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. Counterfactual analyses suggest that between 2010 and 2015 every dollar spent on station subsidies resulted in more than twice as many additional electric vehicle purchases than the same amount spent on 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 vast variation across countries in electric vehicle (EV) incentive programs. 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 which 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 better understanding these relationships, it is not possible to understand the efficacy of different subsidy 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 explicitly accounts for the "two-sidedness" of the EV industry. That is, 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, I demonstrate that subsidies to the different

[1] In 2018, the transportation sector accounted for 24% 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, 2020a).

[2] The International Energy Agency (IEA) estimates that total electric vehicle spending in 2019 by the world's leading governments invested in supporting electric vehicles equaled $11 billion (International Energy Agency, 2020b).

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 (or tax) structure is applicable to all other two-sided markets where network externalities related to membership decisions are present.[3] 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 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 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 number 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] 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

[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. Other examples fitting this definition include media and news markets or shopping malls.

[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.

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 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 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 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 2.5% 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 14.6% 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, next I use a structural approach not only 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. I model automobile demand by using a random coefficients discrete choice model, allowing for heterogeneity in consumer valuation of car prices and the station network. Simultaneously, charging stations make an entry decision determined by their sunk entry costs and discounted stream of profits. 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

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

[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.

between station entry and EV sales leads to endogeneity.

The estimation results confirm the presence of positive feedback effects 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 installed charging network influences buyers' vehicle choice. Furthermore, the findings reveal how the presence of positive network effects changes consumer substitution patterns specific to EVs. While previous studies find that conventional car models are substitutes, the estimated cross-price elasticities in this paper 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 demand for other EV models decreases. In particular, 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 through strong network effects, reducing EV adoption. Negative cross-price elasticities indicate 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.

In the first counterfactual analysis, I use these estimates to study the average impact 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. Specifically, every 100 million Norwegian kroner (12.39 million USD) spent on station subsidies resulted in 1,423 additional EV purchases, while the same amount spent on purchasing price subsidies led to only an additional 502 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 a hypothetical starting point in which neither side of the market receives any subsidies, and I compare their impact on EV sales for a given amount of government spending. I find that the relative effectiveness of the subsidies can change. For relatively smaller government spending on EV incentives, station subsidies are more cost-effective than purchasing incentives. However, as spending continues to increase, eventually this relation inverts. 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), Allcott and Wozny (2014), and Grigolon et al. (2018). 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 (2019) investigates the ambiguous impact of mandating compatibility standards on market outcomes and welfare in the context of the U.S. EV market. Li (2019) 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), Holland et al. (2015), Li et al. (2017) and Muehlegger and Rapson (2018). 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. Holland et al. (2015) show that there is substantial geographic variation in the environmental benefits of EV adoption and argue for spatially differentiated incentives. Li et al. (2017) and Muehlegger and Rapson (2018) both study how policy affects plug-in electric vehicle adoption in the U.S. EV market.

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 Rysman (2004) (Yellow Pages directories), 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.

I Industry and Policy Background

The Norwegian government and its local authorities are using a variety of generous incentives to support electric vehicles, first introduced in the early 1990s.[7] Norway's incentive program mainly targets all-electric vehicles.[8] 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.[9]

[7] In this paper, the local authorities I focus on are at the county level (Statistics Norway, 2015). Counties constitute the intermediate administrative level between the entire nation and municipalities. Norway (during this time period) had 19 counties and 428 municipalities. Counties vary significantly in size, topography and population. The county authorities' responsibilities include regional development and planning business development, culture and cultural heritage, county roads and public transport, secondary education and, importantly, environmental issues (Norwegian Ministry of Local Government and Modernisation, 2012).

[8] 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. Plug-in hybrid vehicles are not eligible for most incentives, with the exception of some recent changes in 2015. Unless otherwise stated, herein all references to "electric vehicles" refer to all-electric vehicles only.

[9] While my work focuses on incentives related to the barriers of high purchasing price and charging availability, Norway has a number of other incentives. 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 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 (Norwegian Tax Administration, 2016a). 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 all-electric vehicles (Norwegian Tax Administration, 2016a). 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 Administration, 2016b). 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). Another state measure that benefits all-electric vehicle owners includes a reduced annual motor vehicle tax since 1996 (Norwegian Tax Administration, 2016a).

To stimulate electric vehicle adoption, the Norwegian government also provides support for the development of electric vehicle charging points, also know as electric vehicle supply equipment (EVSE).[10] EVSE incentives provide a one-time subsidy to investors to cover all or part of the equipment and installation costs. These incentives vary according to the rate (normal vs. fast) at which the charging equipment can charge electric vehicle batteries. The incentives specifically target the development of public charging stations and are generally not available for home charging purchases.

In addition to the national-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 national-level initiative led by

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. I focus solely on consumer purchasing subsidies and charging station subsidies for a number of 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 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.

10 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. However, long travel distances, extreme winter weather, and mountainous terrain in Norway necessitate the establishment of an appropriate public charging network.

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). Therefore, in this paper, station subsidies are measured as the total amount of subsidy (in Norwegian kroner) offered per charging point in a given county and year. The total subsidy is the sum of national- and county-level subsidies available.[11] The national-level station subsidies were determined in accordance with the priorities laid out in National Transportation Plans (NTP) 2010-2019 and 2014-2023 (Samferdselsdepartementet, 2009, 2012).[12] The available amounts varied according these priorities (e.g., based on locations near urban centers vs. highway corridors) across counties and over time as Transnova (and later on its successor Enova) has made these funds available in successive phases. County-level subsidies were determined by county authorities as part of their commonly multi-year plans or action programs for improved climate and/or energy management.[13] Thus, cross-sectional variation in station subsidies comes from two sources. First, national subsidies were not necessarily available in all 19 counties in all years. Second, not all counties prioritized supporting the development of charging stations in form of financial incentives. Time-series variation comes from the national subsidy program as well as the difference in the timing and start of the various multi-year county-level programs.[14] Figure 1 illustrates the variation in station incentives across time and counties.

Norway has the largest number of electric vehicles per capita, with electric vehicles accounting for over 20% of new sales in 2015 (International Energy Agency, 2015) and close to 30% in 2016 (International Energy Agency, 2017). Figure 2 shows countries with the leading EV markets. Norway stands out with its market sales shares for new EVs already in the double digits, while most other countries have adoption rates below 5% (International Energy Agency, 2017). Recent trends in the electric car market show that both cumulative and new all-electric vehicle sales have grown rapidly (see Figures 3 and A1).[15] In comparison, cumulative sales of plug-in hybrids remain

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[11] Some of the 428 municipalities also offered charging station subsidies. These, in most cases, were smaller in magnitude than the national- or county-level subsidies offered. Due to lack of data on these incentives, municipal-level subsidies are not included in the station incentives.

