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Nicolas Koch
Nolan Ritter
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When is the electric vehicle market self-sustaining? Evidence from Norway

Nicolas Koch[*a,b], Nolan Ritter[†a], Alexander Rohlf[†a], and Francesco Scarazzato[c]

[a]Mercator Research Center for Global Commons and Climate Change (MCC), EUREF Campus 19, 10829 Berlin, Germany.

[b]Institute of Labor Economics (IZA), Schaumburg-Lippe-Straße 5–9, 53113 Bonn, Germany.

[c]Vienna University of Economics and Business (WU), Department of Economics, Welthandelsplatz 1, 1020 Vienna, Austria.

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Abstract

This paper investigates whether the world's most mature electric vehicle (EV) market in Norway has overcome critical mass constraints and can achieve sustainable long-term equilibria without subsidies. We estimate a structural model that allows for multiple equilibria emerging from the interdependence between EV demand and charging station supply. We first estimate the resulting indirect network effects using an instrumental variable approach. Then, we simulate long-term market outcomes for each of the 422 Norwegian municipalities. We find that almost 20% of all municipalities faced critical mass constraints in the earliest stage of the market. Half of them are effectively trapped in a zero-adoption equilibrium. However, in the maturing market, all municipalities have passed critical mass. Overall, about 60% of the Norwegian population now lives in municipalities with a high-adoption equilibrium, even if subsidies were removed. This suggests that critical mass constraints do no longer justify the provision of subsidies.

Keywords: electric vehicles, network externalities, critical mass, subsidies
JEL: H23, L62, Q48, Q58, R48

*Corresponding Author: koch@mcc-berlin.net

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1 Introduction

The electrification of vehicles is considered the most promising way to decarbonize road transport. There were about 10 million electric vehicles (EVs) on the road worldwide in 2020. Yet, the International Energy Agency's Sustainable Development Scenario concludes that at least 230 million EVs are needed globally by 2030 to meet the climate goals of the Paris Agreement (IEA, 2021a). Many countries provide substantial financial incentives to reach this goal. In 2020, governments across the world spent USD 14 billion on direct purchase incentives and tax rebates for EVs (IEA 2021). Such measures were implemented as early as the 1990s in Norway, in the United States in 2008, and in China in 2014. However, as the technology of and the markets for EVs mature, some policy makers begin to consider reducing the amount of support. This raises questions about the optimal timing of EV subsidy programs and the conditions under which an EV market becomes self-sustaining.

This paper investigates whether the world's most mature EV market in Norway has overcome the critical mass hurdles that impede the large-scale adoption of EVs and that justify policy interventions. Our empirical analysis is guided by a structural model developed by Zhou and Li (2018) that features both high-adoption and no-adoption equilibria that emerge from the interdependence between the demand for EVs and the supply of complementary charging stations. We estimate these indirect network effects for consumers' EV adoption decisions and investors' charging station investment decisions using an instrumental variable approach and municipality-level panel data from 2012 to 2019. With these estimates, we simulate the long-run equilibria for each of the 422 Norwegian municipalities to evaluate the existence of critical mass constraints and the prevalence of local markets on a sustainable path to a high-adoption equilibrium in the absence of further policy support.

Network effects are "indirect" when users' expected utility depends on the amount and variety of complementary goods, whose supply depends on the size of the user-base (Katz and Shapiro, 1985). The framework can be expanded through the concept of two-sided markets (Armstrong, 2006; Rochet and Tirole, 2006) by introducing platforms that provide the participating sides with either a service or a good. Various studies such as Greaker and Heggedal (2010); Pavan (2017); Meunier and Ponssard (2020) argue that emerging alternative fuel markets are characterized by network externalities and critical-mass constraints. Empirically, Li et al. (2017) and Zhou and Li (2018) find significant indirect network effects in the launch stage of the U.S. EV market. More specifically, Zhou and Li (2018) estimate that more than half of the U.S. Metropolitan Statistical Areas (MSA) faced critical-mass constraints as of 2013. Springel (2019) analyzes the Norwegian EV market within the two-sided market framework and shows that subsidies for charging stations are relatively more effective than purchase subsidies in fostering demand for EVs when the EV market starts to develop.

