Network Externality and Subsidy Structure in Two-Sided Markets:
Evidence from Electric Vehicle Incentives

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Abstract

This paper uses new, large-scale vehicle registry data from Norway and a two-sided market framework to show non-neutrality of different subsidies and estimate their impact on electric vehicle adoption when network externalities are present. Estimates suggest a strong positive connection between electric vehicle purchases and both consumer price and charging station subsidies. The counterfactual analyses suggest that between 2010 and 2015 every dollar spent on station subsidies resulted in 2.16 times more electric vehicle purchases than the same amount spent on consumer price subsidies. However, this relation inverts with increased spending, as station subsidies' impact tapers off faster.

Keywords: network externality, two-sided market, electric vehicle, subsidies

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Greenhouse gas emissions and associated changes in climate severely impact public health, the environment, and communities around the world. Transportation activities have a substantial role in contributing to both greenhouse gas emissions and criteria air pollutants.[1] As a result, governments are using a wide array of incentives to lower emissions from the transportation sector. In particular, the advancement of electric vehicles constitutes an integral part of emission reducing activities in many countries.[2] There is tremendous variation across countries in electric vehicle (EV) incentive programs. The U.S. alone has more than 400 different policies which provide support for EVs (U.S. Department of Energy, 2015). However, there is little consensus on whether the current collection of policies is effective in supporting EV adoption or could be improved upon.

This paper empirically investigates the impact different incentives have on EV adoption using a two-sided market framework. More specifically, is it preferable to subsidize consumers, by lowering the upfront costs associated with EV purchases, or to subsidize charging stations, by lowering their sunk entry costs with a one-time subsidy? A price subsidy directly affects the buyers' vehicle purchasing decision by making the high purchase cost of EVs comparable to (or even lower than) their conventional counterpart. On the other hand, subsidies to charging stations can eliminate the problem of range anxiety through the development of the charging infrastructure. Removing this crucial barrier to the EV industry can indirectly increase buyer demand for EVs. To date, there exists little to no empirical research which explores the ways in which both sides of the electric vehicle market interact with each other. Without explicitly understanding these relationships, it is not possible to understand the efficacy of different subsidy

1 In 2014, the transportation sector accounted for 23% of the global carbon dioxide emissions making it the second largest contributor after the electricity and heat generation sector. Road traffic alone accounted for three-quarters of transport emissions (International Energy Agency, 2016).

2 The International Energy Agency (IEA) estimates that total electric vehicle spending between 2008-2014 by the world's leading governments invested in supporting electric vehicles equaled $16 billion (International Energy Agency, 2016). The participating countries in the Electric Vehicle Initiative include Canada, China, Denmark, France, Germany, India, Italy, Japan, the Netherlands, Norway, Portugal, South Africa, South Korea, Spain, Sweden, the United Kingdom, and the United States.

policies. This paper begins to make progress in this area by explicitly modeling the equilibrium relationships between vehicle adoption and charging station availability. This model then allows me to estimate the underlying parameters of interest and conduct counterfactual analyses to explore the effects of price subsidies versus station subsidies while holding government spending constant. This work contributes to the ongoing global discussion on electric vehicle policy by providing a theoretically motivated analysis of subsidy allocation that accounts for key features of this networked industry.

In designing incentives to foster the adoption of EVs, it is essential to account for the "two-sidedness" of the EV industry. EV owners value the existing charging station network, and charging providers value the circulating base of EVs. More charging stations lead to more consumers deciding to purchase an EV, and more EVs make entry into the market more appealing for charging stations. The positive network externalities between the two sides (EV drivers and battery charging stations) have important implications for policymaking. Specifically, modeling the EV market in the two-sided market framework introduced by Rochet and Tirole (2006) and Armstrong (2006), I demonstrate that subsidies to the different sides of the EV market are "non-neutral," in the sense that one dollar spent on subsidies given to the charging side has a different economic impact as the same amount spent on subsidies given to consumers purchasing EVs. The non-neutrality of subsidy structure is applicable to all other two-sided markets where network externalities relate to membership decisions.[3] Other two-sided market examples fitting this definition include media markets, shopping malls, and exhibition centers. The non-neutrality of the subsidy allocation indicates that it is ultimately an open empirical question as to the most effective way to structure subsidies in the two-sided EV market with positive network externalities. Achieving the policy goal of increasing EV adoption by finding the welfare enhancing subsidy allocation, however, depends on key consumer vehicle demand and charging station primitives.

Whether one incentive is more effective than the other depends on a number of

[3] Membership decisions can be interpreted in present case as follows: if a consumer purchases a vehicle or a station enters into the market by installing charging equipment, then they are members of the market or platform.

underlying structural parameters I derive from my empirical framework. First, the presence of positive feedback effects amplifies the impact of both types of subsidies, although not to the same degree. The importance consumers place on charging availability increases the effect of charging station subsidies more so than price subsidies. Thus, if the charging network plays a key role in consumers' vehicle purchasing decision, then subsidizing charging stations may be more effective. Second, if demand for EV models is highly elastic and there is less substitution between EV models, a price subsidy may be preferable. Finally, if the station entry decision is highly elastic with respect to the station subsidy, then funding stations may again be the more effective way to increase EV demand. By recovering these key primitives, we can answer the empirical question of which side is best to subsidize in a given context.

To address these questions, this paper examines the automobile purchasing decisions of consumers and the entry decisions of charging stations using data on the universe of newly registered vehicles and the public charging network in Norway. The Norwegian EV market is well-suited to study the effect of EV subsidies on buyer decisions regarding car purchases for a multitude of reasons. Norway has the highest market share of EVs among new car sales, with EVs accounting for more than 20% of new vehicle purchases in 2015.[4] Presently, other countries have yet to reach a double-digit market share for EV sales. The high adoption rate of EVs in Norway allows me to draw conclusions regarding the typical EV buyer, as opposed to examining only first-movers or early adopters, which is the case in most other settings. Importantly, while Norway represents a small and distinct market for vehicles, given the strong commitment of policymakers around the globe to substantially increase the share of EVs (or even eliminate fossil-fueled cars), studying the advanced Norwegian EV market can shed light on how to achieve the desired higher EV adoption rate. Another prominent feature of the Norwegian car market is that EV incentives are varied, generous, and they were established considerably before the first commercially marketed EV models appeared. Additionally, power generation in Norway relies predominantly on hydroelectricity, which eliminates the reasonable

[4] The market share of EVs was close to zero percent in 2010 at the beginning of the observed time period. This highlights even more the abrupt growth experienced in the EV market.

concern that road traffic emissions lowered by EVs could be offset by the increase in the emissions of the electricity generation that powers these vehicles.

To explore the relation between EV subsidies and EV purchases, I first present descriptive analysis in which I examine the data by regressing vehicle sales of all fuel types on the different EV incentives, macroeconomic controls, and a rich set of time and county-by-model fixed effects. The identifying variation I use is therefore the model-specific variation within a month and county that differs from the average pattern of model-specific variation within that month and county. The regression results suggest a significant and positive relation between EV incentives and new sales of EVs. Notably, I show that registration tax exemptions strongly correlate with vehicle sales, implying that a 10,000 Norwegian kroner (1,239 USD[5]) per vehicle increase in the incentive is associated with a 3.09% increase in EV sales on average. Importantly, I also find a significant and strong positive relation between subsidies for normal charging stations and EV sales. A 10,000 Norwegian kroner (1,239 USD) per station increase in the station subsidy is associated with an 8.42% increase in EV purchases on average.

While these findings can inform policymakers of the importance of considering EV incentives on both sides for EV adoption, it is essential to use a structural approach not only to be able to explore policy counterfactuals, but also to explicitly account for the simultaneous nature of the two sides of the electric vehicle market. Recovering the underlying primitives is crucial to study how the market outcomes change with the subsidies given the network externalities present. The key primitives are the own- and cross-price demand elasticities, the network effects, and the elasticity of station entry with respect to station subsidies. Therefore, this study implements a modeling framework that considers the simultaneous determination of consumer vehicle choice and battery charging station entry in a two-sided market setting.

In the model, consumers make a vehicle purchasing decision by maximizing their utilities across vehicle models of all fuel types with the outside option of not purchasing any vehicle. Following the work of Berry et al. (1995), I model vehicle demand by using a random coefficients discrete choice model, allowing

[5] 1 USD = 8.074 NOK using the annual exchange rate in 2015 (Norwegian Central Bank, 2016).

for heterogeneity in consumer valuation of product attributes and the station network. Simultaneously, charging stations make an entry decision determined by their sunk entry costs and discounted stream of profits. The entry model builds on the studies by Gandal et al. (2000) and Bresnahan and Reiss (1991). The number of charging stations in a market is the outcome of a complete information entry game, where the installed base of cumulative EVs determines the market size.[6] There are potential endogeneity issues on both sides of the market, which I address using instrumental variables. On the vehicle demand side, endogeneity arises due to the network effects and the simultaneity between vehicle demand and price. On the charging station side, simultaneity between station entry and EV sales leads to endogeneity.

Regarding the presence of positive feedback effects, I find evidence on both the station side and the consumer side. This result indicates that the circulating base of EVs is important for the charging stations' entry decision, and that the charging network influences buyers' vehicle choice. The estimation results also indicate that there is some heterogeneity in consumer valuation of the network term. Another important result relates to the estimated own- and cross-price elasticities that determine the effectiveness of a price subsidy through the implied substitution patterns. The findings show that demand for all EV models in the sample are elastic, and cross-price elasticities suggest that when network effects are accounted for, EVs can act as complements. That is, if the price of the Nissan Leaf increases, for example, then other EV models become relatively cheaper. At the same time, a more expensive Leaf implies fewer sales, providing a lower incentive for charging stations to enter. This lack of station entry ultimately feeds back to the EV demand, reducing EV adoption. Negative cross-price elasticities indicate strong positive network effects between the two sides of the market. If feedback effects are restricted to zero, then all cross-price elasticity estimates are instead positive. This implies that EVs would act as substitutes similarly to conventional car models if network effects are weak or not present in the market.

[6] An interesting aspect of the EV market is the vertical integration of charging provisions or the exclusive contracts with charging stations used by some manufacturers, like Tesla Motors. Such exclusive arrangements have important implications for the regulatory framework, competition, and welfare. Empirical analysis of vertical integration between car manufacturers and charging stations is work in progress.

I use these estimates to study the effects of each type of subsidy on EV purchases in Norway between 2010 and 2015. To this end, I construct policy counterfactuals in which either car purchases or stations are subsidized. Then, I compare the EV sales in each of these scenarios to a counterfactual where there are no subsidies on either side of the market. I find that during the observed period, station subsidies were more than twice as effective per Norwegian kroner spent in increasing the number of EVs sold over price subsidies. Principally, every 100 million Norwegian kroner (12.39 million USD) spent on station subsidies resulted in 835 additional EV purchases, while the same amount spent on purchasing price subsidies led to only an additional 387 EVs being sold.

In a second counterfactual analysis, I investigate whether subsidizing charging stations is always more effective than subsidizing consumers. I consider counterfactual policies, where either station subsidies or price subsidies are increased from the status quo, and I compare their additional impact on EV sales for a given amount of government spending. I find that the relative effectiveness of the subsidies can change. If the Norwegian government only had an additional 100 million Norwegian kroner (12.39 million USD) to spend, then spending it on station subsidies still would be effective. However, if government spending increases by more than 400 million Norwegian kroner (49.54 million USD), then it is more effective to use price subsidies. For example, an additional billion Norwegian kroner (123.9 million USD) in government spending on price subsidies would have led to approximately an additional 3,238 EV purchases against an approximate 2,288 additional sales of EVs if the same amount were spent on station subsidies only. As government spending increases, price subsidies become more effective over station subsidies since the impact of station subsidies tapers off much faster than the effect of price subsidies.

Lastly, I consider the impact a combination of these two policies have on EV sales. I find that the marginal impact of increase to price subsidies is larger when combined with increases in the station subsidies. However, this only holds up to a certain point after which station subsidies quickly reach diminishing returns. The findings of this paper suggest that for a given level of government spending, policymakers can achieve the largest increase in EV adoption by using both types of policies, instead of providing only one subsidy or the other.

This paper relates to several distinct strands in the economic literature. There is a rich body of research studying the effect of environmental policies in the automobile market. Many studies focus on the effectiveness of fuel taxes and fuel standards as a response to environmental issues related to the transportation sector. Recent examples include the works of Jacobsen (2013), Grigolon et al. (2014), and Allcott and Wozny (2014). Langer and Miller (2013) show that market-based policy tools can improve the relative profitability of fuel efficient automobiles. DeShazo et al. (2017) assess California's plug-in electric vehicle (PEV) rebate program, while other recent studies investigate policies targeting hybrid vehicles (Beresteanu and Li (2011) and Sallee (2011)), flex-fuel vehicles (Shiver, 2015), or other alternative fuel vehicles (Pavan, 2015). Li (2017) investigates the ambiguous impact of mandating compatibility standards on market outcomes and welfare in the context of the U.S. EV market. Li (2017) takes a different modeling approach by focusing on the car manufacturers' side and their decision to invest in charging infrastructure rather than the charging stations' entry decision and their interaction with the consumers' side. More closely related to my work are the studies by Langer and McRae (2014), Li et al. (2017) and Holland et al. (2015). Langer and McRae (2014) explore how willingness of drivers to adopt alternative fuel vehicles changes with the density of the alternative fueling network and related policy implications. Li et al. (2017) study how policy affects plug-in electric vehicle adoption and consider indirect network effects exhibited in the market. Holland et al. (2015) show that there is substantial geographic variation in the environmental benefits of EV adoption and argue for spatially differentiated incentives.

This paper contributes to this latter literature in several dimensions. First, this study uses a novel dataset on the universe of vehicle registrations for the entire country of Norway, accounting for substitution between vehicle models of all fuel types. Second, the high EV market share in Norway allows me to study the typical EV driver as opposed to the early adopters and first movers in countries with low adoption rates. Third, by developing a joint structural model on consumer vehicle choices and charging station entry, I allow for more flexible substitution patterns as well as feedback loops between the two sides of the market that are difficult to implement in a reduced-form analysis. Finally, the empirical modeling framework in this work allows for the comparison of revenue-equivalent subsidies using out-of-sample predictions that, in general, require more structure.

This analysis also contributes to the prior work that studied two-sided markets. Theoretical studies on indirect network effects date back to the works of Katz and Shapiro (1985) and Farrell and Saloner (1985). Caillaud and Jullien (2003), Rochet and Tirole (2006), Armstrong (2006), and Armstrong and Wright (2007) extended this literature by introducing a two-sided market framework. These early studies focused on pricing and the coordination issues typical in two-sided markets. Subsequent work, such as Weyl (2010) and White and Weyl (2016), generalized the modeling framework to examine different market structures and type(s) of platforms. There is a growing literature of empirical studies by Lee (2013) (videogame industry), Crawford and Yurukoglu (2012) (broadcasting), Gentzkow et al. (2014) (news media), and Bresnahan et al. (2015) (smartphones). My work adds to this literature by studying the growing industry of electric vehicles in a two-sided market setting and by empirically exploring how the allocation of subsidies might matter for economic outcomes in the presence of network externalities. Finally, my model relates to the vast literature on automobile demand estimation. My structural model builds on the seminal works of Bresnahan (1987), Berry et al. (1995), and Petrin (2002), who demonstrate how to allow substitution patterns to reflect heterogeneity in the consumer valuation of product attributes using aggregate and micro automobile data. This modeling feature, in addition to accounting for network effects, is essential to rigorously estimate the effect of government policies on EV adoption.