[12] Exact subsidy amounts were retrieved from program announcements, year reports, strategy and financing plans, and calls for applications by Transnova and later Enova (Transnova, 2011a,b, 2012, 2013, 2014b; Enova, 2016).

[13] I collected the exact subsidy amounts from the official county websites, county plans and action programs for climate and energy management, county financial plans, county year reports and climate accounting reports, regional transport action programs and regional development plans.

[14] Some of these programs have started as early as 2008 (e.g., in Oslo county) while other counties followed with their own plans in later years (e.g. Hordaland county's climate plan covered the period of 2010-2020 while Nordland county's regional plan to address climate challenges covered the period of 2011-2020). While many of these programs came in effect sometime during the observed time period, decisions regarding these plans have been made in prior years.

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

close to zero during the same time period.[16]

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 (expressed in number of charging points) has experienced a sharp increase in growth between 2010 and 2015. In Online Appendix A, Figure 5 further highlights how much the charging network has evolved during the observed time period.[17] Panel (a) in Figure 5 shows the installed charging outlets 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 points in Norway exceeded 7,000 by the beginning of 2016, including around 250 fast charging points (Nobil, 2016).

II 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 (2016c), or NPRA, and Opplysningsrådet for Veitraffiken AS (2016), or 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.[18] 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) using the consumer price index from Statistics Norway (2016a).

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

16 In 2015, plug-in hybrids received a larger weight discount (26% instead of 15%) than before. This change in registration taxes led to a small increase in plug-in hybrid sales.

17 Maps of Norway's administrative county and municipal divisions were downloaded from the database of global administrative areas (Global Administrative Areas, 2009).

18 During the observed time period used EV car sales were negligible.

period. I exclude "exotic" models with extremely low market shares. The unit of observation in the analysis is defined by model/year/county. With these definitions, I have on average about 130 distinct vehicle models per market (county-by-year), resulting in total number of 14,790 observations.

The charging station data from Nobil (2016) includes information on the number of charging points in Norway by their opening date and coordinates.[19] Charger characteristics include the operator's name and type, whether it received public funding, the connector type of each outlet, and location type. In Online Appendix B, I provide a detailed overview of electric car charging infrastructure.[20]

I obtained information on government tax incentives from the Norwegian Tax Administration (2016a), and on local non-monetary incentives from Norwegian Public Roads Administration (2016a,b). From the Norsk Petroleuminstitutt, I collected information on gas stations (Norsk Petroleuminstitutt, 2016). Macroeconomic variables, such as median household income, GDP, and unemployment were obtained from Statistics Norway (2016b,c,d). Finally, I define market size (I) by the number of households in each market, a measure acquired from Statistics Norway (2016b).

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 set of time and county-by-model fixed effects

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19 Nobil has 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.

20 Online Appendix B explains the difference between terms "charging station," "charger," and "charging point." Unless otherwise stated, herein all references to "charging stations" or "chargers" refer to charging points.

$(\vartheta_{jc}, \vartheta_t)$ 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 bus lanes and exemption from toll fees. Bus 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 time-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. time 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.[21]

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 the final specification imply that a 10,000 Norwegian kroner (1,239 USD) per vehicle increase in the incentive is associated with a 2.5% 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.[22]

[21] 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.

[22] 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

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 14.6% increase in EV purchases on average, holding all other controls constant. I also find statistically significant and positive effects for station subsidies for fast charging, but only at the 10% level 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 presented in Table A1. 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 one-year lagged and lead versions of the station subsidies. 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 the lead or the lagged terms for both normal and fast charging subsidies.[23]

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

frequently used in other countries.

[23] The coefficient estimates on the concurrent subsidies remain qualitatively similar—have the expected signs, but are smaller in magnitude—and, thus, they are not shown in the results.

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.

III 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.[24] 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 whether to enter the market and install charging equipment, (4) consumers choose their demand for charging and operating stations serving electric car drivers.[25;26]

This current setting assumes a static game.[27] That is, 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

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24 In the current modeling framework, vehicle manufacturers' profit maximization problem is not explicitly modeled. This implies that incentives are assumed to be fully captured by consumers which is in line with recent findings in the literature (Sallee, 2011; Gulati et al., 2017; Muehlegger and Rapson, 2018).

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

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

27 Dynamics issues are discussed in more detail in Section IV.

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 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.

In Online Appendix C, I provide a detailed discussion of the estimation methodology and various computational considerations.

III.A 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, $U(x_{jm}, \xi_{jm}, p_{jm}; \theta)$, of consumer i from consuming product j in market m as

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

where p_{jm} denotes the product price that includes CIF, taxes, and importer or dealer profits, divided by consumer income y_m, $\log N_{jm}$ 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.[28] This assumption restricts network effects to EV models and assigns a network effect equal to zero to all other fuel types. Finally, parameter α denotes marginal utility from price valuation, and $\beta_i = (\beta_i^N, \beta^1, ..., \beta^K)$ is a $(K+1)$-dimensional vector of taste coefficients. Note that β_i^N captures individual-specific network effects on the consumer side. For ease of notation, I suppress the market subscript m for the rest of this subsection.

Allowing for individual-specific valuation for prices and the station network, Equation (2) can be written as

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

The consumer terms that interact with product attributes are (v_i^N, v_i^p), where $v_i \sim P_v^*(v)$ is a standard multivariate normal distribution. 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

[28] By taking the logarithm of the number of charging stations, I assume that consumer valuation for stations exhibits diminishing marginal returns. To justify this choice, Figure A2 depicts residualized bin scatter plots of consumer utility against stations under model (2) without random coefficients. Panel (a) shows that the relationship is non-linear whereas panel (b) shows that the relationship is well-approximated with a log functional form.

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 all vehicle characteristics and county, model and time fixed effects, while μ contains the price and network terms.

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

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 Online Appendix C. 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 cost shifters and observed exogenous vehicle characteristics.[29] To construct the cost-side instruments, I use information on the location of the production plants for each vehicle.[30] After identifying the location of each vehicle's assembly plant, I obtain data by country of production on unit labor costs, exchange rates, producer price index (PPI), and steel prices.[31] Hence, the excluded

[29] Including, as an additional set of instruments, the sum of the values of the same characteristics of other vehicle models offered by other car manufacturers, as in Berry et al. (1995), provides qualitatively very similar estimation results.

[30] In particular, I use the vehicle identification number (VIN) to retrieve the location of the plant in which the car was assembled in. The 11th digit of the VIN which reflects the production or assembly plant of the vehicle. Since car manufacturers use their own set of plant codes, I rely on the National Highway Traffic Safety Administration's (NHTSA) VIN database which I supplement with information from company documents. Some car manufacturers do not assign specific plant codes for their vehicles in the VIN, in particular Citroën, Peugeot, and Renault. For Citroën and Peugeot models, I use the ORGA (or RP) number, while for Renault cars I use the Oval Plate number instead of the VIN to identify the location of the vehicle's assembly plant.

