentives by about 5 percentage points per 1000 euros one-off incentives (Appendix, Table 8). An increase of 9.7% to 11.5% in BEV registration share per 1000 euros one-off incentive is expected and is statistically significant. There are no other notable changes in the regression results. Hence, it is possible that small countries do drive up the estimated effect of one-off incentives, which will be discussed further in Section 7.

Third, non-EU countries are dropped from the sample to examine whether EU membership has an effect on the regression estimates, due to common carbon and climate protection laws in the EU. Liechtenstein, Norway and Switzerland are dropped from the sample. Notably all of the excluded countries are also relatively wealthy, which may be an alternate motivation for a possible change in regression estimates. However, the regression results are not substantially altered (Appendix, Table 9). The estimated one-off incentive effect varies slightly more strongly between 15.8% and 19.8%. Hence, EU membership is likely not biasing the estimated incentive effect.

7. Discussion

My results show an increase of 17.6% to 19.4% in BEV registrations per 1000 euros one-off incentives. This is slightly higher than the effect of incentives on EV typically identified in the literature, which may be explained through the focus on BEV. The majority of papers finds an effect of a 1000 euros increase on EV registration or sales shares between 3% and 16% with a concentration in the 5% to 8% area (Mersky et al. 2016; Plötz et al. 2017b; Jenn et al. 2013; Clinton and Steinberg 2019; Jenn et al. 2018). On the other hand, Wang et al. (2019) are unable to identify a significant effect and Sierzchula et al. (2014) identify a significant but very small effect.

However, the vast majority of literature, including all studies above, focus on PEVs rather than BEVs. Since incentives are higher for BEVs than PHEVs in several countries and BEVs have naturally more barriers to adoption than PHEVs, as they are further from the established technology, it is not unreasonable to assume that the effect of incentives on BEVs may be higher. In fact, Yan (2018), the only paper examining BEV adoption internationally, associate a 3% increase in registration share with a 10% increase in monetary incentives. Since this is a relative effect, it is not directly comparable, but within reasonable incentive changes, it predicts similar increases in BEV registration share. In the US, Clinton and Steinberg (2019) find an 5% increase in BEV registrations per 1000 US dollars monetary incentive.

Endogeneity of policy choices, could bias all empirical results to be at the upper bound of the achievable incentive effect, as Gallagher and Muehlegger (2011) argue. Essentially, if the countries in the sample are able to and have chosen the incentives most effective for themselves, the estimated effect is likely only achievable for other countries, if they are able to do the same. Since one-off incentives are mostly lump sum payments (either as taxes or rebates, mostly applied at the time of purchase), it is unlikely that this would have a large effect in this case.

Regarding risks of reverse causality, there is no self-evident reason for policy makers to increase incentives, because EV registrations are increased. However, several policies are explicitly formulated to only be available to a certain number of vehicles or until a given budget is spent. Hence, increased EV registrations may decrease granted incentives and therefore bias the estimate downwards.

The transferability and external validity is facilitated by the application of country fixed effects and a time trend as well as my robustness checks. My sample contains 146 observations, covering 17 European countries with a variety of characteristics and cultures over 7 years. One inherent source of bias is self-selection into the panel, which is examined in the first robustness check by reapplying the models to countries with full observations. That this does not materially alter regression results, speaks towards the transferability of results towards countries that choose not to record or report EV registration numbers internationally.

A leveraging effect from small markets in the sample is another possible source of bias. Since I perform an unweighted panel regression, variation and correlation in small countries is weighted equally to that in larger countries. A robustness check on countries with a vehicle stock of at least 1 million cars finds a slightly lower effect than the full sample, albeit still positive and significant. Hence, while there is evidence of a significant positive association across countries, the magnitude of the effect may differ depending on country size. Since the countries in question (Cyprus, Estonia, Latvia, Malta) are also relatively small countries in terms of land mass, this may instead be an effect of smaller countries, for instance, because smaller driving distances decrease EV adoption barriers, such as driving distance limits and leverage incentives.