The rest of the paper is organized as follows. Section 1 describes the industry and policy background of the Norwegian EV market. Section 2 presents the data and a descriptive analysis of EV incentives. Section 3 describes the empirical framework, and Section 4 presents the structural estimation results. Section 5 investigates the impact of counterfactual policies on EV demand by comparing direct purchasing price subsidies and one-time charging station subsidies. Section 6 concludes.

1 Industry and Policy Background

Norway is committed to supporting the electrification of vehicles to reduce the environmental impact of its transportation sector. In addition, Norway is an ideal market for electric vehicles. The country is wealthy, has a highly educated workforce, and operates on a reliable electric grid that is almost 100% hydroelectric powered. Therefore, given that electric vehicles emit no local pollutants, a transition to electric vehicles would substantially contribute to reducing greenhouse gas emissions.

The central government and local authorities are using a variety of generous incentives to support electric vehicles, first introduced in the early 1990s. Currently there are two types of electric vehicles: all-electric vehicles (AEVs), which are powered by an electric motor that uses energy stored in a battery, and plug-in hybrids (PHEV), which are powered both by an electric motor and an internal combustion engine that uses conventional or alternative fuel.

The Norwegian incentive program mainly targets all-electric vehicles. Plug-in hybrid vehicles are not eligible for most incentives, with the exception of some recent changes in 2015. The supporting measures aim to remove different barriers against all-electric vehicle adoption. Most importantly, Norway has large incentives to lower the upfront cost of all-electric vehicles and also financially supports the development of charging infrastructure to reduce range anxiety.

While my work focuses on incentives related to the barriers of high purchasing price and charging availability, Norway has a number of other incentives.[7] I study these two types of subsidies for several reasons. First, most countries that have electric vehicle incentives are using these two forms of policies (International Council on Clean Transportation , 2015). Second, these incentives are much larger in magnitude than other local non-monetary incentives. Finally, given that

[7] There are incentives that target vehicle ownership and usage related costs. Norwegian authorities work closely with non-government organizations whose primary task is to promote all-electric vehicles through a variety of marketing activities, such as compiling comprehensive information about all-electric vehicle dealerships, charging stations, and available financial support. Finally, electric vehicle models have their own identifying license plates (starting with EL) to raise consumer awareness and the visibility of all-electric vehicles.

these incentives provide a one-time subsidy given at the purchase of a vehicle or charging equipment, the impact of these incentives is less likely to be affected by myopic behavior.

All-electric vehicles are permanently exempt from the one-time registration fee and the value-added tax since 1996 and 2001, respectively. The registration tax is computed based on vehicle weight, internal combustion engine power, and CO_2 and NO_x emissions. This tax constitutes a substantial part of the final costs associated with a vehicle purchase. For vehicles with internal combustion engine, the average registration fee is around 50% of the manufacturer's suggested retail price (MSRP). For larger models, this can add up to as much as the MSRP. Hybrids and plug-in hybrids fare better due to their low emissions, weight discounts accounting for the heavy batteries, and the fact that only combustion engine power is being taxed.

The value-added tax is a flat rate of 25% and applies to all new vehicle purchases, with the exception of battery-electric vehicles. Norwegian automobile use is also subject to taxation in the form of different fuel taxes, leading to relatively high gasoline and diesel prices (Norwegian Tax Authority, 2016). As a result of these tax exemption measures and high fuel savings, all-electric vehicles are cheaper to purchase and operate than their respective diesel or gasoline fueled counterparts (Institute of Transport Economics, 2015). A recent survey of 8,000 vehicle owners also found that competitive pricing of all-electric vehicles plays a vital role in the car purchasing decision of consumers (Institute of Transport Economics, 2015). Another state measure that benefits all-electric vehicle owners includes a reduced annual license fee since 1996 (Norwegian Tax Authority, 2016).

Long travel distances, extreme winter weather, and mountainous terrain in Norway necessitate the establishment of an appropriate charging network.[8] To stimulate electric vehicle adoption, the Norwegian government also provides support for the development of electric vehicle charging points. Electric vehicle supply equipment (EVSE) incentives provide a one-time subsidy to investors to cover all or part of the equipment and installation costs. EVSE incentives vary according to the rate (normal vs. fast) at which the charging equipment can

[8] Many EV owners charge their vehicles overnight at home using a standard electricity outlet or a charging equipment that allows them to charge at a faster rate.

charge electric vehicle batteries.

In addition to the state level charging infrastructure program, several local authorities also have financial incentives supporting the establishment of charging stations as part of plans for improved climate and/or energy management. The state-level initiative led by Transnova, a government entity established to cut greenhouse gas emissions and entrusted with the development of the electric vehicle charging infrastructure, dates back to 2009, while other county programs predate even that (Institute of Transport Economics, 2014). The incentives specifically target the development of public charging stations and are generally not available for home charging purchases.

Norway is currently at the forefront in terms of electro-mobility. It has worldwide the largest number of electric vehicles per capita, with electric vehicles accounting for over 20% of new sales in 2015 (International Energy Agency, 2015). Figure 1 shows that while adoption rates in Norway are already in the double digits, most other countries have adoption rates below 2%. Recent trends in the electric car market show that both cumulative and new all-electric vehicle sales have grown rapidly in the last three years (see Figures 2 and 3).[9] In comparison, cumulative sales of plug-in hybrids remain close to zero during the same period with the exception of 2015. This recent increase coincides with a change in registration taxes for plug-in hybrid models. As a result, plug-in hybrids now receive a larger weight discount (26% instead of 15%) than before, and thus pay significantly less in registration taxes. Norway's electric vehicle battery charging network is also among the most extensive in the world on a per capita basis (International Energy Agency, 2015).

Figure 4 shows that similarly to the all-electric vehicle sales, the charging station network has experienced a sharp increase in growth between 2010 and 2015. In the online appendix, Figure A1 further highlights how much the charging network has evolved during the observed time period. Panel (a) in Figure A1 shows the installed stations on the map of Norway at the end of 2009 when public charging availability was scarce. Panel (b), in comparison shows the expansion of the station network up to the end of 2015. The total number of public charging

[9] For a detailed summary on the history of the Norwegian electric vehicle market, see Institute of Transport Economics (2013).

points in Norway exceeds 7,000 (as of December, 2015) and includes around 250 fast charging points (NOBIL, 2016). Unless otherwise stated, herein all references to "electric vehicles" refer to all-electric or battery-electric vehicles only.

2 Data

I compiled the data from a number of independent sources. My main database is a rich panel of vehicle registration data from the Norwegian car market, obtained from the Norwegian Public Roads Administration (NPRA) and Opplysningsrådet for Veitraffiken AS (OFVAS). I supplement this dataset with information on the charging station network and government incentives in Norway.

The vehicle registration data from NPRA contains the universe of car purchases in Norway from 2010 to 2015. I focus on new vehicle purchases and drop used car purchases. Each registration record contains information on the owner's name, type (private or corporate), street address, the date of registration, and the vehicle specification defined by make, model, and trim. Product characteristics and the price variable are obtained from OFVAS. This dataset provides information on all models commercially marketed in Norway in a given year. Car characteristics include size (defined by length), acceleration (horsepower/weight), fuel type, dummy for automatic transmission, and (inverse) fuel economy (or its equivalent measure for hybrids and electric vehicles). The price variable includes CIF (cost, insurance, and freight), taxes, and importer or dealer profit. All prices are expressed in 2010 Norwegian kroner (NOK).

The vehicle data is available at a very detailed level that allows me to match car sales with characteristics and price at the trim level. Models both appear and exit during the observed time period. I exclude "exotic" models with extremely low market sales. The unit of observation in the analysis is defined by model/year/county. With these definitions, I have on average about 200 distinct vehicle models per market (county-by-year), resulting in an unbalanced panel of 22,084 observations.

The charging station data from Nobil includes information on the number of charging stations and outlets in Norway by their opening date and coordinates.[10] Station characteristics include the operator's name and type, whether the station received public funding, the connector type of each outlet, and location type.

I obtained information on government incentives from the Norwegian Tax Authority (Skatteetaten), Transnova, and Statistics Norway. From the Norsk Petroleuminstitutt, I collected information on gas stations. Macroeconomic variables, such as median household income, GDP, and unemployment were obtained from Statistics Norway. I define market size (I) by the number of households in each market, a measure acquired from Statistics Norway. Finally, I compile data on demographic variables, such as age and gender, at the individual level (from OFVAS).[11]

Summary Statistics. Table 1a provides descriptive statistics (mean and standard deviation) for the variables used in the empirical analysis. The upper panel includes the variables used in the vehicle demand estimation, while the lower panel contains the variables employed in the station entry model. Table 1b illustrates how the variables related to the vehicle market in Norway changed over time. The number of models available increases during the observed time period, while new vehicle sales first increase then revert back close to their initial level. At the same time, real vehicle prices remain relatively unchanged, while there is a sharp increase in electric vehicle adoption and in the number of charging stations. Product characteristics remain fairly stable with the exception of fuel consumption and transmission. Fuel efficiency and the fraction of cars with automatic transmissions increases over time.

Descriptive Analysis. To investigate the impact of EV incentives on EV adoption, I first examine the data by regressing the logarithm of new vehicle sales ($\log R_{jct}$) on the set of available EV policies (V), macroeconomic variables (Y), and a full

[10] Nobil as collected and maintained the central station database of Norway since March, 2010 resulting in a left-censored dataset. Fortunately, the historical development of charging stations is well-documented in Norway. Thus, to mitigate this issue, I supplement the data with information from municipality, county, and government sources, and recover the opening dates of stations established before March, 2010.

[11] The use of consumer-level data in the empirical analysis is work in progress.

set of time and county-by-model fixed effects ($\vartheta_{jc}, \vartheta_t$) given in equation (1).

$$\log R_{jct} = \alpha + \sum_{E \in V} \beta_E V_{jct} + \sum_{G \in Y} \mu_G Y_{ct} + \vartheta_{jc} + \vartheta_t + \varepsilon_{jct} \tag{1}$$

The unit of observation is model j in month t and county c. The set of EV policies includes registration tax exemption, VAT exemption, and EVSE incentives for normal and fast charging. The first two policies are measured as the amount of tax exemption in 10,000 NOK. Hence, they take negative values for vehicles that are required to pay the tax and zero for vehicles exempt from the tax. The EVSE incentives are measured as the amount of support available in county c at time t. For consistency, I also include the more popular local non-monetary incentives, namely free access to HOV lane and exemption from toll fees. HOV lanes are measured as the fraction of total public roads in each county and month. Toll fee exemption is proxied by the average toll fee (in NOK) per market.

I do not restrict the effects of incentives to zero for non-electric vehicles. Thus, with the exception of the tax policies, I also include an interaction term between policies and a dummy variable that takes the value 1 for EVs and zero otherwise. The set of macroeconomic controls includes county-level GDP, median household income, and unemployment. Finally, the year-specific intercepts control for national demand shocks, while the county-by-model fixed effects control for time-invariant product attributes, time-invariant regional demand shocks, and product preferences. The identifying variation used in this analysis is the model-specific variation within a month and county that differs from the average pattern of model-specific variation within that month and county.

I first examine the model with a parsimonious set of controls for macroeconomic trends (i.e. year fixed effects). Then, I include local incentives. Finally, I add additional time-varying macroeconomic controls. Table 2 reports the OLS regression results. All standard errors are two-way clustered by county and model.[12]

The findings of the descriptive analysis indicate that policies supporting the EV sector are strongly and positively related to EV purchases. I show that registration tax exemptions strongly correlate with vehicle sales. The results of

[12] Given that the number of counties is relatively low (19), I re-estimate the regression with bootstrapped standard errors and the results remain qualitatively similar.

the final specification imply that a 10,000 Norwegian kroner (1,239 USD) per vehicle increase in the incentive is associated with a 3.09% increase in EV sales on average, holding all other controls constant. I find little relationship between the type of tax incentive and car sales, but the overall amount or generosity of the tax incentive is strongly correlated with sales.[13]

An interesting and somewhat surprising finding of the analysis is that subsidies for normal charging stations are significantly and strongly positively related to new EV sales. The final specification shows that a 10,000 Norwegian kroner (1,239 USD) per station increase in the station subsidy for normal charging is associated with an 8.42% increase in EV purchases on average, holding all other controls constant. At the same time, I find no statistically significant effects for station subsidies for fast charging, as the rich set of fixed effects included in the analysis absorb most variation in the incentive.

A potential concern is that the identifying assumption is violated due to confounding factors. For this reason, I conduct a number of robustness checks in the online appendix. First, I re-estimate the final specification with all controls as presented above in equation (1). Instead of interacting the policy terms with a dummy for EVs, I interact these terms with a dummy for hybrid vehicles. Given that hybrids are also more environmentally friendly cars, like electric vehicles, finding statistically significant effects for hybrids would suggest that the analysis is not identifying the impact of the EV incentives but rather some preference for "green" products. Column [1] in Table A1 shows that the interacted EVSE incentive terms are all insignificant at the traditional statistical levels.

In an additional robustness check, I regress the logarithm of new vehicle sales on the same controls as in the main specification described in equation (1). This time I randomly reassign both types of station subsidies. The results reported in column [2] of Table A1 show that the estimates on the interaction terms between the EVSE policies and the EV dummy are statistically insignificant and at least an order of a magnitude smaller than the estimates of the descriptive analysis. Finally, I use the same specification from equation (1) as before, but I also include

13 This is not surprising, given that both forms of tax exemptions available in Norway are automatic and have an immediate effect, as opposed to tax exemptions that require foresight and additional effort, like income tax credits frequently used in other countries.

one-year lagged and lead versions of the station subsidy for normal charging.[14] A statistically significant coefficient estimate on the lead station subsidy interaction term would potentially indicate that policymakers are implementing incentives as a response to development in the EV market. Column [3] of Table A1 summarizes the related results, and I find no significant effects for either term but the concurrent station subsidy for normal charging.

The descriptive analysis demonstrates a positive relation between EV adoption and EV incentives on both sides of the market. However, the focus of this study is to compare the effectiveness of price and station subsidies for given levels of government spending. This goal requires conducting counterfactual simulations that involve out-of-sample predictions and thus rely on a more structural modeling approach. Additionally, the key feature of the EV market, the positive network externalities between the two sides, and the resulting feedback loops also call for the use of structure to simulate how consumers respond to the different subsidies. Therefore, in this study I develop and estimate a structural model that encompasses the simultaneous interaction between consumer vehicle choice and charging station entry in a two-sided market framework.

3 Empirical Framework

In the model, I consider the decisions of two types of economic agents: consumers and charging stations. Consumers wish to purchase a new car chosen from all available fuel types, while charging stations choose whether to enter the market for electric charging or not.[15] In a simultaneous-move game, each period consumers and stations make their decisions based on complete knowledge of market conditions.

The timing of the game is as follows: (1) each period starts with a given number of vehicles of all fuel types already circulating in each market, (2) consumers decide whether to purchase a vehicle, (3) charging stations consider

[14] I do not include the lagged and lead versions of the station subsidies for fast charging, as I did not find significant effects for the concurrent version.

[15] In the current modeling framework, vehicle manufacturers' profit maximization problem is not explicitly modeled.

whether to enter the market and install charging equipment, (4) consumers choose their demand for charging and operating stations serving electric car drivers.[16;17]

This current setting assumes a static game. While dynamic effects could be important for a durable good, like an automobile as shown by Hendel and Nevo (2006), Busse et al. (2015) find that consumers might not be able to maximize their intertemporal utility when making purchasing decisions about a durable good due to different behavioral biases.[18] Hence, in this model I assume consumers behave myopically in the sense that their decisions depend only on the concurrent charging station network. Stations are assumed to have perfect foresight. Each charging stations' entry affects their own and all other stations' profits in the market. The purchase decisions of consumers also affect station profits by changing the size of the market for electric charging.