[31] Unit labor costs are from the International Labor Comparisons Program by the Conference Board (2018), PPI and exchange rates are from the International Monetary Fund (2015a,b), while steel prices are from MEPS Online Steel Prices (2015). For Ukraine and Thailand, I constructed unit labor costs using information from the National

cost shifters include steel price index interacted with vehicle weight, exchange rates, unit labor costs, and the origin-to-destination distance.[32] 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). 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 time, county and model 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 and model fixed effects absorb any time-invariant product attributes and 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 these 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 county and model 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 county-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.

Statistical Office of Thailand (2015a,b) and the National Bank of Ukraine (2019).

[32] All cost shifters, except for the origin-to-destination distance measure, are expressed in real terms, i.e. divided by the PPI. To calculate the straight-line distance between the origin (production plant) and the destination locations, I used the Haversine formula.

III.B 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 $f(N_m) \equiv D(p(N_m))\varphi(N_m)/N_m$.

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

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

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

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

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_{ct}^{EV}) 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,[33] the number of electric vehicles bought before period t are not affected by the number of stations, only the newly registered cars as indicated by the vehicle demand model discussed previously. A high error term on the station side induces more charging stations to enter, and thus OLS estimation would produce an inconsistent estimate. To address the problem, I use the instrumental variable approach. Ideally, the instrument would be the difference in fuel costs between gasoline and electric vehicles in a given market. As Norwegian gas prices are only available at the national level, I am not able to construct a relative fuel cost measure. Thus, I use gas station density as an instrument for the cumulative electric vehicle base.[34] 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. This instrument may suffer from relevance concerns if, for example, electricity prices covary with gas prices such that there is no variation across counties and time in the relative fuel costs of gasoline vs. electric vehicles. The correlation between residential electricity prices and the gas station density instrument is -0.012 suggesting that covariation between the two is not likely to pose a serious issue.[35] 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

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33 The data confirms that zero electric vehicles were scrapped during the observed time period.

34 Lagged gas station density (by one year) is also included as station entry depends on cumulative sales and not just concurrent sales of EVs.

35 Additionally, as I discuss in Section IV, the high first stage R-squared and F-statistic for the instrumental variable regressions support (although do not promise) that the instruments are not weak.

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. The gas station density instrument fails to be valid if counties with lower gas station density (and higher gas prices) have sparser population which would also make electricity more expensive or if gas station density is correlated with the rate of growth of EV adoption in a given county. Furthermore, instrument validity is also violated if there are unobserved locational characteristics, such as road features or land price, affecting the cost of operating a charging station that are correlated with the cost of operating gas stations.[36] For these reasons, I re-estimate the model specified in Equation (10) with additional controls as well as using an alternative local EV policy instrumental variable. Results from these various specifications are presented in Table A4 and discussed in Section IV.

III.C 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.[37] To provide a more rigorous motivation for which electric vehicle supporting instrument is preferred, in the Online Appendix E I provide an overview of the factors that determine the effectiveness of different subsidies in the empirical model. In particular, I am mainly interested in comparing the effects of two types of government policies: consumer-side and station-side subsidies.

To summarize, the effectiveness of an EV price subsidy and a one-time station subsidy hinge 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 increases the effect of the two subsidies in the same way, this is not true for feedback effects on the consumer side. 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,

[36] Another potential threat to the validity of the gas station density instrument would be if gas stations and charging stations are likely to be co-owned or share the same retail space. However, between 2010 and 2015, it was fairly uncommon for gas stations to provide electric car charging in Norway. On average, only 0.48% of all available charging outlets were located at gas stations in a given year (Nobil, 2016).

[37] In the Online Appendix D, I show this "non-neutrality" result regarding subsidies in a theoretical model.

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.

IV Results

IV Regression Models Before discussing the results from the full structural model, I first explore the relevance of the instruments using a logit model with instrumental variables for vehicle demand and a simple instrumental variable estimation for station entry. Table A2 shows the estimates obtained by regressing $\log s_{jct} - \log s_{0ct}$ on price, station network, product characteristics, and year, county and model dummy variables. Coefficients on price and station network variables are of the expected sign. The first stage R-squared statistics are relatively high; thus, they do not imply a weak-instrument problem. The reported F-statistics are also very high suggesting that the null hypothesis that the instruments are weak, can be rejected. Table A3 show the estimates for charging station entry obtained from estimating Equation (10). Coefficients on the installed EV base and the charging station incentives are of the expected sign, although the coefficient on station subsidy for fast chargers is not statistically significant at the traditional statistical levels. Importantly, the high first stage R-squared statistic and F-statistic do not imply a weak-instrument issue.

Section III.B discussed potential threats to the validity of the gas station density instrument. To address these concerns, I re-estimate the station entry IV regressions with additional controls as well as using an alternative local EV policy instrument. Table A4 reports the estimates from these additional specifications and the results remain qualitatively similar. All of the specifications provide intuitive and statistically significant coefficient estimates on the key variables of interests: The charging station network expands with a larger circulating electric vehicle base and with higher charging station subsidies for normal charging. The coefficient on station subsidy for fast chargers is again not statistically significant at the traditional statistical levels. The first stage F-statistics are relatively high and exceed the rule-of-thumb critical value of 10 proposed by Staiger and Stock (1997) for all of the instrumental variable regressions with one exception. For the IV regression with only county fixed effects and gas station density as the instrument, the first-stage F-statistic is slightly below 10. Given that the more complex specifications with added controls and/or with the alternative instrumental variables all have a first-stage F-statistic above this threshold, while should be regarded with caution, the results suggest that the instruments are relevant. I turn now to results from the full model.

Full Structural Model The consumer demand for vehicles of all fuel types is derived from the indirect utility function shown in Equation (3), while the station market entry is estimated from Equation (10). Table 3 displays the results from the full structural model. Recall that by allowing heterogeneity in consumer valuation for price and the station network, the marginal utility of each term varies across buyers. Thus, I estimate a mean valuation and a standard deviation for each of these two terms.

The demand estimation results in panel A confirm the presence of positive feedback effects on the consumer side. The positive mean estimate for the station network term indicates that the stock of available charging stations influences buyers' vehicle choice. The results also suggest that there is some heterogeneity in consumer valuation of the charging network, although the estimate for the standard deviation of this characteristic is not statistically significant. Consumer valuation for various other vehicle characteristics are also estimated. Most notably, the negative estimate of -3.68 for the mean of the price to income ratio indicates that the average consumer prefers lower prices. The estimate for the standard deviation for the price to income ratio is 1.24, implying that there is a substantial and statistically significant variation around the mean for consumer valuation of this attribute.