The inclusion of a time trend and explicit examination of a change in one-off incentives effect over time speaks towards the temporal transferability of my results. While a sample covering a longer time period would obviously be preferable, the data availability is limited by both the recent emergence of the EV market and the publication period of data in a comprehensible format internationally. It should be noted, however, that the EV adoption increased strongly after the observed period, as can already be observed in individual countries. For instance, from 2019, the end of the observed period, to 2020 the number of newly registered EVs in Germany increased by 207%, from approximately 63,000 to 194,000 (Gropp and Záboji 2021). This is 30,000 EVs more than were cumulatively registered in the 7 years prior. In the face of such drastic developments, it is possible that the underlying effects have shifted. It will therefore be very interesting to further examine this development, when the necessary data becomes comprehensively available.

The data and controls used in this paper come with some limitations.

First, this paper focuses on national aggregates of monetary one-off incentives and does not evaluate variation at the regional level, recurring incentives and non-monetary incentives. States and big cities have implemented additional (typically recurring and non-monetary) EV incentives, which have not been considered here and may thus lead to an underestimation of incentives, potentially skewing results. Especially charging infrastructure varies regionally and has been found to have sophisticated effects at the regional level (Mersky et al. 2016). Papers focusing on individual countries and examining regional correlations do find incentive effects by exploiting regional variations (Mersky et al. 2016; Clinton and Steinberg 2019; Jenn et al. 2018; Liu et al. 2021). However, consistent data sets on BEV registrations and incentives at regional levels with international comparability are rare. An examination at a regional level would likely be at least partially qualitative, making a generalization and quantifications across countries very challenging. Non-monetary incentives are also usually applied below the national level and were thus excluded from the examination. In the ideal case of complete data availability, an international analysis on a regional or city level would be ideal to enable both the exploitation of the variation between national factors and the complete consideration of regional and city level incentives, benefits and regulations. For now, however, the results of both types of analysis will have to be considered in complement.

Recurring incentives are also not considered, as the holding periods vary strongly across European countries and are not yet predictable for BEVs. If recurring incentives are correlated with one-off incentives and positively influence BEV adoption, this may lead to an overestimation of the effect of one-off incentives.

Second, discrepancies in the local supply and model availability of BEVs may exogenously limit the BEV registration share. A general increase in global supply and model availability is included in the model through the time trend. However, since this could be a country and year specific shock, it would not be filtered out by either the time trend or the country fixed effects. While there was no evidence of limits in the local supply or model availability discrepancy for the examined models in the collection of price data for this paper, there is no historical data available to confirm this for the sample timeframe.

Third, this paper focuses on consumer incentives and does not consider potential manufacturer incentives. There are no data sets that record such incentives, making them both very difficult to analyze and an interesting avenue of future research. What may mitigate this bias, is that EV manufacturers are largely global companies and a certain international diffusion of any granted manufacturer incentive can be expected.

Lastly, there is an element of uncertainty, whether I have managed to capture all one-off incentives, due to the lack of a truly comprehensive data set on EV incentives. In addition to the various indices (see Section 4.2), I cross reference with papers covering EV incentives with an overlapping sample that present some measure of their incentive estimations (Münzel et al. 2019; Plötz et al. 2017b; Wang et al. 2019) as well as European Alternative Fuels Observatory

(2022a) and Wikipedia (2022). I additionally use the Wayback machine for inaccessible articles to ensure maximum coverage. This cross-checking procedure has also made it clear that this is in fact a potential issue in the literature. For instance, Münzel et al. (2019) do not consider or mention an Estonian incentive policy worth 9 million EUR in effect from 2011 to 2014. This shows that the literature and history of EVs would benefit from a comprehensive database recording EV incentives.

There are two more underlying assumptions in the measure and calculation of the incentives: reference vehicles and consumer behavior.