A positive network externality arises in the context of electric vehicles due to complementarities between the (cumulative) sales of EVs and the available electric charging network. That is, if the number of stations increases for some exogenous reason, then demand for all-electric models increases. This leads to a further increase in the number of charging points, and so on. The positive feedback loop between new EV sales and charging station entry suggests that an otherwise small change on either side can lead to a large change in both electric vehicle purchases and charging station entry, which has important implications for government subsidies. Ignoring these network effects when estimating the impact of different electric vehicle policies would bias the results.

First, I model consumers' vehicle purchasing decision by following the random coefficients discrete choice model of Berry et al. (1995). Then, I describe the charging station entry decision following the works of Gandal et al. (2000) and Bresnahan and Reiss (1991). Finally, I compare the effect different electric vehicle incentives (price subsidy vs. station subsidy) have on consumers' vehicle

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[16] Note that among other product characteristics, the fuel type of the car and thus the availability of charging also enters the consumers' decision problem.

[17] Naturally, only consumers who choose to purchase an electric vehicle have positive demand for charging.

[18] Standard economics assumes that consumers can predict their future consumption from a durable good at the time of purchase, but Busse et al. (2015) suggest that instead buyers might purchase the durable good with the highest perceived instantaneous utility.

purchasing decisions in the presence of network effects to uncover the factors that determine the effectiveness of the two types of subsidy in the electric vehicle market.

3.1 Vehicle Demand Model

Assume there are $m = 1,...,M$ markets defined as a county-year combination, each with $i = 1,...,I_m$ number of potential consumers. There are $j = 1,...,J$ vehicle models. I specify the indirect utility, $U(x_{jm}, \xi_{jm}, p_{jm}, y_i; \theta)$, of consumer i from consuming product j in market m as

$$u_{ijm} = \alpha \log(y_i - p_{jm}) + \beta_i^N \log N_{jm} + \beta_i^k x_{jm}^k + \xi_{jm} + \varepsilon_{ijm} \tag{2}$$

where y_i is the income of consumer i, p_{jm} denotes the product price that includes CIF, taxes, and importer or dealer profits, $\log N_{jm}$ is the term for the station network, x_{jm}^k is a K-dimensional vector of the observed product characteristics, ξ_{jm} is the unobserved product characteristic, and ε_{ijm} is a mean-zero stochastic term. The station network term is defined as the interaction between the logarithm of the number of charging stations in market m and a dummy variable for EVs. This assumption restricts network effects to EV models and assigns a network effect equal to zero to all other fuel types. Finally, the parameter α denotes consumer's marginal utility from income, and $\beta_i = (\beta_i^N, \beta_i^1, ..., \beta_i^K)$ is a $(K+1)$-dimensional vector of individual-specific taste coefficients. Note that β_i^N captures the network effects on the consumer side. For ease of notation, I suppress the market subscript m for the rest of this subsection.

Allowing for interaction between individual and product characteristics, equation (2) can be written as[19]

$$u_{ij} = \alpha \log(y_i - p_j) + \beta^N \log N_j + \beta^k x_j^k + \xi_j + \sigma^N \log N_j v_i^N + \sum_k \sigma^k x_j^k v_i^k + \varepsilon_{ij} \tag{3}$$

The consumer terms that interact with product attributes are $(y_i, v_i^N, v_i^1, ..., v_i^K)$, where $v_i \sim P_v^*(v)$, and I assume that $P_v^*(\cdot)$ is a standard multivariate normal distribution. Income enters the utility function in a special way, as described in Berry et al. (1995), to increase the efficiency of the estimation process by

[19] The use of consumer-level data to enrich the present analysis is a work in progress.

making use of exogenously available income data. The income distribution is assumed to follow a Generalized Beta (Type 2) distribution, and I estimate its parameters from population data for each year. ε_{ijm} is assumed to follow an i.i.d. extreme-value distribution. To complete the demand model, I introduce an outside good ($j = 0$). Following standard practice, the utility from the outside good is normalized to zero.

In the spirit of Nevo (2000, 2001), I denote the vector containing all parameters of the vehicle demand model by $\theta = (\theta_1, \theta_2)$, where θ_1 contains the linear parameters and θ_2 the nonlinear parameters. Finally, the indirect utility can be expressed as a sum of δ and μ, where δ contains county-by-model, time fixed effects, and the network term, while μ contains the observed car characteristics, price term, and the network term.

$$u_{ij} = \delta_j(N_j, x_j^k, \xi_j; \theta_1) + \mu_{ij}(p_j, N_j, x_j^k, y_i, v_i; \theta_2) + \varepsilon_{ij} \tag{4}$$

Consumers are assumed to purchase one vehicle, the one that gives the highest utility. To further simplify notation, let ζ_i be the vector of unobserved individual attributes and $P^*(\zeta)$ denote the population distribution function of ζ. Assuming there are no ties, the predicted market share of good j is given by

$$s_j(p, N, x, \xi; \theta_2) = \int \frac{e^{\delta_j + \mu_{ij}(p_j, N_j, x_j, y_i, v_i; \theta_2)}}{1 + \sum_{l=1}^{J} e^{\delta_l + \mu_{ij}(p_j, N_j, x_j, y_i, v_i; \theta_2)}} \, dP^*(\zeta) \tag{5}$$

Identification. Here I consider intuitively the identification of the vehicle demand model parameters (θ). A formal discussion of the estimation methodology is deferred to Section 3.4. The demand-side model introduces two identification problems. First, consumer demand for vehicles and price are determined simultaneously. I address this problem using the instrumental variable approach. Following the literature on the automobile industry, as an instrument for price I use observed exogenous vehicle characteristics and the sum of the values of the same characteristics of other vehicle models offered by other car manufacturers, as in Berry et al. (1995). The included car characteristics are size (defined by length), acceleration (horsepower/weight), fuel type, dummy for automatic transmission, and (inverse) fuel economy (or its equivalent measure for hybrids and electric vehicles). There is sufficient variation in the instruments even with the rich set of fixed effects included, due to variation in the choice set across counties and time.

A valid set of instruments are required to correlate with the price, but not with the disturbance. Given that the unobserved individual attributes were integrated over in equation (5), the econometric error term is the unobserved product characteristic (ξ). The included market- and model-specific fixed effects capture part of this unobserved term. Therefore, the identifying assumption I make is that, controlling for the fixed effects, the instruments are independent of the remaining residual term. The county-by-model fixed effects absorb any time-invariant product attributes as well as time-invariant within-county product preferences. For example, if certain counties are more environmentally conscious than others, or if there are unobserved promotional activities by certain car manufacturers, these fixed effects will absorb those differences. However, heterogeneity in the rate of counties becoming more "green" over time will not be captured by the county-by-model specific intercepts. Similarly, time intercepts capture the impact of any year-specific events, like aggregate demand shocks. Second, there is endogeneity due to network effects. Market shares for EVs and the installed number of charging stations are determined simultaneously. As an instrument for the charging station network, I use the magnitude of the available EVSE incentives. These incentives are differentiated by the rate (normal or fast) at which the electric vehicle batteries are charged, and I include a separate instrument for each type. Charging station subsidies should not affect a consumer's vehicle purchasing decision, but the incentives should have a major impact on station entry decisions.

The validity of these instruments is violated if policymakers react to changes in the unobserved vehicle demand by concurrently changing the incentives. Since most incentives were adopted before the start of the electric vehicle market in 2010, and since these measures are usually introduced in the context of a multi-year plan for transportation or climate improvement, this violation is unlikely. Additionally, the included model-by-county fixed effects capture any local preferences, such as support for green products. Thus, if the counties with large EVSE incentives are more likely to be environmentally friendly than counties without these incentives (or with smaller EVSE incentives), that impact will be absorbed by the regional specific intercepts. Nevertheless, if policymakers correctly expect consumer demand for electric vehicles and time subsidies for charging stations accordingly, then the EVSE subsidy instruments are no longer valid.[20]

3.2 Station Entry Model

Let $s = 1, ..., N_m$ denote the number of stations in each market where a market is defined by the combination of a county c and a year t. To simplify notation, I will use m for market whenever possible and ct to emphasize the given period t or county c. The per-consumer profit function is quasi-concave in price, and can be written as $D_{sm}(p_{sm}, p_{-sm}, N_m)(p_{sm} - MC_{sm})$, where p_{sm} is the price charged by station s, MC_{sm} is the marginal cost of station s, and D_{sm} denotes the per-consumer market demand for station s. This demand faced by station s depends on the price set by station s, the prices set by all other stations, and the number of stations.

Following the works of Gandal et al. (2000) and Bresnahan and Reiss (1991), I make the following simplifying assumptions: the per-consumer demand functions are symmetric, marginal costs and the sunk cost of entry are constant across stations in each market, and each station earns an equal portion of the market due to symmetry. Then there exists an equilibrium in which all stations charge the same price and the per-period post-entry station profit can be characterized by

$$\pi_m = Q_m^{EV} D(p(N_m))\varphi(N_m)/N_m \tag{6}$$

where Q_m^{EV} denotes the cumulative electric vehicle base in market m and $\varphi(N_m)$ is the equilibrium markup ($\equiv p - MC$). The equilibrium price for charging is assumed to decline in the number of stations. To simplify notation, let $f(N_m) \equiv D(p(N_m))\varphi(N_m)/N_m$.

[20] An alternative set of instruments is the number of different establishments, like shopping malls, hotels and restaurants, parking garages, etc. Charging stations are frequently installed at these locations, as shown by the data, but are unlikely to be correlated with unobserved vehicle demand. I use these instruments as a robustness check in my analysis.

If a station decides to enter in period t, the station first incurs the sunk cost of entry F_{ct} related to the purchase and installation of necessary infrastructure and then earns a stream of per-period profits for providing charging starting next period (π_{ct+1}, π_{ct+2}, ...). Thus, the sum of the discounted earnings of a station from entering in period t can be written as

$$-F_{ct} + \frac{1}{1+r}\ \pi_{ct+1} + \frac{1}{(1+r)^2}\ \pi_{ct+2} + ... \tag{7}$$

where r is the discount rate assumed to be identical across all stations. In a free-entry equilibrium, stations are indifferent between entering now or next period, implying that

$$-F_{ct} + \frac{1}{1+r}\ \pi_{ct+1} + \frac{1}{(1+r)^2}\ \pi_{ct+2} + ... = -\frac{1}{1+r}\ F_{ct+1} + \frac{1}{(1+r)^2}\ \pi_{ct+2} + ... \tag{8}$$

After plugging in equation (6) into equation (7) and taking the natural logarithm of both sides, the above expression simplifies to

$$\log f(N_{ct}) = -\log\left(\frac{1}{1+r}\right) - \log Q^{EV}_{ct} + \log(F_{ct} - \frac{1}{1+r}\ F_{ct+1}) \tag{9}$$

To complete the econometric model, I specify that $f(N_{ct}) = (bN_{ct})^{-d}$ and I assume nonrecurring fixed costs are a linear function of exogenous market-level cost shifters (the EVSE incentives), county fixed effects (ρ_c), and a trend term ($h(t)$). County fixed effects absorb any time-invariant region-specific preferences for charging stations, while the time trend captures yearly changes. Noise term (ε_{ct}) captures idiosyncratic shocks as in Gandal et al. (2000). Finally, given these assumptions, the station entry model can be specified as

$$\log N_{ct} = \lambda_0 + \lambda_1 \log Q^{EV}_{ct} + \lambda_2 EVSE_{ct} + \lambda_3 \rho_c + \lambda_4 h(t) + \varepsilon_{ct} \tag{10}$$

Identification. Similarly to the vehicle demand-side model, there is an expected feedback loop between the number of stations (N_{ct}) and the cumulative electric vehicle base (Q^{EV}_{ct}) in a market. Specifically, in period t the installed base of electric vehicles consists of the stock of cars already circulating in the market and the vehicles newly registered in period t. Assuming there is no scrappage,[21] the number of electric vehicles bought before period t are not affected by the number

[21] The data confirms that zero electric vehicles were scrapped during the observed time period.

of stations, only the newly registered cars as indicated by the vehicle demand model discussed previously. To address the problem, I use the instrumental variable approach. As an instrument for the cumulative electric vehicle base, I use gas station density. The main driver of competition in the fuel market, and thus the driving factor behind fuel prices, is the number of competitors within 10 minutes of driving (Norwegian Competition Authority, 2010). Therefore, lower gas station density (or higher gas prices) indicates higher user cost savings from electric vehicles, which is likely to induce more consumers to purchase an electric vehicle. The identifying assumption is that the density of gas stations only affects station deployment through the increased electric vehicle base.

Charging station entry decision depends on the sunk cost of entry and the per-period profit. The non-recurring fixed costs include the cost of charging equipment and labor costs related to its installation. Neither of which are likely to be correlated with gas station density once yearly changes, like aggregate demand shocks, and time-invariant county characteristics, like local taste, are accounted for. The per-period profit is a function of demand for charging and the markup. I use the cumulative electric vehicle base to account for demand faced by stations. The markup depends on factors affecting the stations' marginal cost, such as electricity prices and the price for charging. Again, these are unlikely to be correlated with the instrument after county- and time-specific effects are absorbed. However, the validity of the instrument is violated if there are unobserved factors which vary from the time trend for a given county that are correlated with both the gas station density and the charging station network. [22]

[22] Alternatively, as instruments for the circulating EV base, one might consider the price subsidies which are available to consumers purchasing EVs. While price subsidies should not directly affect a station's entry decision, they have a major impact on consumer car purchasing decisions. However, given that the unit of observation in the charging station entry problem is aggregated to the market level (county-by-year), much of the identifying variation in the price subsidies is lost. Thus, although these instruments produce similar estimates for the parameters of interest, they fail the test of relevance/weak instruments (with a first stage F-statistics less than 2).

3.3 Consumer Effects of Subsidies

In a two-sided market setting with network externalities, like the EV industry, theory does not have clear prediction on how subsidy allocation might matter for economic outcomes. In Appendix B, I show this "non-neutrality" result regarding subsidies. To provide a more rigorous motivation for which electric vehicle supporting instrument is preferred, in this section I provide an overview of the factors that determine the effectiveness of different subsidies. In particular, I am mainly interested in comparing the effects of two types of government policies. First, I determine the impact of a price subsidy on the cumulative sales of all-electric vehicles. Second, I study how a subsidy for charging stations affects the installed base of all-electric vehicles.

Recall that the market share of j in market m is given by

$$s_j(p,N,x,\xi;\theta) = \int \frac{e^{\delta_j+\mu_{ij}(p_j,N_j,x_j,y_i,v_i;\theta)}}{1+\sum_{l=1}^{J} e^{\delta_l+\mu_{ij}(p_j,N_j,x_j,y_i,v_i;\theta)}}\, dP^*(\zeta)$$

where, ζ_i is the vector of unobserved individual attributes and θ denotes the unknown parameters. For the remainder of this section, β_i^N denotes the coefficient for consumer type i on the logarithm of charging stations for electrical vehicles. The station entry equation is simply given by

$$\log(N_m) = \lambda_0 + \lambda_1 \log(Q_m^{EV}) + \lambda_2 EVSE_m + \lambda_3 h(t) + \varepsilon_m$$

where $Q_m^{EV} \equiv \sum_{k\in EV} s_{km}$ denotes cumulative all-electric vehicle sales.