In panel B, 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 positive.[38]

These estimates are used to compute own- and cross-price elasticities that capture the effectiveness of a price subsidy through the implied substitution patterns. Using the full sample, the mean own-price elasticities of EV car models fall between -1.5 and -2.1.[39] 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 column model as a result of a 1% increase in the price of the row model. For instance, a 1% increase in

[38] As an additional robustness check, I have re-estimated the full structural model using a local EV policy, free access to bus lanes, as an instrument for the stock of EVs instead of gas station density. Table A5 displays the results which remain qualitatively similar to the main estimation results.

[39] Although these are at the lower end of price elasticity estimates found in prior work on automobiles, they are in line with the EV literature. Xing et al. (2019) find an average own-price elasticity of -2.67, Li (2019) of -2.7., Li et al. (2017) of -1.29, and Muehlegger and Rapson (2018) of -3.9.

the price of the Nissan Leaf decreases the market share of Leaf models by 1.894% or 1.876% with and without feedback effects respectively. We can make the following three observations.

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, for example, then demand for other EV models decreases. Specifically, while other electric vehicle models become relatively cheaper, a more expensive Leaf implies fewer sales, and thus less entry by charging stations. When strong positive network effects are present, the lack of charging infrastructure 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 indeed 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.

Second, the complementaries between the EV models are strongest at the beginning of the sample when the charging network is relatively small. As the station network grows in size, the importance of the feedback effects decline. Figure A3 depicts this trend. In this figure, I plot the average network effect across all EV model-pairs for each year from 2011 to 2015, where a network effect is defined as the percent change in market share in model k due to feedback effects that are induced by a one percent increase in the price of model j.

Third, 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 row 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 row. 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.

Dynamic issues As discussed in Section III, the current modeling framework is static and does not take into account the timing dimension of consumers' electric vehicle purchase decision. This modeling approach may be reasonable for mature technologies (e.g. traditional automobile industry), when consumers' choice set does not change substantially over time and there are no significant frictions present in the resale market. When one considers the adoption of new technologies, it can be beneficial for consumers to postpone adoption as prices are expected to fall and quality (e.g. EV battery range) is likely to improve considerably over time. Hence, a static model that ignores dynamic effects could underestimate consumer price sensitivity and, in turn, the purchase subsidy impact. However, if forward-looking consumers believe that current subsidies might not be available in the near future or they expect that the station network will continue to expand in the future, then they might decide to purchase their EV sooner than they would have otherwise. Thus, a static demand model that does not incorporate forward-looking behavior could overestimate consumer price sensitivity.

Due to distinct features of the Norwegian EV market a static framework may be an appropriate approximation to consumer purchase decisions made during this time. First, the Norwegian price incentives, which are the most important type of policy that affects EV purchases, were put in place well before the start of the EV market and consumers fully expected these incentives to stay in effect for the foreseeable future.[40] Thus, it is less likely that consumers would bring forward their EV purchase to ensure that they benefit from EV purchasing subsidies. Second, since consumers might be limited in changing the location of their residence and workplace in the short run, their car purchase decisions are likely to be predominantly (though not necessarily exclusively) affected by their current driving needs as opposed to their needs in the future. Hence, the static assumption that consumers only care about the current state of market can be interpreted as consumers weighing present charging station infrastructure much more heavily than future expansions of the network. Finally, due to limited improvements in battery technology and vehicle production, consumers had to wait until well after the end of the observed time period to purchase electric vehicle models with significantly larger battery range at lower prices. Therefore, the option value of a better and cheaper future EV might have been somewhat limited at this time.

Since dynamic concerns are especially important for durable goods like cars, as an additional robustness check, I estimate a version of the dynamic model proposed by De Groote and Verboven (2019). In this model, households decide in each period whether they will adopt a new technology (i.e. purchase a vehicle) or postpone this decision to the following period. The estimating equation is:

$$\ln(s_{j,t}/s_{0,t}) = (x_{j,t} - \beta x_{1,t+1})\gamma - \alpha(p_{j,t} - \beta p_{1,t+1}) + \beta s_{1,t+1} + e_{j,t} \tag{11}$$

where j denotes the product, t the year, x the vector of vehicle characteristics (including the station network), p the vehicle price, and e the econometric error term. The estimated parameters are

[40] While in the United States federal tax credits are phased out for a manufacturer's cars once the automaker has sold over 200,000 qualifying vehicles, for example, there are no similar rules in place in Norway.

the discount factor β, consumer utility for characteristics γ, and for price α. The static model is embedded as the special case where $\beta = 0$, i.e. if consumers are myopic. Note that the county subscript is omitted for clarity. To account for endogeneity concerns, I use the same vector of instruments Z as I do for the vehicle-side of the full structural model. Since the model is non-linear in the parameter vector, I estimate it using the GMM moment conditions $\mathbb{E}[Z_{j,t} e_{j,t}] = 0$.

Table A6 presents the results. In column [1], I estimate the static version of the model setting $\beta = 0$, and in column [2], I estimate the dynamic version with no restrictions on β.[41] The following findings emerge from this analysis. First, the estimates for the coefficients on price and the station network are virtually identical in both specifications. Second, in the dynamic specification, we cannot reject the null that consumers are myopic ($\beta = 0$).

V 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.[42] Second, the parameter estimates from the GMM estimation presented in Section IV are used to jointly determine the equilibrium number of charging stations and market shares in each county for each year.[43] I discuss the methodology and issues relating to the existence and uniqueness of the equilibrium in Appendix C. Third, 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

[41] I fix the terminating action $j = 1$ to be the most popular model in the sample, the Volkswagen Golf. The results are not sensitive to this choice as the parameters of interest do not vary when alternative models are chosen. See De Groote and Verboven (2019) for more details about this modeling choice.

[42] 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.

[43] Given that manufacturers are not explicitly modeled, the analysis also assumes complete pass-through of subsidies from the manufacturer to the consumer. Busse et al. (2006), Sallee (2011), Gulati et al. (2017), and Muehlegger and Rapson (2018) 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.

targeting the station side versus the vehicle side in spurring the development of the EV market.

V.A 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

$$G = \Sigma_m \Sigma_j s_{jm} I_m \varsigma^P_{jm} + \Sigma_m n_m \varsigma^S_m \tag{12}$$

where ς^P_{jm} denotes the per-vehicle car purchase subsidy for model j in market m, and ς^S_m denotes the per-station subsidy in market m.[44] 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 approximately 23,000 more EVs which represents a 63% increase in total EV sales in this sample (see Table 5).[45] In comparison, Xing et al. (2019) find that tax incentives led to a 29% increase in EV sales in the US car market and 70% of the federal income tax credits were given to households that would have purchased an EV even in absence of the federal tax incentives. They show that the federal support for EVs had limited impact on hybrid vehicle sales in the US. Their findings suggest that EVs replace relatively fuel-efficient vehicles. Muehlegger and Rapson (2020) use quasi-experimental variation in an EV subsidy program targeting low- and middle-income households in California and also finds that participating households would have purchased relatively fuel-efficient vehicles without the program.