The calculation of incentives rests on the reference vehicles used, both their prices and technical specifications. Sufficient data on model sales or registration data is not broadly available to enable a model-based estimation across a variety of countries. Hence, in a similar approach to previous papers, I have chosen two reference vehicles for BEV and ICEV respectively. While individual incentives may deviate, the large market share and mid-prizing of the chosen BEV should enable a representative estimation. While it is then additionally difficult to find a good counterfactual ICEV vehicle, I base my choice on results from Xing et al. (2021), who examine what the closest ICEV substitute for an EV is.

Another assumption is that consumers know of and claim all available incentives. Jenn et al. (2018) find significant differences in the effect of incentives across US states by instrumentalizing mentions of EVs in newspapers for public awareness of incentives. This supports the intuitive assumption that public awareness of incentives does influence their effect and provides an interesting opportunity for further research.

8. Policy Implications, Environmental and Social Considerations

My results, consistent with the majority of literature on the subject, show that policy makers can expect one-off incentives to have a substantial positive impact on BEV adoption. However, BEV adoption is not one-dimensional and the economic, environmental and social consequences must be considered to successfully encourage and incentivize EV adoption.

The degree of efficiency is an important performance indicator for incentives, as they should ideally reach those whose behavior they will affect. Xing et al. (2021) find that a large share of US EV subsidies (70%) are received by households that would have likely bought an EV regardless. Hence, a matter of importance to policymakers and interesting avenue of future research is the question of how EV incentives can be structured to target most efficiently those whose behavior will be impacted by them. One obvious example would be the efficiency of incentives for different personal income levels or vehicle characteristics, because these are relatively easy to determine and address for policy makers in their legislation process. Examining the effect of incentives on different consumer groups using micro-level data, is therefore an interesting research opportunity.

The government budget implications of EV adoption incentivization are highly relevant to policy makers and evolve over time.

First, the magnitude of granted incentives per vehicle that are dependent on the purchase price, may autonomously increase over time. In recent years, the substantially higher priced Tesla model 3 has taken over the spot of most popular EV from the Renault Zoe and Nissan Leaf (Statista 2022a). As the market shifts toward more expensive models, granted incentives based on price will automatically increase in value per vehicle, unless regulatory measures (such as values caps) are taken.

Second, as EVs enjoy higher popularity, policy makers may naturally need to rethink the subsidization of EVs as a whole. Norway is on the forefront of EV adoption and has recently had EV registrations shares of 90.5% (Kane 2022). The country substantially subsidizes EVs, by waiving sales tax, VAT, tolls and parking fees for them. This culminates in annual costs of nearly 19.2 billion NOK (1.9 billion Euros) (Norwegian Ministry of Transport and Communications 2021) and eliminates an important source of income for the Norwegian government (Meaker 2021). Currently, a variety of taxes is being considered to be introduced or reintroduced for EVs, including differential taxation for PHEV and BEV. While Norway does have comparatively high incentives, it is clear that policy makers need to find a balance between using incentives to encourage EV adoption and managing income flows.

Naturally, there are further limits and barriers to EV adoption that may hamper the effectiveness of incentives beyond a certain degree of adoption.

First, policy action that targets the share of EVs on the roads, as opposed to the share of EVs in new registrations is likely limited through cars’ holding period, which is currently 10,7 years on average in the EU (Autoalan Tiedotuskeskus 2021).

Second, EV adoption may be delayed or hampered due to production capacity limits. Since EVs are a relatively new technology, a sufficient supply chain to satiate the increasing demand for EVs has to be build. Should there be a significant acceleration of EV adoption, beyond current projections, it is possible that the supply of vital batteries may not be able to keep up (McKinsey & Company 2021), since batteries are especially susceptible to supply chain issues (The Oxford Institute for Energy Studies 2019).