3.3.1 EV Price Subsidy

I begin by analyzing the effect of a subsidy on the price of an arbitrary, all-electric car model on the total sales of all-electric vehicles. I consider only the contemporaneous effect of the subsidy in the market, and hence drop the subscript m. Let j denote without loss of generality the model which is subsidized.

Denote the object of interest, the partial effect of the price of j on the cumulative all-electric vehicle base, by $\partial Q^{EV}/\partial p_j$. Let I denote the number of households in the market, and EV denote the set of models which are all-electrical vehicles. Differentiating Q^{EV} with respect to p_j and simplifying, I obtain

$$\frac{\partial Q^{EV}}{\partial p_j} = \left(\sum_{k \in EV} \eta_{kj} + \frac{\lambda_1}{Q^{EV}} \frac{\partial Q^{EV}}{\partial p_j} \sum_{k \in EV} \gamma_k \right) I \tag{11}$$

where η_{kj} is the partial derivative of the share of model k with respect to the price of model j in the case where there are no network effects (i.e. $\beta^N = 0$ or $\lambda_1 = 0$) given by

$$\eta_{kj} = \begin{cases} \int \frac{-\alpha s_{ij}(1-s_{ij})}{y_i - p_j} dP_v^*(v) & \text{if } j = k, \\ \int \frac{\alpha s_{ij} s_{ik}}{y_i - p_j} dP_v^*(v) & \text{otherwise.} \end{cases} \tag{12}$$

Let γ_j denote the partial derivative of the market share with respect to the logarithm of charging stations under the condition $\lambda_1 = 0$ (i.e. if there is only a one-way feedback effect due to no feedback effects on the station side) then

$$\gamma_j = \int \frac{\beta_i^N s_{ij}(1 - s_{ij})}{y_i - p_j} dP_v^*(v) \tag{13}$$

Thus, equation (11) shows the decomposition of the change in the cumulative all-electric car base into two terms. The first term is due to the price elasticities of demand while the second term is due to the change in the size of the charging station network. Finally, isolating $\partial Q^{EV}/\partial p_j$, I obtain the expression

$$\frac{\partial Q^{EV}}{\partial p_j} = \frac{\sum_{k \in EV} \eta_{kj} I}{1 - \sum_{k \in EV} \gamma_k \lambda_1 / Q^{EV}} \tag{14}$$

Hence, the effectiveness of electric vehicle price subsidies is tied to the own- and cross-price elasticities of demand captured by η_{kj}, which, importantly, is not the case for charging station subsidies. Furthermore, the effectiveness of price subsidies is amplified by the network externalities, which are captured by the terms λ_1 and $\gamma_k(\beta_i^N)$. To see the effect of a uniform price subsidy on all battery-electric vehicles, I simply sum up the right-hand terms in (14) for each all-electric vehicle model as given in

$$\sum_{j \in EV} \frac{\partial Q^{EV}}{\partial p_j} = \sum_{j \in EV} \frac{\sum_{k \in EV} \eta_{kj} I}{1 - \sum_{k \in EV} \gamma_k \lambda_1 / Q^{EV}} \tag{15}$$

The above formula also indicates the importance of allowing for more general substitution patterns between the different vehicle models motivating the random-coefficient discrete-choice model I use to model consumers' vehicle choices. A simple logit or nested logit model produces demand elasticities that are unrealistic and restrictive (Train, 2009), hence, this leads to estimates predicting unrealistic consumer responses to a price subsidy for electric vehicles.

3.3.2 Subsidy for Charging Stations

Next, I consider the effect of an incentive that provides a one-time subsidy to charging stations. Differentiating the market share of an all-electric vehicle model with respect to the quantity of station subsidies (EVSE) and summing over all models, I obtain

$$\frac{\partial Q^{EV}}{\partial EVSE} = \left(\sum_{k \in EV} \gamma_j \lambda_2 + \frac{\lambda_1}{Q^{EV}} \frac{\partial Q^{EV}}{\partial EVSE} \sum_{k \in EV} \gamma_k \right) I \tag{16}$$

As a result, I can decompose the effect of the subsidy into several terms. The first term captures the direct effect of the subsidy on the deployment of stations while ignoring feedback effects. The second term captures the feedback effects that are caused by the subsidy, increasing the base of electric vehicles. Finally, I can write the expression as

$$\frac{\partial Q^{EV}}{\partial EVSE} = \frac{\sum_{k \in EV} \gamma_k \lambda_2 I}{1 - \sum_{k \in EV} \gamma_k \lambda_1 / Q^{EV}} \tag{17}$$

Thus, the effectiveness of a charging station subsidy on the number of EV purchases is tied closely to the importance that consumers place on the operating charging station network (captured by γ_k) and the elasticity of station deployment with respect to EVSE subsidies (captured by λ_2).

The above analysis shows that the effectiveness of an EV price subsidy and a one-time station subsidy hinges on several factors. First, positive feedback loops between the charging station network and total all-electric vehicle sales amplify the impact of both types of subsidy. However, while the magnitude of feedback effects on the station side (captured by λ_1) increases the effect of the two subsidies in the same way, this is not true for feedback effects on the consumer side (captured by γ_k). The higher the magnitude of the latter term is, the more likely it is that a station subsidy is more effective than a direct EV price subsidy. Second, a direct purchasing price subsidy given to all-electric drivers is more effective with more price-elastic all-electric vehicle models. Likewise, all-electric vehicle models acting as complements rather than substitute products, increases the effectiveness of a price subsidy. Finally, more elastic charging deployment with respect to a station subsidy amplifies the impact of a direct one-time subsidy for stations. Ultimately, it is an empirical question which government subsidy is more effective. Using counterfactual policies, I answer this question after simultaneously estimating the two-sides of the system.

3.4 Estimation Methodology

The equilibrium for the model is defined by the number of operating charging stations N^* and the number of electric vehicle sales Q^{EV*} that simultaneously satisfy the system of equations in (5) and (10).[23] I jointly estimate this system using the Generalized Method of Moments (Hansen, 1982), since some of the parameters enter in a nonlinear fashion. I construct a matrix of exogenous variables (Z_S and Z_D) where matrices Z_S and Z_D contain the exogenous variables and excluded instruments for the station and the consumer side, respectively. The excluded instruments include the instruments discussed before for the endogenous price variable (p), the endogenous station network term ($\log N$), and the endogenous cumulative electric vehicle base $\left(\log Q^{EV}\right)$.

The identifying assumption I make is that $\mathbb{E}([\varepsilon\ \xi] \mid Z_S, Z_D) = 0$. Given that the unobserved individual attributes were integrated over in (5), the disturbance term is the unobserved product characteristic on the consumer side. The included fixed effects capture part of this unobserved term, thus the remaining residual term (to simplify notation, denoted as ξ) enters the identifying assumption.

Given that this error term enters (5) in a nonlinear way, following the work

[23] Note that in a two-sided market setting with network externalities, multiple equilibria are typical. While I do not have a uniqueness result for the equilibria of this game, the multiplicity of equilibria does not pose a challenge in the estimation of the system. However, it hinders the analysis of counterfactual policies. Therefore, I numerically search for multiple equilibria, and it does not seem to occur in my case.

of Berry, Levinsohn, and Pakes (1995), I first approximate the predicted market shares given by (5) using Monte Carlo simulations. Then I solve the system of equations that set predicted shares equal to the observed shares using a contraction mapping and obtain ξ in each market. ε is simply the error term on the station side given by (10).

The optimization problem is to choose parameters $[\theta \;\; \lambda]$ that minimize the Generalized Method of Moments objective function $m'\Phi^{-1}m$, where Φ^{-1} is the positive definite weighting matrix, $\hat{\varepsilon}$ and $\hat{\xi}$ are estimates of ε and ξ based on the estimates of the parameters θ and λ, and

$$m = \begin{bmatrix} Z_S' & \hat{\varepsilon} \\ Z_D' & \hat{\xi} \end{bmatrix}$$

4 Results

The consumer demand for vehicles of all fuel type is derived from the indirect utility function shown in equation (3), while the station market entry is estimated from equation (10). Tables 3a and 3b display the results from the full structural estimation. Recall that by allowing for heterogeneous consumer valuation of product characteristics and the station network, the marginal utility of each of these terms varies across buyers. Thus, I estimate a mean valuation for each term and the standard deviations around these means.

The demand estimation results confirm the presence of positive feedback effects on the consumer side. The result indicates that the charging network influences buyers' vehicle choice. The estimation results also indicate that there is heterogeneity in consumer valuation of the network term.[24] Both the mean and standard deviation of the network term enters the consumer's utility positively. However, given that the heterogeneity around the mean is smaller, when a price of an EV model increases, consumers will not tend to substitute disproportionately toward other EV models. I find that all car attributes, including the price term, enter consumer utility with the expected sign. The means (β^k) are estimated

[24] While in the results presented here the standard deviation of the network term is not statistically significant, when I reduce the number of parameters estimated by restricting heterogeneity in some vehicle attributes to zero, the term becomes significant.

precisely enough to be significant at traditional statistical levels. In addition, there is substantial and statistically significant variation around the mean for the size and consumption attributes.

Another important result relates to the estimated own- and cross-price elasticities that capture the effectiveness of a price subsidy through the implied substitution patterns. Table 4 presents a sample of mean price elasticities for EV models. The upper panel of the table displays price elasticities I estimate by simulating how market shares of each model change as a result of a price increase if I do not allow for feedback loops between the consumer and station side. The lower panel of the table presents the price elasticities when the positive network effects are accounted for. Each elasticity in a column provides the percentage change in the market share of the row model as a result of a 1% increase in the price of the column model. For instance, a 1% increase in the price of the Nissan Leaf decreases the market share of Leaf models by 1.398% or 1.381% with or without feedback effects. We can make the following observations from the estimated elasticities.

First, I find that demand for all EV models in the sample are elastic and slightly higher when feedback effects are accounted for. Furthermore, the cross-price elasticities between EV models suggest that when network effects are accounted for, electric vehicles can act as complements, hence the negative off-diagonal elements in the lower panel of the table. That is, if the price of the Nissan Leaf increases, then other electric vehicle models become relatively cheaper. A more expensive Leaf implies fewer sales, and thus less entry by charging stations, which ultimately negatively affects demand for other electric vehicle models. Negative cross-price elasticities in the lower panel as opposed to the positive cross-price elasticities in the upper panel indicate that network effects dominate. If feedback effects are restricted to zero, then all cross-price elasticity estimates are instead positive, indicating that electric vehicles would act as substitutes, just like conventional car models if network effects are weak or not present in the market.

Note that by allowing for heterogeneity in consumer taste, the random coefficient discrete choice model provides more flexible substitution patterns, a feature that plays a key role in determining which EV policy may be more preferred: price or station subsidies. A logit (or even nested logit) model restricts buyers to substitute towards other brands in proportion to market shares, regardless of characteristics. Moreover, since the market share of the outside good is very large relative to the other products, the substitution to the inside goods on average will be downward biased. Given that the logit model restricts all cross-price elasticities within a column to be equal, there is a simple way to highlight the difference in substitution patterns implied by a random coefficient discrete choice model. This can be done by calculating the ratio of the maximum and minimum cross-price elasticity within each column. In case of the logit model, all of these ratios are equal to one, while for the estimates shown in Table 4, this ratio is larger than one for all models.

The estimation results from the station market entry indicate the existence of strong positive feedback effects on the station side. That is, the circulating base of EVs is highly important for the charging stations' entry decision. EVSE incentive for normal charging has a significant positive effect on station entry, as expected. Nonetheless, in line with the results of the preliminary analysis, I find that the coefficient estimate on EVSE incentive for fast charging is insignificant at traditional statistical levels and slightly negative. The next section explores what these results indicate for the effectiveness of EV policies.

5 Policy Counterfactuals

The previous sections of this paper develop and estimate an empirical model motivated by economic theory to recover the underlying structural primitives. Namely, own- and cross-price demand elasticities, network effects, and elasticity of station entry with respect to station subsidy. The obtained key parameters provide an opportunity to conduct counterfactuals that allow me to determine the relative effectiveness of EV subsidies and discuss their implications for government intervention in the Norwegian EV market.

I conduct a number of simulations to compare the effects of counterfactual incentive structures. For each counterfactual policy, I use the following methodology. First, either the subsidies for EV purchases or for charging station entry are altered to a counterfactual level.[25] Second, the parameter estimates from the GMM estimation presented in Section 4 are used to jointly determine the equilibrium number of charging stations and market shares in each county for each year.[26] Finally, the change in total government spending is computed by summing the changes in subsidy spending on the two sides of the market. Hence, for any given amount of government spending, this allows for the comparison of the effectiveness of incentives targeting the station side versus the vehicle side in spurring the development of the EV market.

5.1 Comparison of Car Purchase to Station Subsidies in Norway

I consider a first set of counterfactual policies that simulates the average impact of current subsidies in order to compare the effectiveness of the subsidies used in Norway throughout the 2010–2015 period. The total amount of subsidies spent on charging stations and on car purchase subsidies is given by

$$G = \Sigma_m \Sigma_j s_{jm} I_m \varsigma^P_{jm} + \Sigma_m n_m \varsigma^S_m \tag{18}$$

where ς^P denotes the per-vehicle car purchase subsidy for model j in market m, and ς^S denotes the per-station subsidy in market m. As usual, a market is defined as county-by-year. Recall that s_{jm} denotes model j's market share, and I_m the number of households in market m. Here n_m denotes the number of new charging stations built in the given county-year, rather than the cumulative number of stations (N_m).

During the observed period, the combination of price and station subsidies resulted in 37.3% increase in total EV sales (see Table 5). This counterfactual analysis also permits the comparison of buyer vehicle choice in the absence of the

[25] In case of the EVSE incentives, I choose to alter the level of the subsidy for normal charging while leaving subsidies for fast charging constant.

[26] The conducted counterfactuals are "partial" in the sense that they do not account for other potential equilibrium responses, such as adjustments in product characteristics, quality, and availability. Given that manufacturers are not explicitly modeled, the analysis also assumes complete pass-through of subsidies from the manufacturer to the consumer. Sallee (2011) and Busse et al. (2006) provide empirical evidence that a complete or very high rate of pass-through is a reasonable assumption in cases of well-publicized incentives and tightly supplied vehicles, attributes that are true for the Norwegian EV market.

EV incentives to the data. I find that 78.8% of the increase in EV sales results from consumers substituting away from non-electric vehicles. The majority of those consumers who opt for an EV model due to the incentives substitute away from diesel fueled cars, followed by cars running on gasoline. The remaining 21.2% are from households that would not have purchased a new car otherwise.

The key question here is to determine, for a given amount of government resources, which side of the market to subsidize for the most effective promotion of EV adoption. To this end, I determine the number of additional EVs purchased between 2010 and 2015 for each type of subsidy as summarized in Table 5. Solving for the equilibrium number of stations and market shares in each county-year pair when only car purchases are subsidized, I find that there are 16,921 more EVs purchased compared to the simulated scenario where there are no subsidies.

Oppositely, if only stations were subsidized, I find that 869 fewer EVs are purchased compared to the simulated policy setting where there are no subsidies. Hence, car purchase subsidies account for 95% of the increase in EV sales, which are due to the subsidies in the Norwegian market. However, the government also spent substantially more on car purchase subsidies. In fact, government spending would have added up to 4,374 million Norwegian kroner (541.74 million USD) by using only price subsidies in comparison with 104 million Norwegian kroner (12.88 million USD) in spending when using station subsidies only. With regard to these facts, I find that station subsidies resulted in 835 additional EV purchases per 100 million Norwegian kroner (12.39 million USD) spent by the government compared to car purchase subsidies, which resulted in only 387 additional EVs per 100 million Norwegian kroner (12.39 million USD) spent. Thus, the results suggest that in the case of the Norwegian market between 2010 and 2015, station subsidies were more than twice as effective per million Norwegian kroner spent than car purchase subsidies.