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

[44] A car purchase subsidy consists of a reduction in the price paid by consumers when purchasing an EV. At the baseline of zero subsidies, the tax on EVs is assumed to be the same as that for a similar combustion engine vehicle (i.e. VAT + registration tax + motor tax). Any reduction in the price paid by consumers below this baseline is considered a vehicle purchase subsidy.

[45] There are at least two important caveats to this result. First, only equilibrium responses through the station network are considered; therefore, this analysis ignores the possibility that large changes to the incentive structure could cause other equilibrium responses in for example product characteristics, quality, or availability. Second, by controlling for county, model and time fixed effects, indirect ways in which subsidies affect car sales are not accounted for: for example, if a subsidy increases sales of EVs through peer effects, this effect would be partially absorbed by the fixed effects.

shares in each county-year pair when only car purchases are subsidized, I find that there are 20,193 more EVs purchased compared to the simulated scenario where there are no subsidies.

Oppositely, if only stations were subsidized, I find that 1,786 more EVs are purchased compared to the simulated policy setting where there are no subsidies. Hence, car purchase subsidies account for over 90% 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. I find that station subsidies resulted in 1,423 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 502 additional EVs per 100 million Norwegian kroner 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. Similar to the findings presented here, Li et al. (2017) estimate the indirect network effects in the early stage of the US EV market and also find that subsidizing the charging infrastructure is more effective per dollar spent than subsidizing consumers' EV purchases. They show that if the $924.2 million spent on tax incentives were instead used to build charging stations, then the resulting EV sales would have been double of the realized EV sales. Notably, indirect network effects explain 40% of this increase in EV sales.

V.B 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 different sums 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 stations or car subsidies? I tackle the question by considering a second set of counterfactuals that simulate the marginal impact of changes in subsidies. That is, these policy counterfactuals simulate settings where either the station or car price subsidies are increased from a hypothetical starting point in which neither side of the market receives any subsidies. 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. The results of these simulations are presented in panel (a) and (b) of Figure 6.

Figure 6(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. 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.

Figure 6(a) demonstrates that while station subsidies are more effective for relatively small increases in government spending from the starting point, as spending continues to increase they eventually become less effective than price subsidies. 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 subsidies tapers off more quickly than the impact of the price subsidies. Figure 6(b) illustrates that direct subsidies to stations would unsurprisingly result in significantly higher station entry when compared to price subsidies.

So far, when analyzing 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 again from a hypothetical situation in which there are no subsidies, I construct counterfactuals in which either price subsidies, station subsidies, or both are altered to some positive level. To measure the effectiveness of the different subsidy allocations, panel (a) of Figure 7 presents the increase in EV sales per million Norwegian kroner as a result of changes in the price and station subsidies. Brighter 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 amount of government spending implied by the subsidies is displayed in panel (b) of Figure 7. 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, solely increasing price subsidies is more effective than solely increasing station subsidies. Panel (a) and (b) of Figure 7 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 brighter colors in the bottom-left corner of panel (a).

The counterfactual analyses presented here only considered uniform policies that do not differentiate based on household income. Prior work on EV incentives suggests that alternative policy designs such as EV purchase subsidies targeted at low-income households might be more cost effective. Xing et al. (2019) find that cost-effectiveness of the US EV income tax credits is sensitive to the price elasticity of demand, implying that removing tax incentives for higher-income households and instead focusing on subsidizing lower-income households could potentially be more cost-effective.

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 as government spending increases, such that it would be more effective to subsidize a mixture of station and car purchases past a certain level of government spending. 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 III and in Online Appendix E).

VI 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. 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 alternative subsidy structures. The findings suggest that between 2010 and 2015, station subsidies were more than twice as effective as price subsidies. 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. 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.

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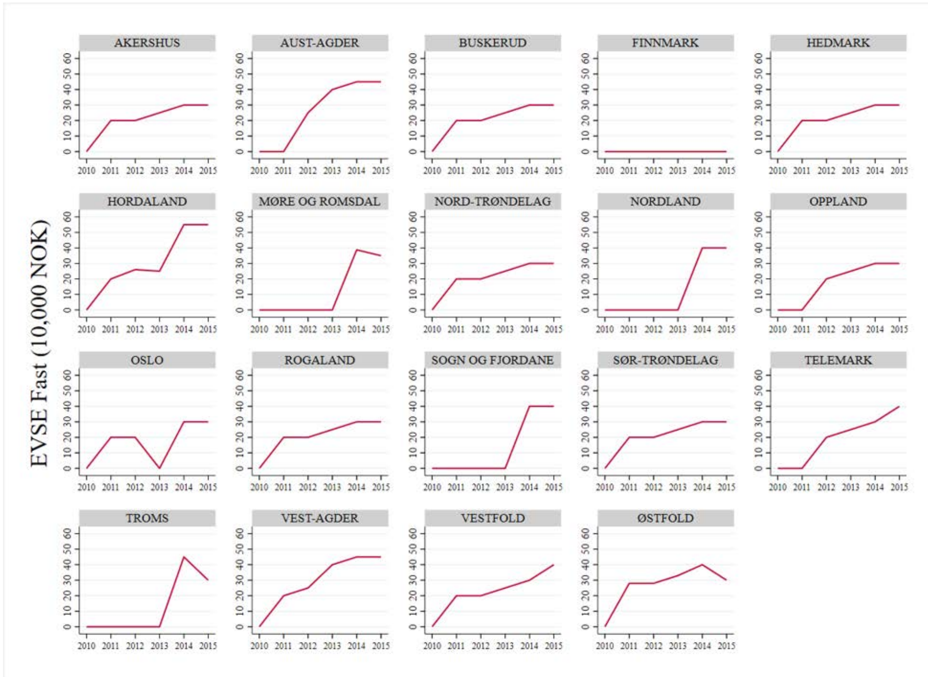
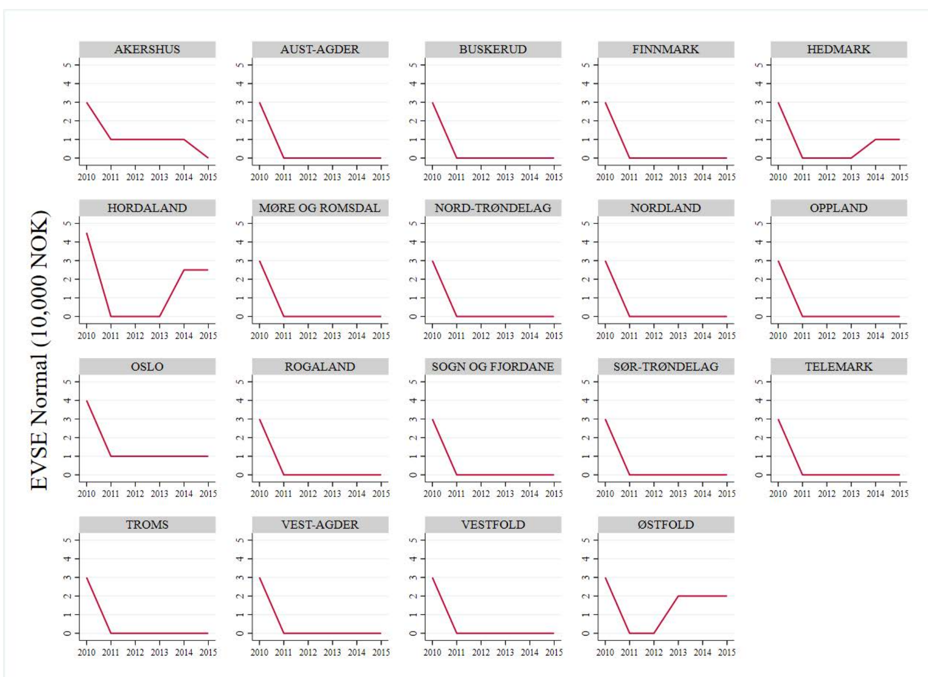
VII Figures and Tables