EVs are commonly considered to be zero-emission vehicles and are typically incentivized with the underlying aim of reducing emissions, but this mechanism is not guaranteed.

It is insufficient to only evaluate the emissions of the vehicles themselves when evaluating EV emissions, the emissions produced in the production of the EV and the production of electricity that fuels the EVs must be considered as well. Ajanovic and Haas (2015) examine and compare vehicles' emissions intensity by summarizing the emissions needed to produce and scrap the vehicle, the emissions needed to provide the vehicles' fuel and the vehicles' internal energy efficiency. They find that EVs fueled with coal energy are more emission intense than traditional ICEVs. Additionally, Xing et al. (2021) propose, based on US data, that the reduction in emissions due to the adoption of EVs is typically overestimated by about 39%, since EVs largely replace relatively fuel-efficient gasoline vehicles, which is not typically considered in the calculation of emission reductions. Ajanovic and Haas (2018) also provide a review of more estimations, with slight variations in the estimated emissions depending on assumptions such as lifetime usage.

When incentivizing EVs with an aim of reducing emissions, it is therefore vital to consider the local energy mix and its planned mid-term and long-term development to evaluate the true emission benefits of EV adoption.

Furthermore, from a societal and political perspective, with the push towards EV adaptation, the management and equity of the associated infrastructure are a topic of consideration.

Firstly, public chargers are needed for both long-distance trips and people without access to private charging at home or their place of work. It naturally is important to consider how the distribution of charging stations impact their effectiveness, city-planning and the equity of access to charging infrastructure, e.g. in remote areas. Alhazmi et al. (2017), for instance model different charging station allocations, depending on battery capacities.

Secondly, EVs are expected to be responsible for 5% or Europe's electricity demand by 2030 (McKinsey & Company 2021). Network load distribution and management, including the mitigation of charging loads around peak hours are therefore another political challenge (The Oxford Institute for Energy Studies 2019; Kumar and Alok 2020).

Thirdly, EV owners are currently particularly vulnerable to natural disasters that would displace them from their familiar charging infrastructure or restrict electricity access for several days.

9. Conclusions

EVs have enjoyed a continuous rise in popularity over the last years. Governments have supported and continue to support EV adoption by granting monetary and non-monetary incentives in the effort to reduce carbon emissions. Although the market is currently dominated by PEVs, the long-term goal is typically complete BEV adoption. The purpose and contribution of this paper is to comprehensively evaluate the effect of government incentives on BEV adoption, and to evaluate how that effect changes when considering socio-economic characteristics, in relation to charging infrastructure, and over time.

Previous examinations of the effects of government incentives can be categorized into cross-country, national and city-based studies, in accordance with the analyzed data. The overwhelming majority of papers finds a statistically significant positive effect of government incentives on EV adoption, with only individual studies finding insignificant results or very small effects.

Effective incentives work by exogenously increasing the utility of the desired behavior, in this case the purchase of an EV, to encourage choosing the desired option. EVs face a variety of barriers to adoption, that decrease the utility of an EV purchase, such as higher total cost of ownership, reliance on charging infrastructure or general aversion to change. EV incentives mostly aim to decrease the total cost of EV ownership, but occasionally aim to improve ease of use, e.g. by the use of bus lanes in crowded cities.

I collect data on BEV registration shares and vehicle market, socio-economic and socio-demographic controls and construct my own sustainability indicator.. In addition to the collected data, I construct a data set of estimated average one-off incentives. First, I find the pool of granted incentives and tax schemes affecting EVs by cross-referencing multiple sources. Second, I use the policies and assumptions about representative vehicle characteristics and prices to calculate an average incentive granted for each country.