5.2 Alternate Levels of Government Spending

The findings of the previous subsection lead naturally to the question of whether station subsidies are always more effective than directly subsidizing buyers. In particular, if Norwegian policymakers had a larger sum of resources at their disposal to spend on the development of the EV market in this time period, would these resources be more effectively spent on additional stations or car subsidies? I tackle the question by considering a second set of counterfactuals that simulate the marginal impact of increase in current subsidies. That is, these policy counterfactuals simulate a setting where either the station subsidies are increased or car price subsidies are increased from the status quo. For each incremental change in a subsidy, I compute the effect on the equilibrium of the number of stations and car purchases in all counties from 2010 to 2015, and determine the total change in government spending relative to the status quo. The results of these simulations are presented in Figures 5(a) and 5(b).

Figure 5(a) plots the change in cumulative EV purchases for the period between 2010 and 2015, implied by the increased total government spending due to alternative incentive structures. Note that the horizontal axis measures implied government spending in addition to the spending in status quo. The dashed line represents the outcomes when station subsidies are increased, while the solid line represents the outcomes when car price subsidies are increased. The figure highlights the fact that the relative effectiveness of the two types of subsidies can change as the amount of resources the government spends changes. Note that the functional form assumptions specified in Section 3 allow both station subsidies and consumer price subsidies to exhibit diminishing returns. The difference in the rate at which their respective impact on electric vehicle sales tapers off is however not driven by functional form assumptions. The diminishing returns to the respective subsidies are pinned down by the relevant identifying variation in the number of stations, the electric vehicle shares, and both types of incentives, while the modeling framework allows the relative diminishing returns to vary with the estimated parameters.

Figure 5(a) demonstrates that while station subsidies are more effective in the status quo and for relatively small increases in government spending from the status quo, they become less effective for increases in government spending of over approximately 400 million Norwegian kroner (49.54 million USD). For instance, an additional billion Norwegian kroner (123.9 million USD) in government spending on price subsidies would have led to around 3,238 of additional EV purchases against an approximate 2,288 additional sales of EVs if the same amount were spent on station subsidies only. Hence, to determine which type of subsidy is more effective in a two-sided market, generosity of incentives and government spending must be taken into account. The effect of station subsidy tapers off quicker than the impact of the price subsidy. Figure 5(b) illustrates that station subsidies also exhibit more significant diminishing returns on station entry compared to price subsidies.

So far, when thinking about the effectiveness of station and price subsidies, I have only considered cases of implementing one incentive or the other, but not their combination. Now, I compare the effectiveness of subsidy structures that are a mix of the two subsidies. Starting from the status quo in the Norwegian EV market, I construct counterfactuals in which either price subsidies, station subsidies, or both are altered to a counterfactual level. To measure the effectiveness of the different subsidy allocations, panel (a) of Figure 6 presents the increase in EV sales per million Norwegian kroner as a result of changes in the price and station subsidies. Darker colors illustrate higher efficiency, that is, per million Norwegian kroner a larger number of EV purchases. Hence, the figure indicates that the effectiveness of price subsidies increases as they are complemented with the provision of station subsidies. This tapers off as station subsidies are further and further increased.

While the figure in panel (a) might give the impression that station subsidies are more effective than price subsidies, it is important to note that in this part of the analysis government spending is not being held constant across the different policy scenarios. To facilitate direct comparison between the various subsidy allocations, the addition to government spending implied by the change in subsidies is displayed in panel (b) of Figure 6. This second figure indicates that for a given level of government spending, policymakers can choose to have a larger price discount and little change in station subsidies, a very small increase in price subsidies coupled with very large increases in station subsidies, or a mixture somewhere in between those two options. Previously, I found that for a large enough governmental budget, increasing price subsidies is more effective than increasing station subsidies. Panel (a) and (b) of Figure 6 together indicate that a combination of the two policies could be even more effective by slightly lowering price discounts in exchange for a parallel increase in station subsidies.

If there are limited resources available (bottom-left corner of panel (b)) then, as I found before, station subsidies are more effective than price subsidies, which is indicated by the darker colors in the bottom-left corner of panel (a).

In conclusion, the policy counterfactuals show that although the Norwegian station subsidies are found to be more than twice as effective as the price subsidies in the data, the result is not generalizable for all settings. Indeed, station subsidies appear to reach diminishing returns more rapidly than price subsidies, such that it would be more effective to subsidize car purchases past a certain point. In the Norwegian case, this point is at an additional 400 million Norwegian kroner (49.54 million USD) from the status quo. This amount is likely to vary substantially from setting to setting depending on factors, such as the own-price and cross-price demand elasticities, the magnitude of network effects, and the elasticity of station entry with respect to subsidies (as highlighted by the model in Section 3).

6 Conclusion

There are a variety of opportunities to reduce greenhouse gas emissions from the transportation sector, such as improving fuel efficiency, reducing travel demand, improving driving practices, and switching to alternative fuel. In many countries around the world, EVs play an increasingly important role in achieving lower emissions related to transportation. However, there is no general consensus on the design of the supporting policies that work best to encourage EV adoption.

This work highlights the necessity for accounting for the network externalities present in the EV market due to its "two-sided" nature when designing EV promoting policies. Notably, I empirically investigate the impact of price subsidies and charging station subsidies on EV sales using a two-sided market framework. I show that the most efficient side of the market to subsidize depends on key structural primitives, such as the own- and cross-price automobile demand elasticities, network effects on both sides of the EV market, and the elasticity of station entry with respect to the station subsidies. Thus, the effectiveness of the two types of subsidies is an open empirical question.

To examine consumer vehicle choices and charging station entry decisions, this paper uses data from Norway on the universe of newly registered automobiles and its public charging station network. I present descriptive analysis that demonstrates a strong positive relation between EV incentives and EV purchases. However, to be able to study policy counterfactuals comparing consumer readjustment in response to subsidies when feedback loops are present, it is crucial to use a structural approach. Hence, I develop a modeling framework in which consumers make their car purchasing decisions by maximizing their utility across automobile models of all fuel types, with the outside option of purchasing no vehicle. Simultaneously, charging stations make an entry decision that is driven by their discounted stream of per-period profits and their sunk costs of entry.

I find evidence of positive feedback effects on both sides of the market, suggesting that cumulative EV sales affect charging station entry and that public charging availability has an impact on consumers' vehicle choice. Furthermore, I find evidence that there is heterogeneity in the consumer valuation of the charging network. Estimated own- and cross-price demand elasticities of EV models indicate that when network effects dominate, EV models can act as complement products.

The counterfactual analyses examine the average impact of current subsidies and the marginal impact of increase to those subsidies. The findings suggest that between 2010 and 2015, every 100 million Norwegian kroner (12.39 million USD) spent on station subsidies alone resulted in 835 additional electric vehicle purchases compared to a counterfactual in which there are no subsidies on either side of the market. The same amount spent on price subsidies led to only an additional 387 electric vehicles being sold compared to a simulated scenario where there were no EV incentives. However, this relation inverts with increased spending, as the impact of station subsidies on electric vehicle purchases tapers off faster. Additionally, I find that the marginal impact of the increase to price subsidies is larger when combined with increases in the station subsidies. Given that station subsidies reach diminishing returns quicker than price subsidies, this relation only holds up to a certain point. The findings of this paper suggest that for a given level of government spending, policymakers can get the biggest "bang for the buck" with regard to EV adoption if they use both types of policies, instead of implementing either one incentive or the other.

References

Allcott, H. and Wozny, N. (2014). Gasoline prices, fuel economy, and the energy paradox. Review of Economics and Statistics, pages 779–795.

Armstrong, M. (2006). Competition in two-sided markets. The RAND Journal of Economics, 37(3):668–691.

Armstrong, M. and Wright, J. (2007). Two-sided markets, competitive bottlenecks and exclusive contracts. Economic Theory, 32(2):353–380.

Beresteanu, A. and Li, S. (2011). Gasoline prices, government support, and the demand for hybrid vehicles in the united states. International Economic Review, 52(1):161–182.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. Econometrica: Journal of the Econometric Society, pages 841–890.

Bresnahan, T., Orsini, J., and Yin, P.-L. (2015). Demand heterogeneity, inframarginal multihoming, and platform market stability: Mobile apps. Mobile Innovation Group Working Paper.

Bresnahan, T. F. (1987). Competition and collusion in the American automobile industry: The 1955 price war. The Journal of Industrial Economics, pages 457–482.

Bresnahan, T. F. and Reiss, P. C. (1991). Entry and competition in concentrated markets. Journal of Political Economy, pages 977–1009.

Busse, M., Silva-Risso, J., and Zettelmeyer, F. (2006). $1,000 cash back: The pass-through of auto manufacturer promotions. The American Economic Review, 96(4):1253–1270.

Busse, M. R., Pope, D. G., Pope, J. C., and Silva-Risso, J. (2015). The Psychological Effect of Weather on Car Purchases. Quarterly Journal of Economics, 130(1):371–414.

Caillaud, B. and Jullien, B. (2003). Chicken & Egg: Competition among Intermediation Service Providers. The RAND Journal of Economics, 34(2):309–328.

Crawford, G. S. and Yurukoglu, A. (2012). The Welfare Effects of Bundling in Multichannel Television Markets. American Economic Review, 102(2):643–685.

DeShazo, J., Sheldon, T. L., and Carson, R. T. (2017). Designing policy incentives for cleaner technologies: Lessons from california's plug-in electric vehicle rebate program. Journal of Environmental Economics and Management, 84:18–43.

Farrell, J. and Saloner, G. (1985). Standardization, Compatibility and Innovation. The RAND Journal of Economics, 16(1):70–83.

Gandal, N., Kende, M., and Rob, R. (2000). The dynamics of technological adoption in hardware/software systems: The case of compact disc players. The RAND Journal of Economics, pages 43–61.

Gentzkow, M., Shapiro, J. M., and Sinkinson, M. (2014). Competition and Ideological Diversity: Historical Evidence from US Newspapers. American Economic Review, 104(10):3073–3114.

Grigolon, L., Reynaert, M., and Verboven, F. (2014). Consumer valuation of fuel costs and the effectiveness of tax policy: Evidence from the European car market. CEPR Discussion Paper No. DP10301.

Hendel, I. and Nevo, A. (2006). Measuring the Implications of Sales and Consumer Inventory Behavior. Econometrica, 74(6):1637–1673.

Holland, S. P., Mansur, E. T., Muller, N. Z., and Yates, A. J. (2015). Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors. NBER Working Paper 21291.

Institute of Transport Economics (2013). Electromobility in Norway - Experiences and Opportunities with Electric vehicles. Technical report.

Institute of Transport Economics (2014). Electric Vehicles - Environmental, Economics and Practical Aspects. As Seen by Current and Potential Users. Technical report.

Institute of Transport Economics (2015). Learning from Norwegian Battery Electric and Plug-in Hybrid Vehicle users. Technical report.

International Council on Clean Transportation (2015). Transition to a Global Zero-Emission Vehicle Fleet: A Collaborative Agenda for Governments. Retrieved October 9, 2016.

International Energy Agency (2015). Global EV Outlook 2015. Retrieved September 24, 2016.

International Energy Agency (2016). Key CO_2 Emissions Trends. Retrieved October 8, 2016.

Jacobsen, M. R. (2013). Evaluating us fuel economy standards in a model with producer and household heterogeneity. American Economic Journal: Economic Policy, 5(2):148–87.

Katz, M. L. and Shapiro, C. (1985). Network Externalities, Competition and Compatibility. American Economic Review, 75(3):424–440.

Langer, A. and McRae, S. (2014). Fueling Alternatives: Evidence from Real-World Driving Data. Working Paper.

Langer, A. and Miller, N. (2013). Automakers' Short-Run Responses to Changing Gasoline Prices. Review of Economics and Statistics, 95(4):1198–1211.

Lee, R. (2013). Vertical Integration and Exclusivity in Platform and Two-Sided Markets. American Economic Review, 103(7):2960–3000.

Li, J. (2017). Compatibility and Investment in the U.S. Electric Vehicle Market. Working Paper.

Li, S., Lang, T., Xing, J., and Zhou, Y. (2017). The market for electric vehicles: Indirect network effects and policy impacts. Journal of the Association of Environmental and Resource Economists, 4(1):89–133.

Nevo, A. (2000). A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand. Journal of Economics & Management Strategy, 9(4):513–548.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. Econometrica, 69(2):307–342.

NOBIL (2016). Nobil Charging Station Database. Retrieved May 30, 2016.

Norwegian Central Bank (2016). Annual Exchange Rates (from 1960). Retrieved October 23, 2016.

Norwegian Competition Authority (2010). Det norske drivstoffmarkedet (In Norwegian). Retrieved September 25, 2016.

Norwegian Tax Authority (2016). One-off registration tax and scrap deposit tax. Retrieved September 24, 2016.

Pavan, G. (2015). Green Car Adoption and the Supply of Alternative Fuels. PhD thesis. Job Market Paper.

Petrin, A. (2002). Quantifying the Benefits of New Products: The Case of the Minivan. Journal of Political Economy, 110(4):705–729.

Rochet, J.-C. and Tirole, J. (2006). Two-sided markets: A progress report. The RAND journal of economics, 37(3):645–667.

Sallee, J. M. (2011). The surprising incidence of tax credits for the toyota prius. American Economic Journal: Economic Policy, 3(2):189–219.

Shiver, S. K. (2015). Network Effects in Alternative Fuel Adoption: Empirical Analysis of the Market for Ethanol. Marketing Science, 34(1):78–97.

Train, K. E. (2009). Discrete choice methods with simulation. Cambridge university press.

U.S. Department of Energy (2015). Alternative Fuel Data Center. All Laws and Incentives. Retrieved October 11, 2016.

Weyl, G. E. (2010). A price theory of multi-sided platforms. The American Economic Review, 100(4):1642–1672.

White, A. and Weyl, E. G. (2016). Insulated platform competition. Available at SSRN 1694317.

7 Figures and Tables

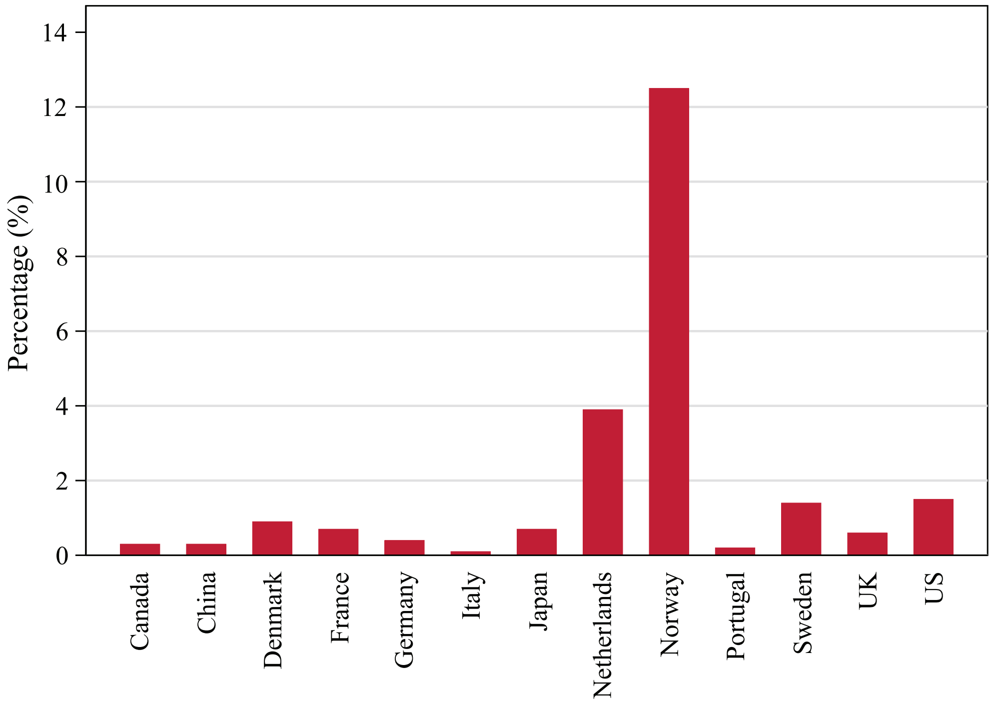


Figure 1: Market Shares of Electric Vehicles Sales Around the World (2014)

Notes: The figure compares market shares of new electric vehicle sales in countries around the world in the year of 2014.