(a) Station subsidies for fast chargers over time, by county



(b) Station subsidies for normal chargers over time, by county

Figure 1: Station Subsidies across County and Time

Notes: This figure depicts variation in station subsidies for fast and normal chargers across counties and time. The subsidies are collected from national and county government documents.

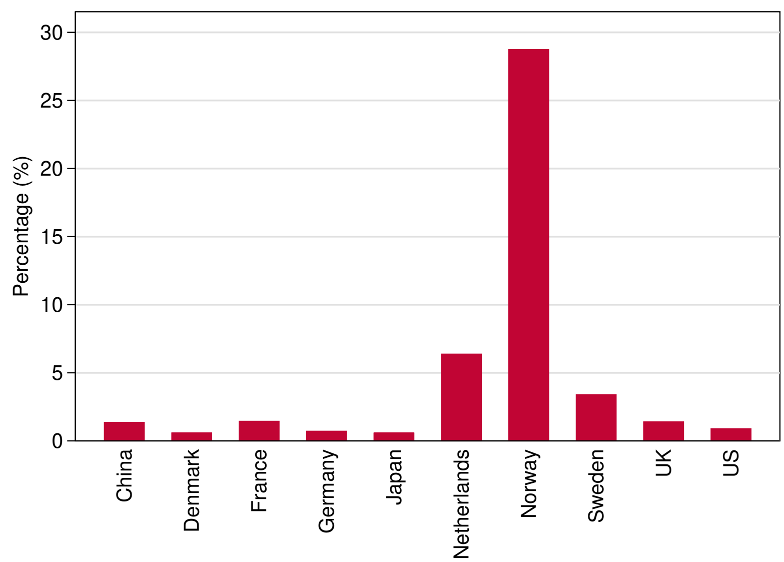


Figure 2: Market Shares of Electric Vehicles Sales Around the World (2016)

Notes: The figure compares market shares of new electric vehicle sales in countries around the world in the year of 2016 (International Energy Agency, 2017).

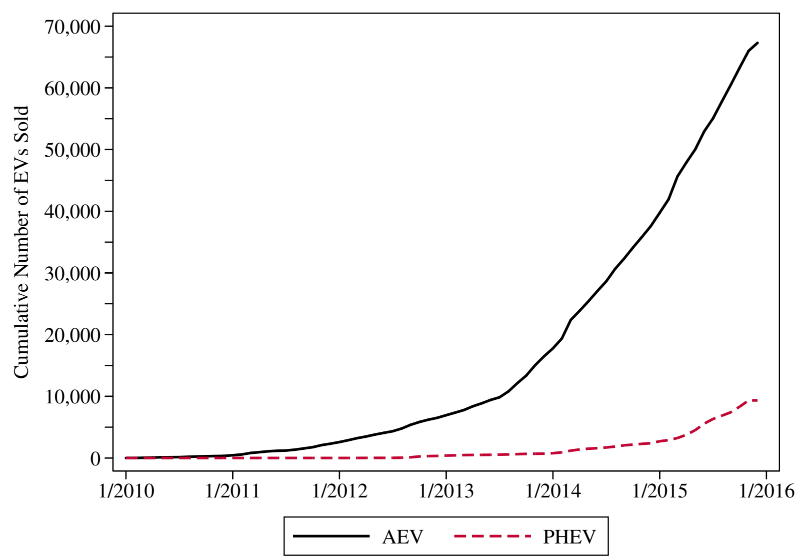


Figure 3: Cumulative Electric Vehicle Sales in Norway

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

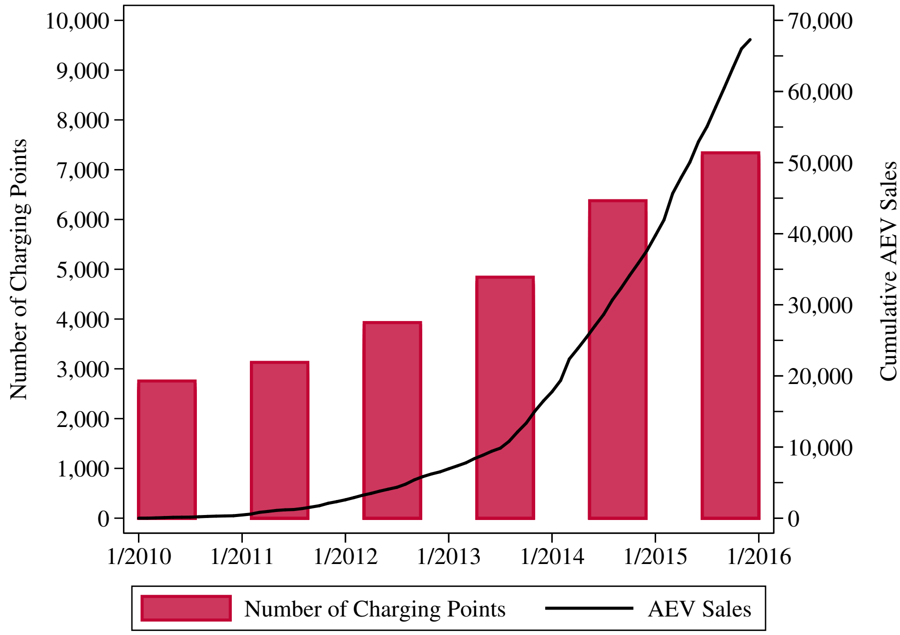


Figure 4: Number of Charging Points and Cumulative All-Electric Vehicle Sales in Norway