I find a statistically significant increase in BEV registrations between 17.6% and 19.4% associated with an additional 1000 euros of monetary incentive, by utilizing multilinear ordinary least square panel regressions with country fixed effects and a time trend after critically examining alternatives. The effect is consistent through the inclusion of various control variables and robust to panel self-selection and EU membership. A robustness check, using only countries with vehicle stocks below 1 million finds a diminished significant effect between 9.7% and 11.5% per 1000 euros one-off incentive. A positive, but not statistically significant change in the effect of incentives over time is found. I cannot find a statistically significant relationship between charging stations and EV adoption or indication of a significant interactive effect of charging stations and incentives. Possible reasons for this are, for example, a reliance on private charging options or data quality. I find the motorization rate, national median income and dwelling types to have a significant effect on BEV adoption.

This result is within, but at the upper bound of effects previously estimated, possibly indicating a stronger effect of incentives on BEVs than PEVs. There are also several potential sources of bias and uncertainty, most importantly the examination of aggregate data on national level and simplification assumptions in order to compute comparable incentive measures across countries.

Opportunities for future research are, for instance, the evaluation of incentive efficiency for different consumer demographics via micro-level data and an examination of supply side incentives. Work on the effect of EV incentives would likely benefit from a comprehensive, accessible and transparent database of EV incentives, as this information is available but currently not centrally collected.

The incentivization of EVs does not happen in a vacuum. Significant adoption of EVs carries societal and infrastructure implications in addition to the obvious economic and environmental effects that policy makers need to diligently consider to successfully reduce emissions in a larger effort towards climate neutrality.