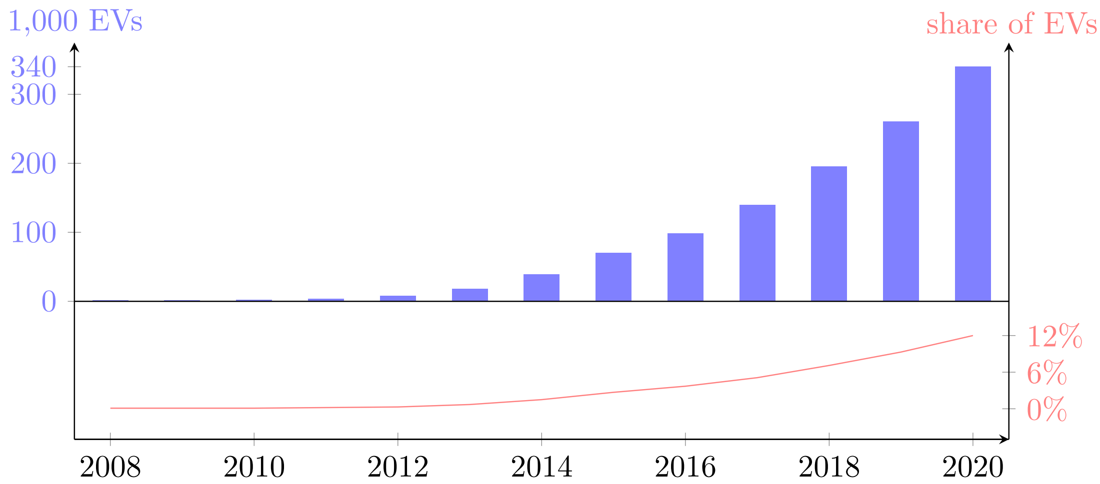
Our analysis addresses questions regarding the external validity of these pioneer studies. The current understanding of indirect network effects and critical mass issues is largely based on evidence from the earliest stages of the EV market, in which buyers are predominantly "early-adopters" who face considerable range limitations because of a lack of public charging infrastructure. For instance, the evidence from the U.S. is based on observations from 2013 when only 0.5% of newly registered vehicles were EVs, when there were only 26 charging stations per MSA, and when only 10 EV models were available. In sharp contrast, in 2019 in Norway almost 50% of all new registrations were EVs, there were on average 123 charging stations per metropolitan region[1], and there were 33 mass-produced EV models. Given these stark differences, we seek to contribute to the literature by providing evidence on the role of critical mass constraints over a long time frame in this well-developed market. Whether critical mass constraints remain a relevant consideration in more mature markets is an open question of high relevance to policy discussions because it is the critical mass issue that justifies policy interventions. Thus, our paper shifts the research focus to the question whether critical mass constraints can become non-binding over time, even when subsidies are abolished.

We find that in 2012 when the EV market was in its infancy, almost 20% of the Norwegian municipalities faced critical mass constraints despite subsidies. Moreover, about half of them were effectively trapped in a zero-adoption equilibrium. In stark contrast, under mature market conditions in 2019, all municipalities surpass their critical mass constraints and are on a stable path to EV adoption. Importantly, this holds true even when subsidies are abolished. This is particularly notable because the exemptions from value added and vehicle registration taxes may exceed half of the pre-tax vehicle purchase price (IEA, 2021a). Thus, the goal to move markets beyond critical mass constraints does not justify the current level of subsidies. Without subsidies, about 60% of the Norwegian population in 2019 would have already lived in municipalities securely locked into high-adoption equilibria. Finally, we show that the continuation of EV subsidies may be justified if a long-term EV market penetration is a distinctive policy goal in semi-urban municipalities that would otherwise not adopt EVs. Moving away from the current nation-wide subsidy to localized schemes may allow better targeting and less windfall profits.