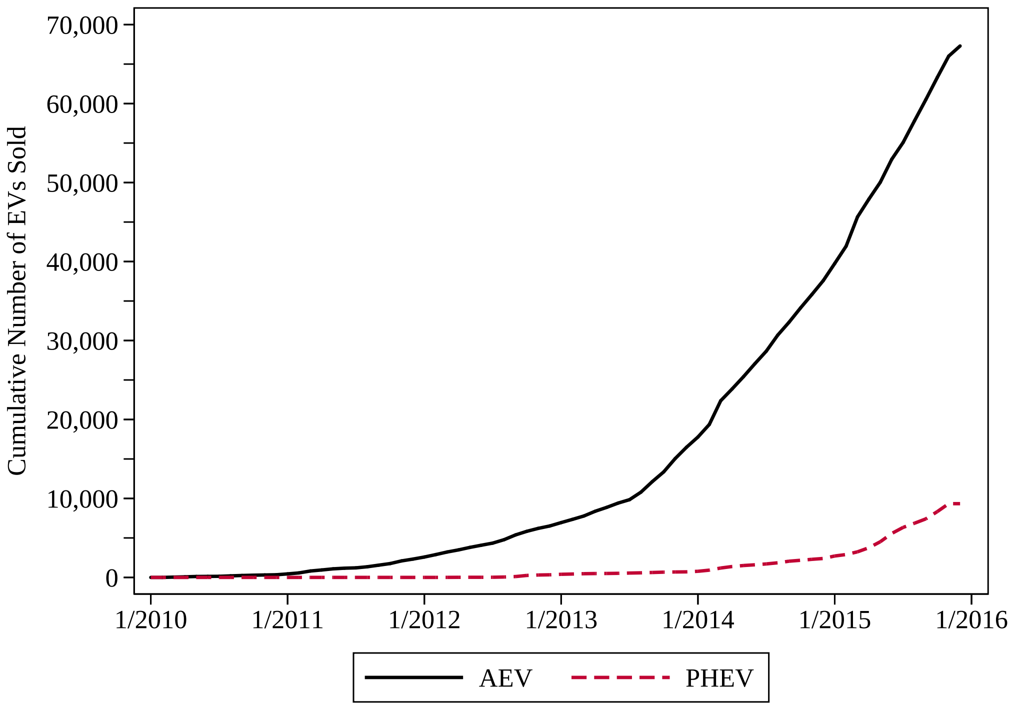


Figure 2: Cumulative Electric Vehicle Sales in Norway

Notes: The figure shows the monthly cumulative sales of all-electric and plug-in hybrid vehicles in Norway between 2010 and 2015.

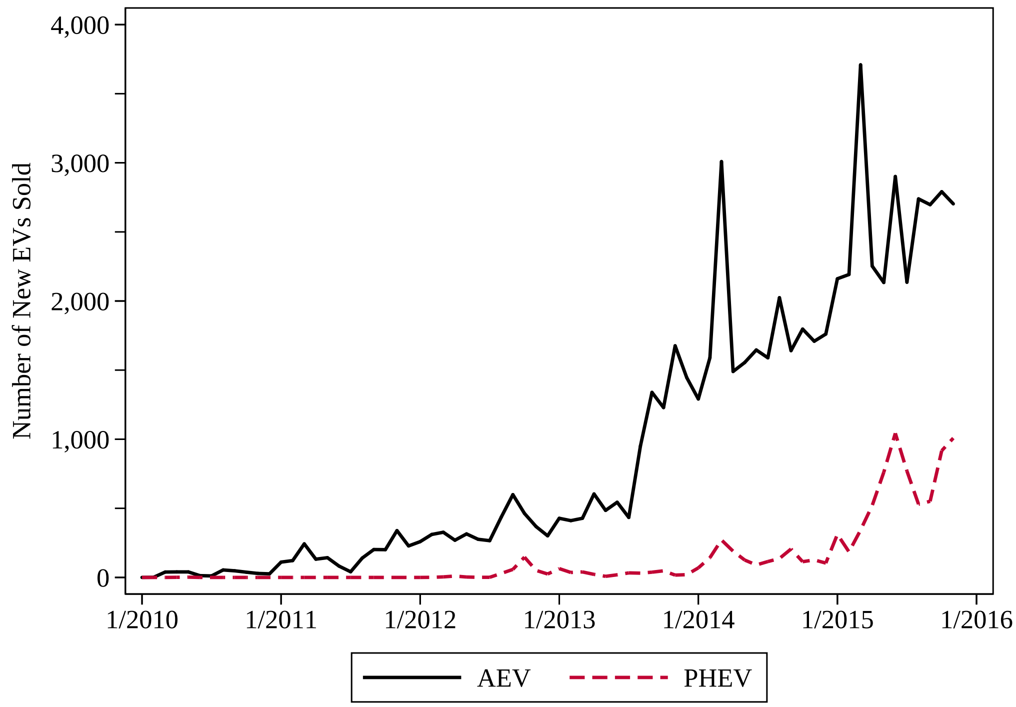


Figure 3: New Electric Vehicle Sales in Norway

Notes: The figure shows the monthly new sales of all-electric vehicles and plug-in hybrid vehicles in Norway between 2010 and 2015.

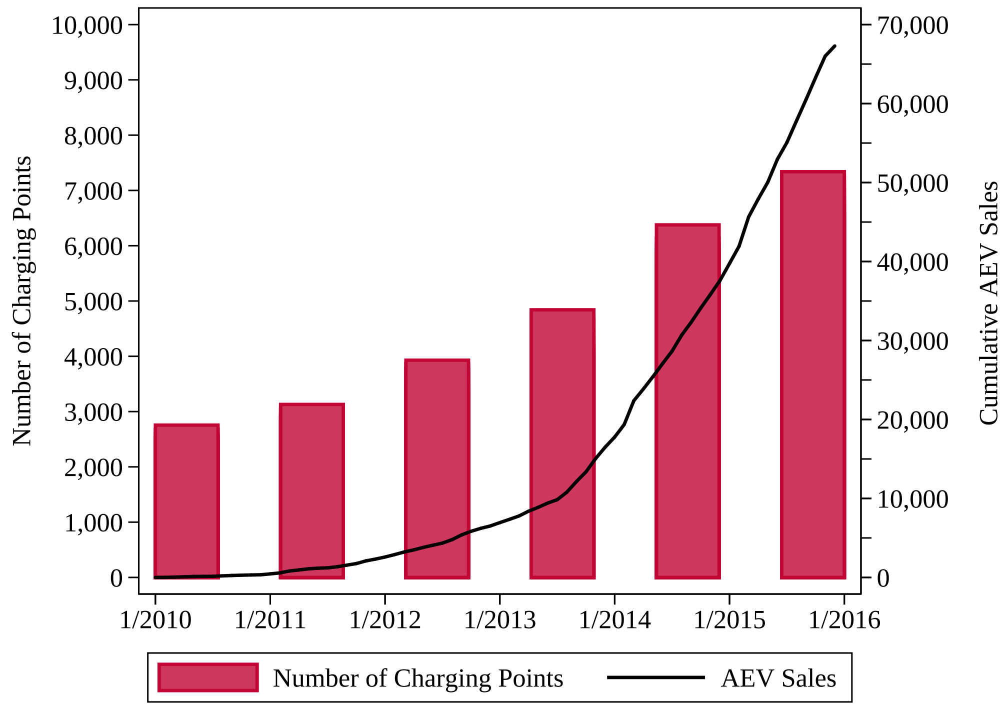
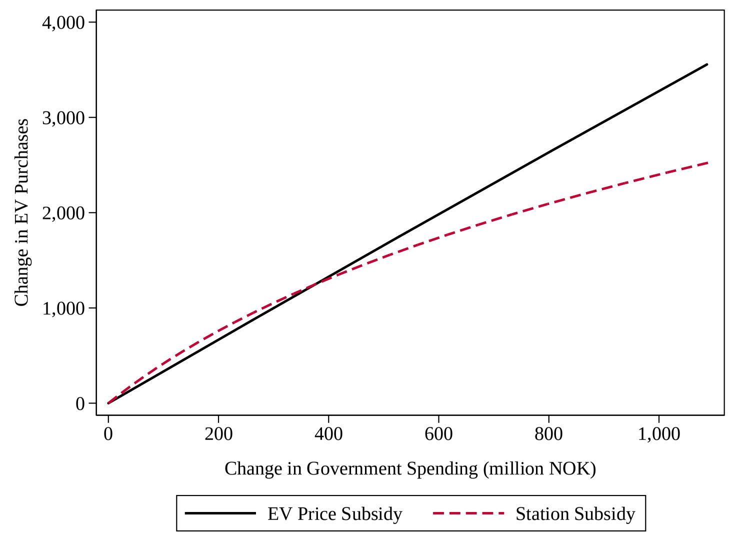
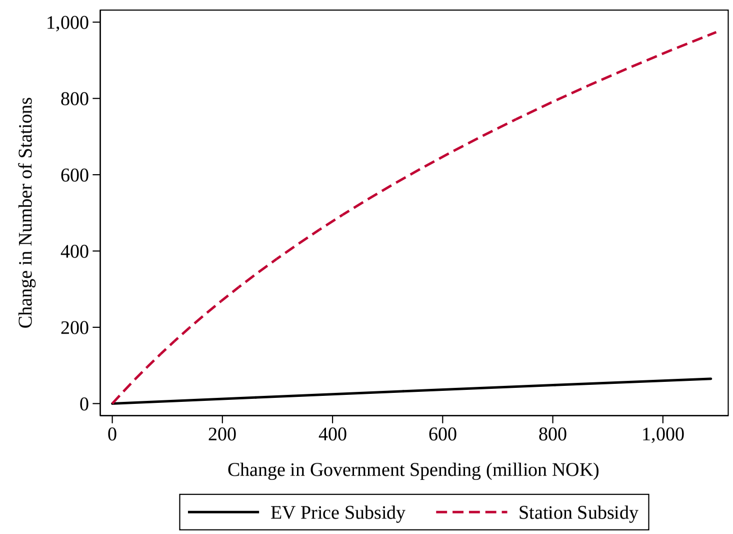


Figure 4: Number of Charging Points and Cumulative All-Electric Vehicle Sales in Norway

Notes: The figure shows the monthly cumulative sales of all-electric vehicles against the yearly total number of operating charging stations in Norway between 2010 and 2015.



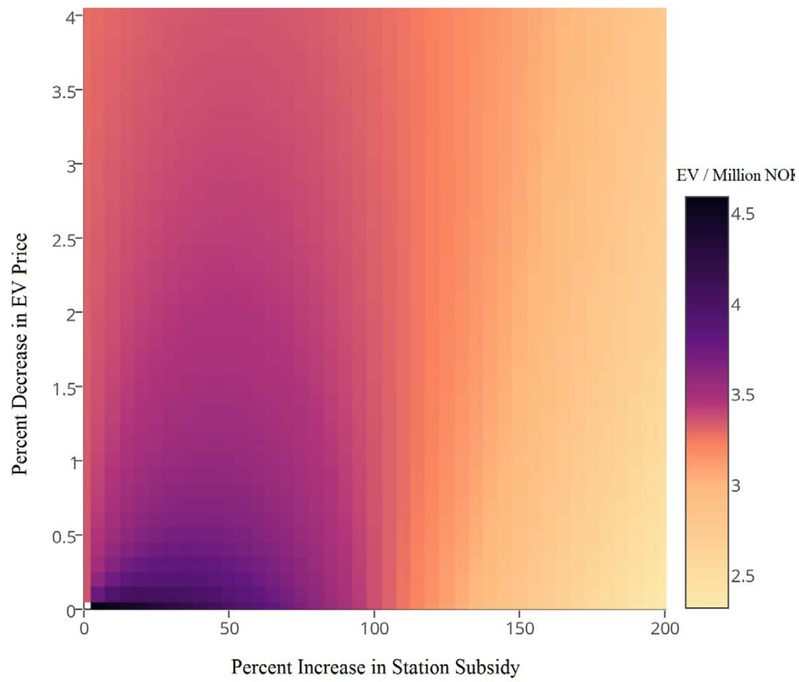
(a) Subsidies and EV Purchases



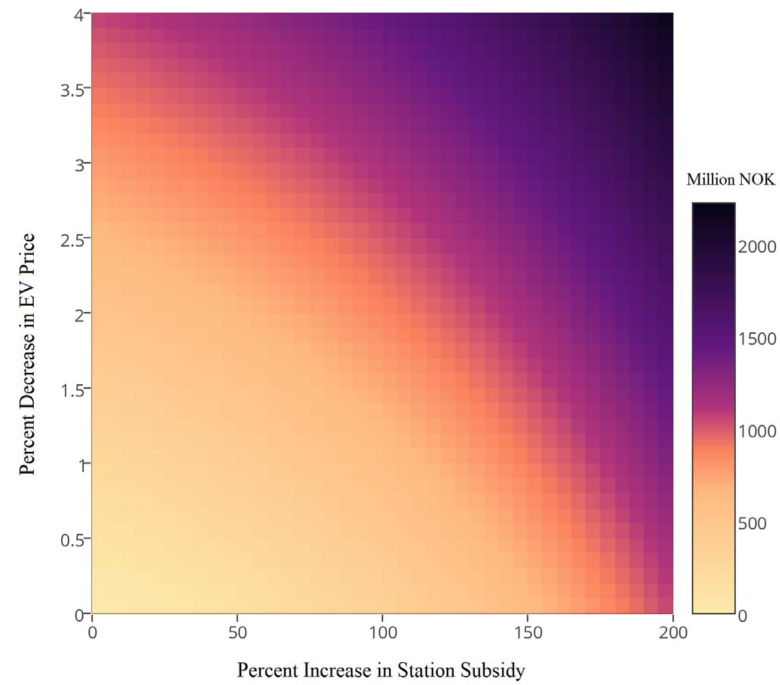
(b) Subsidies and Station Entry

Notes: The figures present the simulation results showing how cumulative sales of EVs (Figure 5(a)) and cumulative number of stations (Figure 5(b)) change for increases in government spending on station subsidies or car price subsidies, respectively. Starting from the status quo in the Norwegian EV market, either the price subsidies or the station subsidies are altered to a counterfactual level. Specifically, each point of the black line shows policy counterfactuals in which the station subsidies are unchanged from the status quo while price subsidies are increasing. Similarly, each point of the red dashed line shows a scenario in which the station subsidies are increasing while price subsidies remain unaltered. Then, I use the GMM parameter estimates to jointly determine the equilibrium number of charging stations and vehicle market shares in each market under the new policy settings. Finally, I compute the change in total government spending implied by the change in a respective subsidy. This allows me to compare the impact of station subsidies against the effect of price subsidies on EV sales and station entry (shown on the y axes of the respective figures) for given levels of government spending (shown on the x-axis).