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11. Appendix

11.1. Figures

Figure 7: Histograms of BEV registration shares

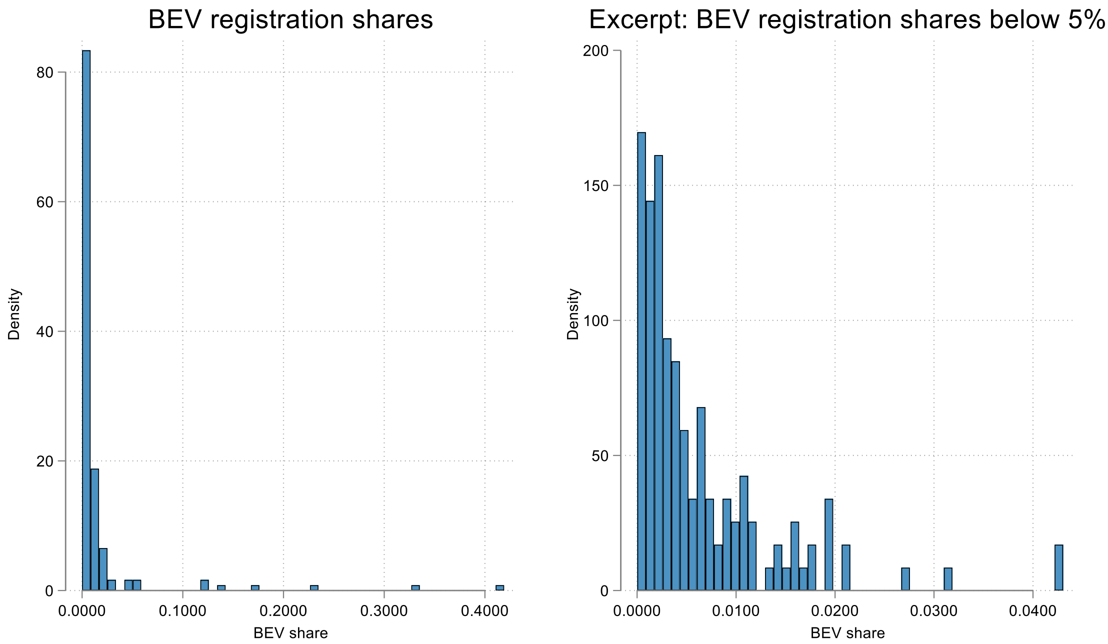
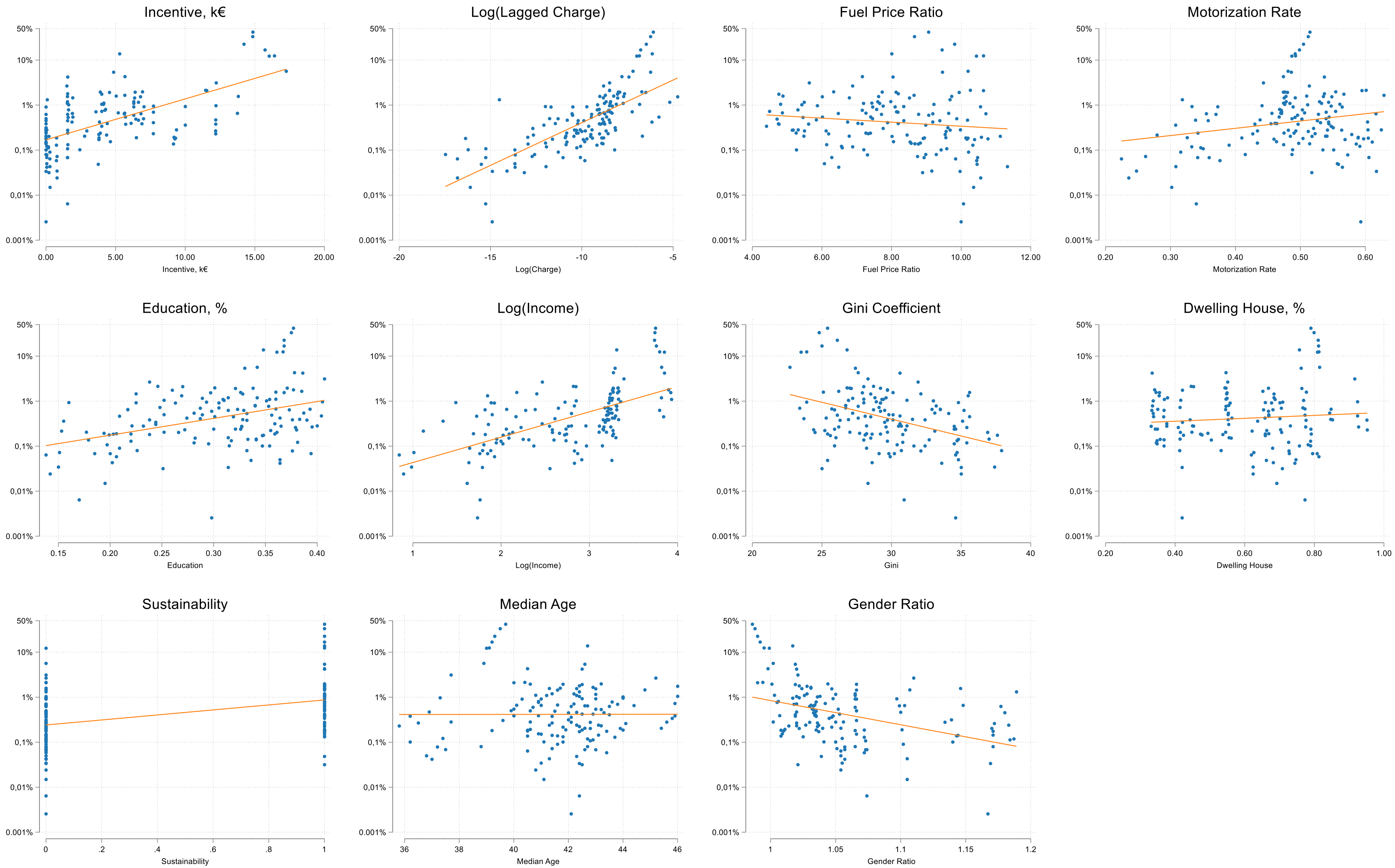