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

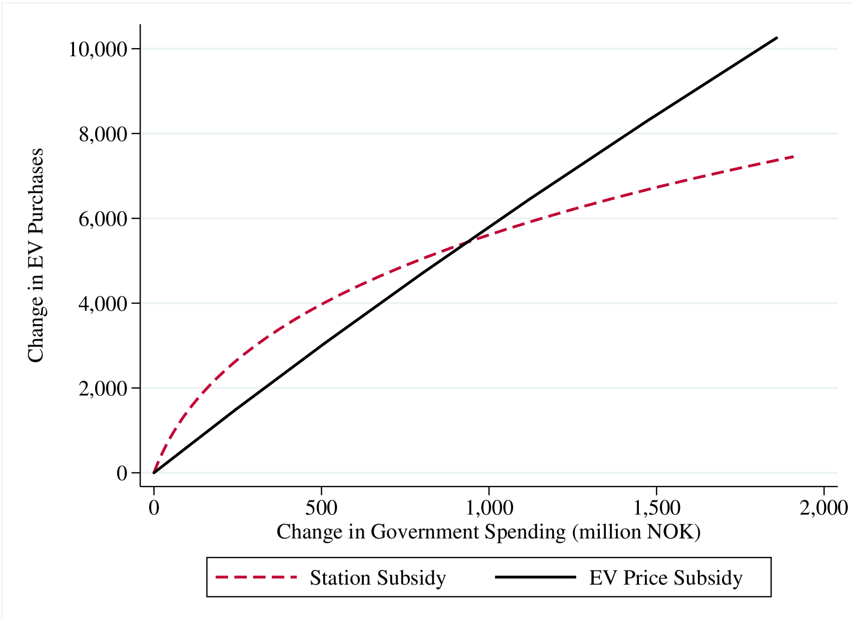
(a) Number of Charging Points at the Start of the EV Market (2009)

(b) Number of Charging Points at the End of the Observed Time Period (2015)

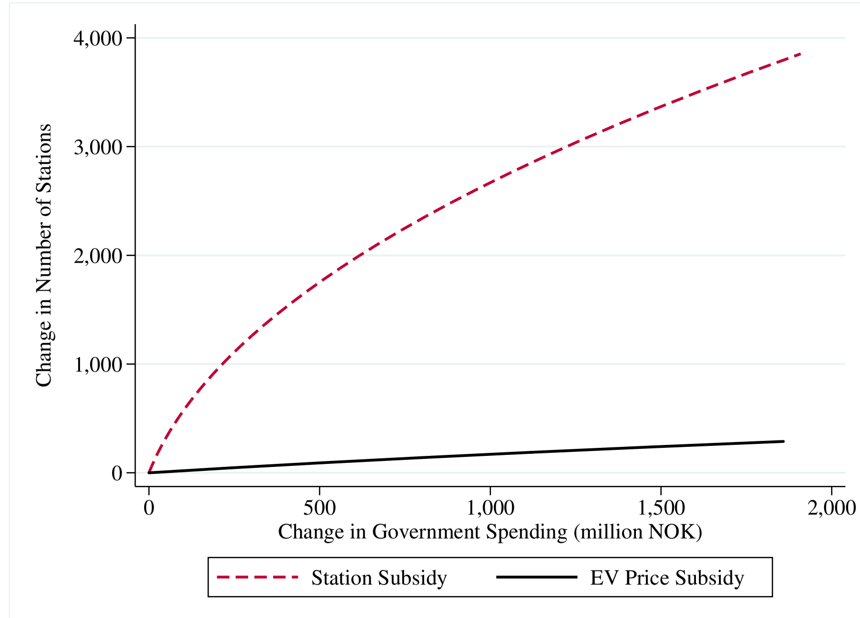
Figure 5: Number of Stations in Norway (2009 and 2015)

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

Figure 6: Counterfactual Analysis of the Marginal Impact of Subsidies on EV Sales and Station Entry



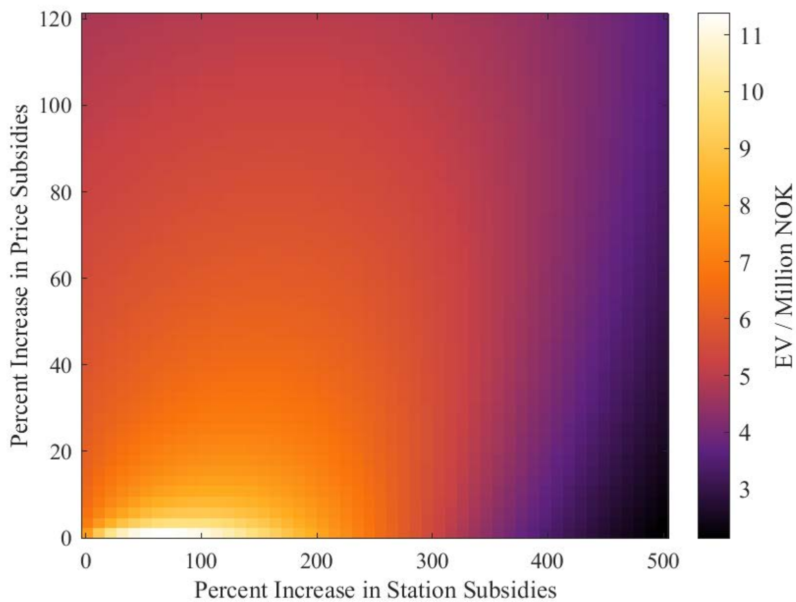
(a) Subsidies and EV Purchases



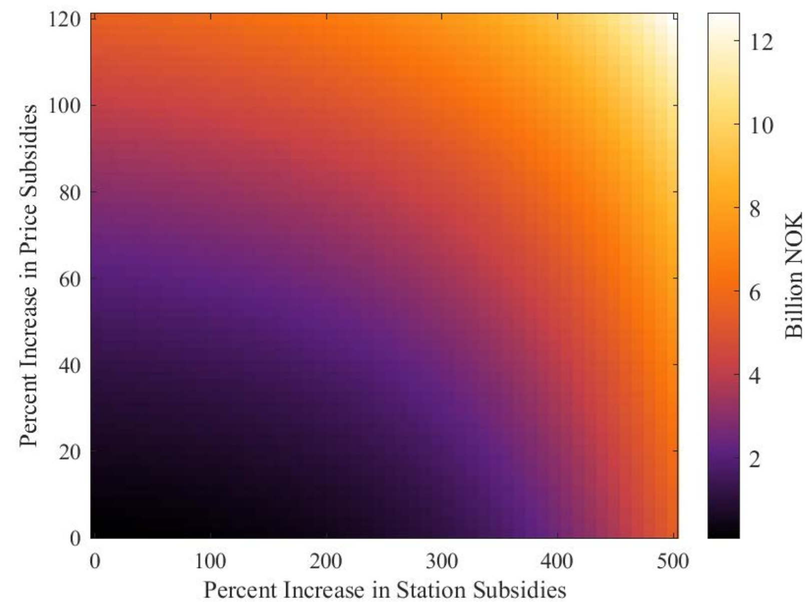
(b) Subsidies and Station Entry

Notes: The figures present the simulation results showing how cumulative sales of EVs (Figure 6(a)) and cumulative number of stations (Figure 6(b)) change for increases in government spending on station subsidies or car price subsidies, respectively. Starting from a hypothetical point in which there are no subsidies, 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 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 7: 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 an increase in price and/or station subsidies (as a percentage of the status-quo subsidies). The figure on the right displays how 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 vehicle price subsidies is shown on the vertical axis. The origin represents a counterfactual market in which both types of subsidies are set to zero. I use the following methodology to construct the graph. First, either the price and/or station subsidies are altered to a counterfactual level. Each pixel on the graph represents a pair of counterfactual subsidy 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 implied changes on total government spending and on the number of new EVs sold per NOK.