Figure 6: The Impact of Different Subsidy Allocations on EV Sales and the Implied Government Spending



(a) Efficiency of Price and Station Subsidies



(b) Change in Government Spending

Notes: The figure on the left presents the increase in EV sales per million Norwegian kroner as a result of a percentage change in price subsidies and/or station subsidies. The figure on the right displays how the government spending varies with the changing subsidies. In both figures, percentage change in station subsidies is shown on the horizontal axis and percentage change in EV prices is shown on the vertical axis. Starting from the status quo in the Norwegian EV market, I use the following methodology to construct the counterfactuals in the graphs. First, either the price subsidies or the station subsidies or both are altered to a counterfactual level. Specifically, each point in both figures shows a policy counterfactual in which either the station subsidies or the price subsidies or both are altered from their status quo levels. Second, I use the GMM parameter estimates to jointly determine the equilibrium number of charging station and vehicle market shares in each market under the new policy settings. Finally, I compute the change in total government spending implied by the change in the subsidies. This allows me to calculate the growth in EV sales as a result of the change in the incentives.

Table 1a: Summary Statistics

Variable	Mean	Std. Dev.
Panel (a) Consumer side		
Sales	41.015	100.953
Price (1,000 NOK)	300.785	123.526
Horsepower (kW)	85.864	29.650
Weight (1,000 kg)	1.377	0.243
Consumption (l/km)	0.452	0.155
Transmission (0-1)	0.438	0.496
Length (m)	4.412	0.341
EV (0-1)	0.073	0.260
Number of charging stations	265.101	339.288
EVSE subsidy for normal charging (1,000 NOK)	5.323	10.962
EVSE subsidy for fast charging (1,000 NOK)	232.367	145.638
Number of observations	22,084	
Panel (b) Station side		
Number of charging stations	51.355	71.550
Cumulative EV base (1,000 units)	1.106	2.296
EVSE subsidy for normal charging (1,000 NOK)	5.887	11.543
EVSE subsidy for fast charging (1,000 NOK)	223.678	147.856
Current gas station density	1.923	4.133
Gas station density last year	1.986	4.302
Number of observations	114	

Notes: The table reports the summary statistics for the variables used in the vehicle demand estimation (upper panel) and in the station entry model (lower panel). For the vehicle characteristics and price variable vehicle sales weighted means are presented.

Table 1b: Summary Statistics

Year	Mean No. of Models	Sales	Stations	Price	HP/Wt	Consumption	EV	Length	Transmission
2010	170	140,763	2,755	296,367	0.0593	0.5194	0.0001	4.4063	0.2250
2011	182	150,976	3,129	294,038	0.0592	0.4912	0.0123	4.4049	0.3075
2012	199	154,451	3,929	303,686	0.0604	0.4789	0.0269	4.4140	0.3751
2013	206	158,383	4,841	299,364	0.0626	0.4569	0.0618	4.4181	0.4861
2014	208	156,592	6,377	305,873	0.0637	0.4106	0.1327	4.4129	0.5783
2015	203	144,614	7,361	305,075	0.0640	0.3587	0.2026	4.4129	0.6466

Notes: The table shows yearly descriptive statistics for the main variables and product characteristics. The entry in each cell of the last six columns is the vehicle sales weighted mean.

Table 2: Descriptive Analysis of Relation between EV Incentives and EV Sales

	log(No. of Registered Cars)		
	[1]	[2]	[3]
Registration Tax Exemption (10,000 NOK)	0.031	0.031	0.031
	(0.004)	(0.004)	(0.004)
VAT Exemption (10,000 NOK)	0.003	0.003	0.003
	(0.015)	(0.015)	(0.015)
EVSE Normal (10,000 NOK)	-0.034	-0.031	-0.025
	(0.017)	(0.016)	(0.015)
EVSE Normal × EV	0.168	0.086	0.084
	(0.026)	(0.028)	(0.028)
EVSE Fast (10,000 NOK)	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
EVSE Fast × EV	0.003	0.004	0.004
	(0.005)	(0.006)	(0.006)
Observations	191,616	191,616	191,616
Adj. R-squared	0.40	0.40	0.40
Model × County and Time Fixed Effects	Y	Y	Y
Cluster on Model and County	Y	Y	Y
Local Incentives	N	Y	Y
Macroeconomic Controls	N	N	Y

Notes: The table reports the coefficient estimates and standard errors from the preliminary analysis of EV incentives using different OLS regression specifications. The dependent variable is the logarithm of new vehicle sales of all fuel types. Unit of observation is model j in market m (county c by month t). All regressions include time fixed effects and county-by-model fixed effects. Macroeconomic variables include regional GDP, median household income, and unemployment. Standard errors are reported in parentheses. Standard errors are two-way clustered at the county and the model level. The three specifications are building up in complexity: specification [1] does not include macroeconomic variables or local incentives, [2] includes local incentives, and specification [3] also includes macroeconomic controls.

Table 3a: Results from the GMM Estimation: Vehicle Demand

Vehicle Demand	Variable	Parameter Estimate	Standard Error
	log(Income - Price)	4.3905	0.8329
Means	Station Network	0.4184	0.1430
	EV	0.7574[a]	0.0481
	Transmission	0.0480[a]	0.0149
	Acceleration	11.5859[a]	0.4150
	Size	0.1069[a]	0.0166
	Consumption	-0.2588[a]	0.0656
Std. Deviations	Station Network	0.2809	1.0849
	EV	0.6613	4.4303
	Transmission	0.2331	0.0772
	Acceleration	0.9643	4.0888
	Size	1.1458	0.0844
	Consumption	3.6586	1.0488

[a] Estimates from minimum-distance procedure.

Notes: The table reports the coefficient estimates and standard errors for vehicle demand from the GMM estimation. Unit of observation is model (j) in county (c) and year (t). Based on 22,084 observations. Excluded instruments include electric vehicle supply equipment (EVSE) incentives, exogenous car characteristics and sum of the value of the same characteristics for other products offered by other car manufacturers, as described in the text. The model assumes heterogeneous valuations for the station network and the car characteristics.

Table 3b: Results from the GMM Estimation: Station Entry

Station Entry	Parameter Estimate	Standard Error
log(EV base)	0.1628	0.0537
EVSE normal (10,000 NOK)	0.1832	0.0544
EVSE fast (10,000 NOK)	-0.0017	0.0018
Trend	0.0751	0.0518

Notes: The table reports the coefficient estimates and standard errors for station entry from the GMM estimation. Unit of observation is county (c) by year (t). Based on 114 observations. Excluded instruments include gas station density and lagged gas station density, as described in the text. County-specific fixed effects are included.

Table 4: Sample of Mean Own- and Cross-Price Elasticities for EV Models

AEV Make and Model	i3	C-Zero	i-Miev	Leaf	Ion	E-Up!
No Feedback Effects						
BMW i3	-1.486	0.004	0.004	0.004	0.003	0.004
Citroen C-Zero	0.001	-1.071	0.000	0.001	0.000	0.000
Mitsubishi i-Miev	0.001	0.001	-1.112	0.001	0.001	0.000
Nissan Leaf	0.022	0.012	0.011	-1.381	0.011	0.016
Peugeot Ion	0.001	0.001	0.001	0.001	-1.150	0.001
Volkswagen E-Up!	0.004	0.003	0.003	0.003	0.003	-1.160
With Feedback Effects						
BMW i3	-1.487	0.001	0.001	0.002	0.001	0.002
Citroen C-Zero	-0.001	-1.074	-0.003	-0.002	-0.003	-0.001
Mitsubishi I-Miev	-0.002	-0.010	-1.127	-0.007	-0.011	-0.003
Nissan Leaf	0.005	-0.010	-0.010	-1.398	-0.010	-0.006
Peugeot Ion	0.000	-0.003	-0.003	-0.002	-1.153	-0.001
Volkswagen E-Up!	0.002	0.000	0.000	0.001	0.000	-1.163

Notes: The top panel of the table reports the mean price elasticities of AEV models without accounting for feedback effects, while the bottom panel shows them accounting for feedback effects. Each cell entry, where i denotes rows and j denotes columns, provides the percentage change in market share of model i with respect to a 1% change in the price of model j.

Table 5: Counterfactual Analysis of the Average Impact of Subsidies on EV Sales

	Status quo	Counterfactuals		
	[1]	[2]	[3]	[4]
Total EV Purchases	66,278	65,195	49,142	48,273
Total Stations	7,369	7,014	7,005	6,662
Total Government Spending (Million NOK)	4,552	4,374	104	0
ΔEV Purchases / Government Spending	3.96	3.87	8.35	-
Normal EVSE incentives	Y	N	Y	N
Car Purchase Incentives	Y	Y	N	N

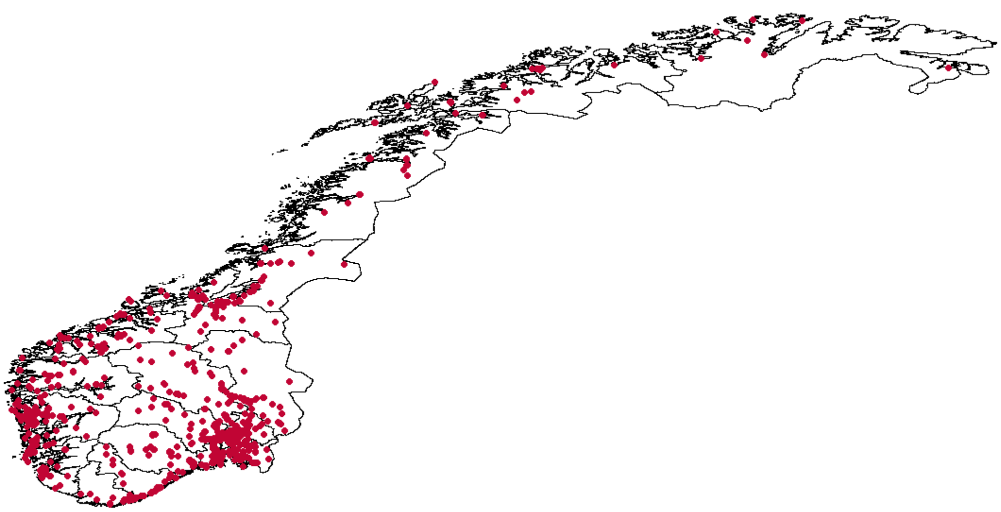
Notes: This table summarizes results from the counterfactual analysis that simulates the average impact of current subsidies. For each simulated policy scenario I solve for the equilibrium number of stations and vehicle market shares in each county-year pair and provide an estimate for the total government spending implied by the implemented incentives. The first column describes the status quo by providing the cumulative numbers of EV sales and charging stations. The second column presents the results when only vehicle purchases are subsidized and station subsidies are restricted to zero. The third column shows the results when instead only stations are subsidized and price subsidies are set to equal zero. Finally, the last column describes the simulation results for a scenario where there are no station or price subsidies.

APPENDIX to
Network Externality and Subsidy Structure in Two-Sided Markets:
Evidence from Electric Vehicle Incentives

Katalin Springel

Appendix A Figures and Tables

(a) Station Network at the Start of the EV Market (2009)



(b) Station Network at the End of the Observed Time Period (2015)

Figure A1: Number of Stations in Norway (2009 and 2015)

Notes: The figure shows the development of the battery charging station network in Norway starting from the end of 2009 until the end of 2015.

Table A1: Descriptive Analysis - Robustness Checks

	log(No. of Registered Cars)		
	[1]	[2]	[3]
EVSE Normal	-0.021		
	(0.012)		
EVSE Normal × Hybrid	-0.017		
	(0.047)		
EVSE Fast	-0.001		
	(0.001)		
EVSE Fast × Hybrid	-0.000		
	(0.003)		
Placebo EVSE Normal		-0.003	
		(0.002)	
Placebo EVSE Normal × EV		0.010	
		(0.017)	
Placebo EVSE Fast		-0.000	
		(0.000)	
Placebo EVSE Fast × EV		-0.001	
		(0.001)	
EVSE Normal × EV			0.129
			(0.054)
Lead EVSE Normal × EV			0.003
			(0.032)
Lagged EVSE Normal × EV			-0.016
			(0.106)
Observations	191,616	191,616	62,758
Adj. R-squared	0.39	0.40	0.45
Model-County and Time Fixed Effects	Y	Y	Y
Cluster on Model and County	Y	Y	Y
Local and Tax Incentives	Y	Y	Y
Macroeconomic Controls	Y	Y	Y

Notes: The table reports the coefficient estimates and standard errors from the robustness checks related to the descriptive analyses. The dependent variable is the logarithm of new vehicle sales of all fuel types. Unit of observations is model j in market m (county c by month t). All regressions include the tax and local incentives, time fixed effects and county-by-model fixed effects. Standard errors are reported in parentheses. Standard errors are two-way clustered at the county and the model level. Specification [1] investigates whether the incentives specifically targeting battery-electric vehicles only have an impact on hybrid sales. Specification [2] examines the impact of randomly reassigned the EVSE incentives. Specification [3] explores the impact of including lead, concurrent, and lagged versions of the EVSE incentives on vehicle sales.

Appendix B Subsidy Non-Neutrality in Two-Sided Markets

The EV market can be considered within the framework of two-sided markets, that is, a market in which one or several platforms facilitate interactions between two set of end-users.[1] The platform tries to get the two sides on board by appropriately charging each side, where the decisions of agents on one side affect the participation and welfare of agents on the other, typically through usage and/or membership externality (Rochet and Tirole, 2006). In the context of the EV industry, the platform can be thought of as the technology for EVs or the EV manufacturer like Tesla Motors or Nissan, while the two sides consist of buyers of EVs and electric charging station providers like Fortum Charge & Drive. The interaction between the two sides is the actual charging of an automobile, a transaction not observed (in most cases) by the platform.[2]

Following the work of Armstrong (2006), the framework that best applies to the EV market is the pure membership externality model.[3] Membership externalities are generated by membership decisions insofar as the benefits enjoyed by end-users on one side depend upon how well the platform does in attracting customers from the other group (Rochet and Tirole, 2006). This model is associated with the existence of transaction-insensitive end-user costs (or membership charges). There are no usage charges in this setting as the platform is not likely to observe transactions between the two sides of the EV market.[4]

The focus of present study is to understand the effectiveness of the various subsidies the government might give in a two-sided market with membership

[1] Note that by electric vehicle I mean battery- or all-electric vehicle models only, hybrid or plug-in hybrid models are not considered here.

[2] An exception is for example the case of Tesla Motors where the platform and one side of the market (charging stations) are vertically integrated. Present analysis ignores this aspect of the EV market.

[3] Sometimes referred to as the indirect network effects model.

[4] It is arguable whether a combination of usage and membership externalities would better fit the EV industry (Rochet and Tirole, 2006). However, I believe that a pure membership externality model reasonably represents the industry. Nevertheless, if the non-neutrality result holds for the case of pure membership externality model, it is likely it will also hold for the model that combines both types of externalities.

externalities. A key feature of two-sided markets is non-neutrality in the allocation of prices between the two sides which simply means that it is not just the level of price (total price charged by the platform to the two sides of the market) that affects economic outcomes, but the price structure (the allocation of the total price between the two sides) as well. In what follows I show that this failure of price neutrality carries over to the application of subsidies. Specifically, I show that for a given level of government spending which side is being subsidized, the buyers or the stations, has an impact on economic outcomes like EV demand.