Figure 8: Relationships between Incentives and Regressors



11.2. Tables

Table 6: Charging Variable without Lag

	(1) Basic	(2) Add. Controls	(3) Add. Controls	(4) Charging	(5) Time
One-Off Incentive, k€	0.168***	0.175***	0.162***	0.167***	0.140***
	(0.0262)	(0.0201)	(0.0198)	(0.0262)	(0.0298)
Log(Charge)	0.0315	0.0102	0.0464	0.0340	0.0649
	(0.0829)	(0.0647)	(0.0637)	(0.0860)	(0.0808)
Time Trend	0.324***	0.363**	0.277***	0.322***	0.268***
	(0.0404)	(0.116)	(0.0396)	(0.0429)	(0.0577)
Fuel Price Ratio		0.0777	0.0389		
		(0.143)	(0.0976)		
Motorization Rate		-7.440**	-5.544***		
		(2.429)	(1.306)		
Education, %		5.883	3.597		
		(4.607)	(3.045)		
Log(Income)		-0.696	0.791*		
		(1.114)	(0.384)		
Gini Coefficient		0.0810	0.0389		
		(0.0637)	(0.0510)		
Dwelling House, %		8.531	-1.816+		
		(5.605)	(1.083)		
Sustainability		-0.182	-0.0734		
		(0.126)	(0.125)		
Median Age		0.121	0.112		
		(0.256)	(0.111)		
Gender Ratio		-3.800	-5.534		
		(21.42)	(3.472)		
Incentive* Log(Charge)				0.00162	
				(0.00575)	
Incentive*Time					0.00852
					(0.00579)
Fixed Effects	YES	YES	NO	YES	YES
R-Squared	0.709	0.758	0.759	0.709	0.713
Adj. R-Squared	0.702	0.737	0.738	0.700	0.705
Observations	146	146	146	146	146

Standard errors in parentheses
Standard errors are clustered by country.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Robustness test without countries with incomplete time series

	(1) Basic	(2) Add. Controls	(3) Add. Controls	(4) Charging	(5) Time
One-Off Incentive, k€	0.175^{***} (0.0274)	0.189^{***} (0.0164)	0.192^{***} (0.0163)	0.174^{***} (0.0253)	0.166^{***} (0.0353)
Log(Lagged Charge)	0.0347 (0.0479)	0.0199 (0.0506)	0.0464 (0.0445)	0.0423 (0.0490)	0.0416 (0.0497)
Time Trend	0.323^{***} (0.0461)	0.115 (0.110)	0.257^{***} (0.0471)	0.312^{***} (0.0529)	0.306^{**} (0.0842)
Fuel Price Ratio		-0.0245 (0.0795)	0.00536 (0.0519)		
Motorization Rate		-4.770^{+} (2.222)	-6.872^{***} (0.780)		
Education, %		21.90^{*} (8.841)	5.406^{*} (2.508)		
Log(Income)		-0.605 (1.024)	1.147^{***} (0.241)		
Gini Coefficient		0.103 (0.0742)	0.0667 (0.0462)		
Dwelling House, %		9.119^{*} (4.047)	-1.150 (0.786)		
Sustainability		-0.115 (0.172)	-0.0763 (0.129)		
Median Age		0.404 (0.305)	0.0748 (0.0678)		
Gender Ratio		-33.96 (20.80)	-5.305^{+} (2.791)		
Incentive* Log(Lagged Charge)				0.0176 (0.0163)	
Incentive*Time					0.00264 (0.00787)
Fixed Effects	YES	YES	NO	YES	YES
R-Squared	0.767	0.840	0.924	0.768	0.767
Adj. R-Squared	0.759	0.817	0.913	0.758	0.757
Observations	98	98	98	98	98

Standard errors in parentheses

Countries with incomplete time series dropped: Ireland, Spain, Latvia, Netherlands, Austria, Poland, Portugal, Slovenia and the United Kingdom. Standard errors are clustered by country.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Robustness test without small vehicle markets