The paper is structured as follows. Section 2 describes the Norwegian EV market and the policies that have facilitated its rapid development. Section 3 presents the theoretical framework

[1] There are 14 statistical metropolitan areas ("Byregioner") in Norway. The number of installed charging stations in 2019 ranged from the 16 stations in the Tromsø region, to 770 stations in the Greater Oslo region.

Figure 1: *EV stock*



Notes: The upper part of this Figure shows the EV stock between 2008 and 2020. The lower part of this Figure indicates the share of EVs in the vehicle stock. All figures according to IEA (2021b).

that allows for multiple equilibria. Section 4 describes the data underlying our analysis. We outline the empirical strategy in Section 5. We present and discuss the estimation results in Section 6 before introducing our policy simulation in Section 7. The final Section summarizes and concludes.

2 Norwegian Electric Vehicle Policy

With a battery electric vehicle (BEV) share of almost 12% in its vehicle stock in 2020, Norway is the country with the highest per capita share of EVs. Figure 1 illustrates the development of the stock of electric vehicles over time. In addition to the 54.4% of sold passenger vehicles in 2020 that were BEVs, an additional 19.9% were plug-in hybrids. While in the early 2010s, owners of EVs predominately lived in densely populated areas such as Oslo, there are few municipalities without any EV owners today (see Figure 6 in the Appendix). Until 2025, the Norwegian government intends all newly registered vehicles to be emissions free (Figenbaum, 2018, p. 14)).

The increase in the share of EVs was supported by several policy measures. First, EVs have been exempt from vehicle registration taxes since 1990 and exempt from value added tax (VAT) since 2001 (Figenbaum, 2017). Given a VAT of 25%, this exemption alone is of significant economic magnitude. Together with registration tax exemptions, the tax rebate may exceed half the initial (pre-tax) vehicle purchase price (IEA, 2021a). Second, Norway produces cheap electricity using a share of 95% hydro (Statistics Norway, 2020) while simultaneously levying high taxes on motor fuels. This reduces the operational costs of EVs compared to conventional vehicles. Moreover, EVs are subject to reduced tolls on toll roads (since 1997), reduced fares for ferries (since 2009), enjoy access to bus lanes (since 2003), face significantly reduced or waived parking fees (since 1999), and enjoy free charging in some municipalities.

In addition to monetary incentives for EV adopters, the Norwegian government also supports investments in the charging infrastructure, a complementary good to EVs. Figure 2 illustrates the development of the number of charging points by charging speed over time. From 2009 onward, the government earmarked an annual 50 million Norwegian Krona (NOK), about 5 million EUR, to support the installation of charging stations. This measure increased the number of slow charging points from $3,500$ in 2010 to over $10,000$ in 2019. Between 2010 and 2014, the annual subsidies were shifted to support fast charging stations. This policy measure has increased the number of fast charging points from zero to over $15,000$ over the course of ten years. Overall, the government's aim is to provide at least one fast charging station for every 50 km of main roads (Lorentzen et al., 2017). Although the daily average travel distance does not exceed 47 km, fast charging stations significantly increase the utility of EV owners who commute long distances.