Table 1a: Summary Statistics

Variable	Mean	Std. Dev.
Panel (a) Consumer side		
Sales	51.774	117.572
Price (1,000 NOK)	296.283	109.380
Horsepower (kW)	85.586	29.799
Weight (1,000 kg)	1.380	0.231
Consumption (l/km)	0.446	0.152
Transmission (0-1)	0.435	0.496
Length (m)	4.426	0.321
EV (0-1)	0.074	0.261
Number of charging stations	258.139	334.433
EVSE subsidy for normal charging (1,000 NOK)	6.378	11.404
EVSE subsidy for fast charging (1,000 NOK)	189.219	146.326
Number of observations	14,790	
Panel (b) Station side		
Number of charging stations	248.965	326.477
Cumulative EV base (1,000 units)	0.913	1.919
EVSE subsidy for normal charging (1,000 NOK)	7.046	12.054
EVSE subsidy for fast charging (1,000 NOK)	181.718	148.426
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	110	110,371	2,754	279,671	0.0578	0.5131	0.0000	4.3885	0.1914
2011	113	121,375	3,128	285,268	0.0582	0.4849	0.0086	4.4190	0.2775
2012	136	131,221	3,927	297,742	0.0597	0.4744	0.0240	4.4310	0.3582
2013	152	143,033	4,839	295,040	0.0625	0.4543	0.0614	4.4311	0.4820
2014	132	132,962	6,375	308,129	0.0634	0.4102	0.1240	4.4465	0.5830
2015	135	126,776	7,359	308,757	0.0646	0.3521	0.2123	4.4323	0.6683

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)	0.025	0.025	0.025
	(0.004)	(0.004)	(0.004)
VAT Exemption (10,000 NOK)	0.018	0.018	0.018
	(0.019)	(0.019)	(0.019)
EVSE Normal (10,000 NOK)	-0.004	-0.008	-0.010
	(0.002)	(0.004)	(0.001)
EVSE Normal × EV	0.121	0.144	0.146
	(0.052)	(0.045)	(0.046)
EVSE Fast (10,000 NOK)	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
EVSE Fast × EV	0.015	0.014	0.014
	(0.007)	(0.007)	(0.007)
Observations	181,643	181,643	181,643
Adj. R-squared	0.61	0.61	0.61
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. Local incentives include free access to bus lanes and exemption from toll fees. 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 3: Results from the GMM Estimation

	Variable	Parameter Estimate	Standard Error
Panel A: Vehicle Demand			
Means	Price / Income	-3.6835	0.3485
	Station Network	0.4184	0.0381
Std. Deviations	Price / Income	1.2444	0.0993
	Station Network	0.0288	0.1148
Panel B: Station Entry			
Means	log(EV base)	0.1695	0.0456
	EVSE normal (10,000 NOK)	0.1588	0.0383
	EVSE fast (10,000 NOK)	0.0008	0.0026

Notes: The table reports the coefficient estimates and standard errors from the GMM estimation. Panel A displays results from the vehicle demand side, in which the unit of observation is a model (j) in county (c) and year (t). The instruments include electric vehicle supply equipment (EVSE) incentives, exogenous car characteristics and the cost-side instruments, as described in the text. The model includes controls for vehicle characteristics (EV dummy, transmission, acceleration, size and consumption) and county, model and year fixed effects. Panel B reports estimates from the station entry side, where the unit of observation is county-by-year. Excluded instruments are gas station density and lagged gas station density, as described in the text. County-specific fixed effects and a time trend are included.

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

AEV Make and Model	i3	Soul	i-Miev	Leaf	E-Golf	E-Up!
			No Feedback Effects			
BMW i3	-2.0456	0.0016	0.0015	0.0015	0.0017	0.0016
Kia Soul	0.0020	-1.6572	0.0018	0.0019	0.0020	0.0019
Mitsubishi i-Miev	0.0002	0.0002	-1.6530	0.0004	0.0002	0.0002
Nissan Leaf	0.0031	0.0030	0.0026	-1.8759	0.0044	0.0044
Volkswagen E-Golf	0.0082	0.0078	0.0072	0.0047	-2.0333	0.0047
Volkswagen E-Up!	0.0010	0.0009	0.0009	0.0011	0.0015	-1.5387
			With Feedback Effects			
BMW i3	-2.0475	-0.0003	-0.0004	-0.0003	-0.0002	-0.0003
Kia Soul	-0.0007	-1.6600	-0.0009	-0.0009	-0.0007	-0.0009
Mitsubishi i-Miev	-0.0001	-0.0001	-1.6681	-0.0035	-0.0001	-0.0001
Nissan Leaf	-0.0009	-0.0010	-0.0149	-1.8936	-0.0040	-0.0087
Volkswagen E-Golf	-0.0033	-0.0037	-0.0042	-0.0036	-2.0416	-0.0036
Volkswagen E-Up!	-0.0001	-0.0001	-0.0002	-0.0014	-0.0012	-1.5411

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 j with respect to a 1% change in the price of model i.

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

	No incentives	With Incentives		
	[1]	[2]	[3]	[4]
ΔEV Purchases	0	1785.83	20192.50	22983.72
		(560.32)	(3673.94)	(4151.18)
ΔTotal Stations	0	684.25	502.94	1245.81
		(175.63)	(124.10)	(299.15)
ΔTotal Government Spending	0	124.91	4086.75	4414.11
		(7.47)	(944.61)	(992.05)
ΔEV Purchases / Government Spending		14.23	5.02	5.28
		(4.12)	(0.58)	(0.57)
Normal EVSE incentives	N	Y	N	Y
Car Purchase Incentives	N	N	Y	Y

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. The first column describes the baseline in which there are no normal station or price subsidies. The second column presents the differences in EV sales, total stations and government spending when only stations are subsidized. The third column shows the results when instead only vehicle purchases are subsidized, and the last column when both sides of the market are subsidized. Bootstrapped standard errors are in parentheses.