	(1)	(2)	(3)	(4)	(5)
	Basic	Add. Controls	Add. Controls	Charging	Time
One-Off Incentive, k€	0.0970**	0.109**	0.101***	0.0974**	0.0910*
	(0.0268)	(0.0341)	(0.0259)	(0.0268)	(0.0353)
Log(Lagged Charge)	0.0331	-0.000207	0.0366	0.0326	0.0386
	(0.0461)	(0.0531)	(0.0421)	(0.0461)	(0.0542)
Time Trend	0.375***	0.345**	0.369***	0.377***	0.364***
	(0.0429)	(0.107)	(0.0419)	(0.0438)	(0.0873)
Fuel Price Ratio		-0.0401	0.0127		
		(0.0858)	(0.0847)		
Motorization Rate		-6.245*	-5.025**		
		(2.923)	(1.782)		
Education, %		5.330	0.332		
		(3.731)	(2.712)		
Log(Income)		0.0641	1.144***		
		(1.060)	(0.309)		
Gini Coefficient		0.0334	-0.0181		
		(0.0994)	(0.0544)		
Dwelling House, %		4.366	-2.240^{+}		
		(6.024)	(1.357)		
Sustainability		-0.230	-0.182		
		(0.161)	(0.170)		
Median Age		0.202	-0.0132		
		(0.260)	(0.138)		
Gender Ratio		-8.018	-3.159		
		(19.82)	(4.526)		
Incentive* Log(Lagged Charge)				-0.00125	
				(0.00330)	
Incentive*Time					0.00170
					(0.00845)
Fixed Effects	YES	YES	NO	YES	YES
R-Squared	0.776	0.809	0.826	0.777	0.777
Adj. R-Squared	0.771	0.787	0.806	0.769	0.769
Observations	119	119	119	119	119

Standard errors in parentheses

Small vehicle market countries with total vehicle stock below 1,000,000 are excluded: Cyprus, Estonia, Latvia, Malta. Standard errors are clustered by country.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Robustness test without non-EU memberstates

	(1) Basic	(2) Add. Controls	(3) Add. Controls	(4) Charging	(5) Time
One-Off Incentive, k€	0.170***	0.181***	0.150***	0.171***	0.138**
	(0.0278)	(0.0217)	(0.0282)	(0.0281)	(0.0470)
Log(Lagged Charge)	-0.00340	-0.0101	0.0180	-0.00354	0.0159
	(0.0582)	(0.0486)	(0.0431)	(0.0583)	(0.0585)
Time Trend	0.339***	0.377**	0.298***	0.340***	0.290**
	(0.0509)	(0.119)	(0.0474)	(0.0509)	(0.0868)
Fuel Price Ratio		0.0791	0.0144		
		(0.148)	(0.0886)		
Motorization Rate		-7.552**	-4.933**		
		(2.428)	(1.769)		
Education, %		6.280	1.323		
		(4.980)	(3.045)		
Log(Income)		-0.416	0.974*		
		(1.419)	(0.457)		
Gini Coefficient		0.0694	0.0193		
		(0.0717)	(0.0453)		
Dwelling House, %		8.452	-2.075*		
		(5.842)	(0.993)		
Sustainability		-0.202	-0.0776		
		(0.162)	(0.157)		
Median Age		0.0505	0.0954		
		(0.323)	(0.0961)		
Gender Ratio		2.407	-2.505		
		(26.21)	(3.219)		
Incentive* Log(Lagged Charge)				-0.00112	
				(0.00486)	
Incentive*Time					0.00873
					(0.0100)
Fixed Effects	YES	YES	NO	YES	YES
R-Squared	0.698	0.750	0.706	0.698	0.701
Adj. R-Squared	0.691	0.725	0.677	0.689	0.692
Observations	132	132	132	132	132

Standard errors in parentheses
Non-EU member states excluded: Liechtenstein, Norway, Switzerland. Standard errors are clustered by country.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$