The baseline model presents the analysis for a monopoly platform with constant marginal cost serving both sides of the market. End-users on both sides (buyers and electric charging stations) are price takers in their relation to the platform who set the prices (EV manufacturer). I assume a simultaneous-move static game.[5] Network effects are only across (intergroup externalities) and not within (intragroup externalities) the two sides. This means that agents on one side only care about the number of users on the other.[6] In addition, I assume linear network effects.[7] Agents are assumed to choose only one platform, the so-called "single-homing" assumption.

Model Setup. There are two sides of the market, I use $\mathcal{I}$ to refer to a generic side of the market and $\mathcal{B}$ and $\mathcal{S}$ to refer to a specific side, that is, $\mathcal{B}$ represents drivers' or buyers' side, while $\mathcal{S}$ represents charging stations' side. There is a continuum of potential users on each side $\mathcal{I} \in \{\mathcal{B}, \mathcal{S}\}$ with mass normalized to 1. Therefore, the number of agents joining on side $\mathcal{I}$, denoted by $N_{\mathcal{I}}$, shows the fraction of potential users choosing to participate. To keep notation simple, individual indices (in general) are suppressed.

Each agent i on side $\mathcal{I}$ derives an inherent fixed benefit or cost $B_{\mathcal{I}}$, called

5 While dynamics might play an important role in the adoption of EVs, I believe that my findings of subsidy non-neutrality in the static case can be easily extended to dynamic models. I discuss dynamics in relation to my empirical framework in Section 3.

6 This assumption is unlikely to hold for the charging station side in the long run as the network becomes less sparse, but it is unlikely to change the qualitative results of this analysis.

7 Again, this assumption is unlikely to hold in the long run since market participants' incentives might change as the installed base of EVs and number of operating charging stations increases and reaches a critical mass.

membership value, from joining the platform, independently from the number of agents on the other side. Users are assumed to have heterogeneous membership values; this is the only source of heterogeneity allowed. $B_{\mathcal{B}}$ can be thought of as a fixed benefit obtained from owning an EV, it will depend on individual characteristics and product attributes.[8] $B_{\mathcal{S}}$ is the fixed cost stations on side $\mathcal{S}$ incur, thus it is likely that $B_{\mathcal{S}} < 0$ will hold. Furthermore, each agent i on side $\mathcal{I}$ enjoys a net transaction benefit $b_{\mathcal{I}}$ for every agent that joins the platform on side $\mathcal{J}$.[9] I assume that users have homogeneous interaction values ($b^i_{\mathcal{I}} = b_{\mathcal{I}}$ for each side $\mathcal{I}$).

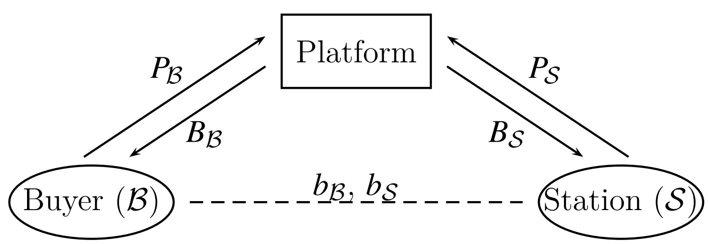


Figure B2: Graphical representation of the baseline model

End-users on side $\mathcal{I}$ pay a fixed membership fee $P_{\mathcal{I}}$ to the platform. These prices are assumed to be independent of the number of participating agents on side $\mathcal{I}$ or $\mathcal{J}$. $P_{\mathcal{B}}$ can be thought of as the purchase price for an EV. $P_{\mathcal{S}}$ is akin to a fixed fee that the car manufacturer might pay to the charging station providers to attract them, thus it is likely that $P_{\mathcal{S}} \leq 0$ holds. Turning to the cost side, the platform incurs a constant marginal cost $C_{\mathcal{B}}$ on side $\mathcal{B}$ (marginal cost of car manufacturing), while the marginal cost on side $\mathcal{S}$, denoted by $C_{\mathcal{S}}$, is assumed to be zero. Figure B2 highlights the discussed relationships between the end-users and the platform in this model.

Formally, the utility function of a buyer on side $\mathcal{B}$ and the profit function of

8 Because of the possibility of home charging, a positive buyer membership value is a reasonable assumption.

9 I use $\mathcal{J} = -\mathcal{I}$ to refer to the other side than $\mathcal{I}$.

a station on side $\mathcal{S}$ are given by

$$\begin{aligned} U_{\mathcal{B}} &= b_{\mathcal{B}} \times N_{\mathcal{S}} + B_{\mathcal{B}} - P_{\mathcal{B}} \\ \pi_{\mathcal{S}} &= b_{\mathcal{S}} \times N_{\mathcal{B}} + B_{\mathcal{S}} - P_{\mathcal{S}} \end{aligned} \tag{19}$$

Then the number of side $\mathcal{I}$ agents who choose to join the platform can be expressed as

$$\begin{aligned} N_{\mathcal{B}} &= Pr(U_{\mathcal{B}} \geq 0) = \phi_{\mathcal{B}}(b_{\mathcal{B}} N_{\mathcal{S}} - P_{\mathcal{B}}) = \phi_{\mathcal{B}}(N_{\mathcal{S}}, P_{\mathcal{B}}) \\ N_{\mathcal{S}} &= Pr(\pi_{\mathcal{S}} \geq 0) = \phi_{\mathcal{S}}(b_{\mathcal{S}} N_{\mathcal{B}} - P_{\mathcal{S}}) = \phi_{\mathcal{S}}(N_{\mathcal{B}}, P_{\mathcal{S}}) \end{aligned} \tag{20}$$

where I assume that the ϕ functions are continuously differentiable.

Profit Maximization of the Monopoly Platform. The monopolist platform's profit can be expressed as

$$\pi_{\text{platform}} = \underbrace{(P_{\mathcal{B}} - C_{\mathcal{B}}) N_{\mathcal{B}}}_{\text{profit from Buyers/Drivers}} + \underbrace{P_{\mathcal{S}} N_{\mathcal{S}}}_{\text{profit from Sellers/Stations}} \tag{21}$$

where the platform chooses prices $(P_{\mathcal{B}}, P_{\mathcal{S}})$ to maximize the sum of profits. The first-order conditions for the platform's profit maximization problem are given by

$$\overbrace{\underbrace{P_{\mathcal{I}}}_{\text{price}} - \underbrace{\frac{D_{\mathcal{I}}(N_{\mathcal{J}}, P_{\mathcal{I}})}{D'_{\mathcal{I}}(N_{\mathcal{J}}, P_{\mathcal{I}})}}_{\text{market power}} + \underbrace{b_{\mathcal{J}} N_{\mathcal{J}}}_{\text{external benefit}}}^{\text{marginal revenue}} = \underbrace{C_{\mathcal{I}}}_{\text{marginal cost}} \tag{22}$$

The first two terms on the left-hand side are the familiar terms of marginal revenue from the standard optimization problem for a monopolist: the price minus the expression representing market power (let $\mu_{\mathcal{I}} \equiv \frac{D_{\mathcal{I}}(N_{\mathcal{J}}, P_{\mathcal{I}})}{D'_{\mathcal{I}}(N_{\mathcal{J}}, P_{\mathcal{I}})} = \frac{P_{\mathcal{I}}}{\varepsilon_{\mathcal{I}}}$, where $\varepsilon_{\mathcal{I}}$ is the elasticity of demand). The third term is specific to two-sided markets with pure membership externalities and represents the external benefit an additional side $\mathcal{I}$ user brings to a side $\mathcal{J}$ user, multiplied by the actual number of side $\mathcal{J}$ users participating.

Government Incentives. This paper investigates the effect of two types of government incentives: (1) subsidies to buyers for purchasing electric cars, given by $\tau_{\mathcal{B}}$ and (2) subsidies to charging station owners for purchasing and installing charging equipment, given by $\tau_{\mathcal{S}}$. In order to be able to compare the effect of these two subsidies on economic outcomes such as buyer demand for EVs, I assume that the two incentives are government revenue equivalent

$$T = \tau_{\mathcal{B}} N_{\mathcal{B}}^{*}(\tau_{\mathcal{B}}, 0) = \tau_{\mathcal{S}} N_{\mathcal{S}}^{*}(0, \tau_{\mathcal{S}}) \tag{23}$$

Then buyer utility and station profits can be re-written as shown in (24) while the monopolist platform's profit function stays the same.

$$\begin{aligned} U_{\mathcal{B}} &= b_{\mathcal{B}} \times N_{\mathcal{S}} + B_{\mathcal{B}} - P_{\mathcal{B}} + \tau_{\mathcal{B}} \\ \pi_{\mathcal{S}} &= b_{\mathcal{S}} \times N_{\mathcal{B}} + B_{\mathcal{S}} - P_{\mathcal{S}} + \tau_{\mathcal{S}} \end{aligned} \tag{24}$$

To illustrate how the incentives might affect buyer participation on the platform, I need to specify a functional form for the membership functions $N_{\mathcal{I}} = \phi_{\mathcal{I}}(N_{\mathcal{J}}, P_{\mathcal{I}})$. I assume linear functions by specifying the cumulative distribution functions of the membership values

$$\begin{aligned} B_{\mathcal{B}}^{i} &\sim_{iid} U[\mu_{\mathcal{B}}, \upsilon_{\mathcal{B}}] \\ B_{\mathcal{S}}^{i} &\sim_{iid} \pi[\mu_{\mathcal{S}}, \upsilon_{\mathcal{S}}] \end{aligned} \tag{25}$$

To further simplify the analysis, without loss of generality I can choose $\mu_{\mathcal{B}} = \mu_{\mathcal{S}} = 0$ and $\upsilon_{\mathcal{B}} = \upsilon_{\mathcal{S}} = 1$. Then, it is convenient to solve the system of equations (20) and express memberships $N_{\mathcal{B}}$ and $N_{\mathcal{S}}$ as functions of prices $(P_{\mathcal{B}}, P_{\mathcal{S}})$ and subsidies $(\tau_{\mathcal{B}}, \tau_{\mathcal{S}})$ only

$$\begin{aligned} N_{\mathcal{B}} &= \hat{\phi}_{\mathcal{B}}(P_{\mathcal{B}}, P_{\mathcal{S}}, \tau_{\mathcal{B}}, \tau_{\mathcal{S}}) = \frac{1 + b_{\mathcal{B}} - P_{\mathcal{B}} - b_{\mathcal{B}} P_{\mathcal{S}} + \tau_{\mathcal{B}} + b_{\mathcal{B}} \tau_{\mathcal{S}}}{1 - b_{\mathcal{B}} b_{\mathcal{S}}} \\ N_{\mathcal{S}} &= \hat{\phi}_{\mathcal{S}}(P_{\mathcal{B}}, P_{\mathcal{S}}, \tau_{\mathcal{B}}, \tau_{\mathcal{S}}) = \frac{1 + b_{\mathcal{S}} - P_{\mathcal{S}} - b_{\mathcal{S}} P_{\mathcal{B}} + \tau_{\mathcal{S}} + b_{\mathcal{S}} \tau_{\mathcal{B}}}{1 - b_{\mathcal{B}} b_{\mathcal{S}}} \end{aligned} \tag{26}$$

In principle, participation rates need not be unique for given prices, however, under a set of regularity conditions, the system of equations above has a unique solution. Next, we can solve for the prices $\left(P_{\mathcal{B}}^{*}, P_{\mathcal{S}}^{*}\right)$ set by the monopolist platform by substituting in the expressions for participations rates given by (26) into the first order conditions of the monopolist platform. Once I obtain the prices I can express the equilibrium participation rates as

$$N^*_{\mathcal{B}}(P^*_{\mathcal{B}}(\tau_{\mathcal{B}},\tau_{\mathcal{S}}),P^*_{\mathcal{S}}(\tau_{\mathcal{B}},\tau_{\mathcal{S}})) = \frac{2+b_{\mathcal{B}}+b_{\mathcal{S}}-2C_{\mathcal{B}}+2\tau_{\mathcal{B}}+b_{\mathcal{B}}\tau_{\mathcal{S}}+b_{\mathcal{S}}\tau_{\mathcal{S}}}{4-b^2_{\mathcal{B}}-2b_{\mathcal{B}}b_{\mathcal{S}}-b^2_{\mathcal{S}}}$$

$$N^*_{\mathcal{S}}(P^*_{\mathcal{B}}(\tau_{\mathcal{B}},\tau_{\mathcal{S}}),P^*_{\mathcal{S}}(\tau_{\mathcal{B}},\tau_{\mathcal{S}})) = \frac{2+b_{\mathcal{B}}+b_{\mathcal{S}}-b_{\mathcal{B}}C_{\mathcal{B}}-b_{\mathcal{S}}C_{\mathcal{B}}+2\tau_{\mathcal{S}}+b_{\mathcal{B}}\tau_{\mathcal{B}}+b_{\mathcal{S}}\tau_{\mathcal{B}}}{4-b^2_{\mathcal{B}}-2b_{\mathcal{B}}b_{\mathcal{S}}-b^2_{\mathcal{S}}} \tag{27}$$

Finally, I can solve for $\tau_{\mathcal{B}}$ and $\tau_{\mathcal{S}}$ subject to the revenue equivalence condition that can be expressed as

$$\tau_{\mathcal{B}}N^*_{\mathcal{B}}(P^*_{\mathcal{B}}(\tau_{\mathcal{B}},0),P^*_{\mathcal{S}}(\tau_{\mathcal{B}},0)) = \tau_{\mathcal{S}}N^*_{\mathcal{S}}(P^*_{\mathcal{B}}(0,\tau_{\mathcal{S}}),P^*_{\mathcal{S}}(0,\tau_{\mathcal{S}})) \tag{28}$$

Neutrality of the government subsidies holds if for all pairs $(\tau_{\mathcal{B}},\tau_{\mathcal{S}})$ that satisfy equation (28) it is true that $N^*_{\mathcal{B}}(\tau_{\mathcal{B}},0)=N^*_{\mathcal{B}}(0,\tau_{\mathcal{S}})$. By solving equation (28) I find that there are always exactly two pairs of revenue equivalent subsidies for which neutrality is true (the degenerate case of zero subsidies and a non-degenerate case shown below) in this setting, for all other subsidy pairs neutrality fails.

$$\begin{aligned}\tau_{\mathcal{B}} = {} & \frac{1}{4}(-2-b_{\mathcal{B}}-b_{\mathcal{S}}+2C_{\mathcal{B}})+ \\ & \frac{1}{4}\left(\sqrt{(2+b_{\mathcal{B}}+b_{\mathcal{S}}-2C_{\mathcal{B}})^2+8\tau_{\mathcal{S}}(2+b_{\mathcal{B}}+b_{\mathcal{S}}-b_{\mathcal{B}}C_{\mathcal{B}}-b_{\mathcal{S}}C_{\mathcal{B}}+2\tau_{\mathcal{S}})}\right)\end{aligned} \tag{29}$$

Note that the result of subsidy non-neutrality hinges on the initial assumptions made. However, I believe it is reasonable to assume that by relaxing each of those assumptions and allowing for a more complex setting, the result of non-neutrality is even more likely to be true.

In sum, I show that subsidies are non-neutral in two-sided markets with pure membership externalities in the sense that it matters for economic outcomes such as participation rates, which side is being subsidized. Since the structure of subsidies between the two sides of the market matters for consumers' vehicle purchase decision, dependent on model parameters, it becomes an empirical question which incentive is more effective in promoting EV adoption. Thus, I construct a structural model which encompasses both sides of the market to estimate the impact of the two policies on EV adoption.