3 Theoretical Framework

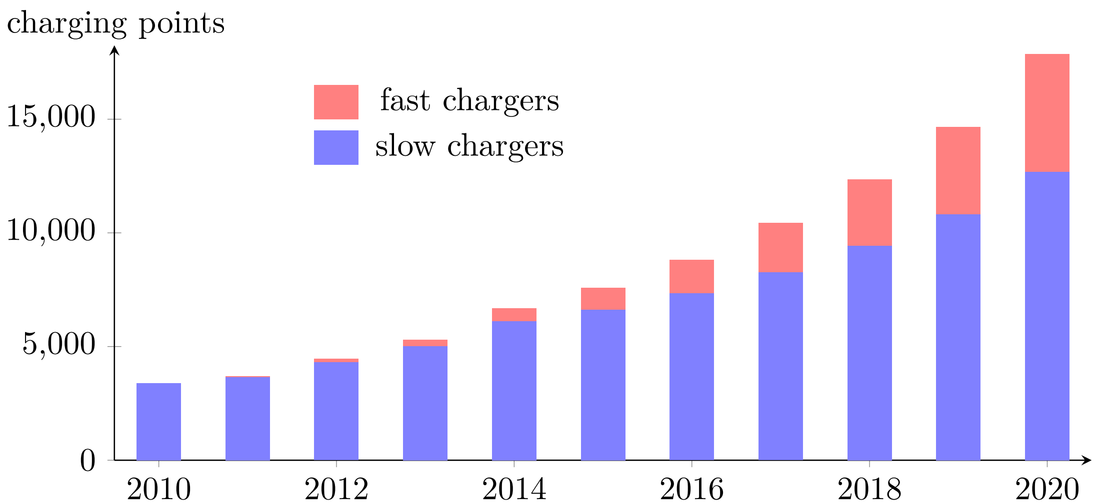
Our goal is to understand the long-term equilibrium of the EV market in the presence of critical-mass constraints that arise from indirect network effects. While reduced-form analyses may suffice to identify network effects in the Norwegian EV market (Delacrétaz et al., 2020), it is necessary to use structural approaches and conduct counterfactual analyses to learn about the role of critical mass constraints under alternative policy scenarios.

We implement the approach of Zhou and Li (2018) with some minor adaptations. We maintain their notation to facilitate comparison and to allow readers to fully benefit from their model discussion. The model characterizes consumers' EV adoption decisions on the demand side and investors' charging station investment decisions on the supply side. It allows for multiple equilibria and captures indirect network effects.

3.1 Demand for Electric Vehicles

At the beginning of period t, there are N_{t-1} charging stations, Q_{t-1} EVs, and $\bar{q}_t$ potential buyers of EVs. Consumer i's expected utility from an EV is $E(u_{it}) = \theta_i v(N_t^e) - \alpha_t P_t$. $\theta_i v(N_t^e)$ is the

Figure 2: *Number of charging points*



Notes: This Figure indicates the number of charging points by charging speed. A charging point is considered fast if its output exceeds 22 kW. All figures according to IEA (2021b).

expected utility of the charging network that arises from a combination of individual i's preference for the public charging network θ_i and a function of the number of expected charging stations $v(\cdot)$. The higher the expected number of charging stations N, the higher is i's utility. The term $-\alpha_t P_t$ captures that i's utility decreases as the price P_t of the EV increases. i only adopts an EV if her utility is positive. Overall, the number of new EV sales in t is

$$q_t = \bar{q}_t \left[1 - G_t \left(\frac{\alpha_t P_t}{v(N_t^e)} \right) \right] \ , \tag{1}$$

where $G_t(\cdot)$ is a smooth cumulative density function with a lower bound of 0 and an upper bound that depends on individual i's preference for the charging network θ.

Assuming a vehicle scrappage rate ρ, the stock of EVs Q in t is:

$$Q_t = \bar{q}_t \left[1 - G_t \left(\frac{\alpha_t P_t}{v(N_t^e)} \right) \right] + (1-\rho) Q_{t-1} \ . \tag{2}$$

Substituting the market share of EVs $s_t = q_t/\bar{q}_t$ into equation (1) and taking logarithms returns an expression that explains the market share of conventional vehicles $(1 - s_t)$

$$ln(1 - s_t) = \beta_1 ln(N_t) + \beta_2 ln(P_t) + \xi_t \tag{3}$$

as a function of the number of charging stations, the price of EVs, and a number of additional market conditions ξ_t. β_1 captures indirect network effects and β_2 captures consumers' sensitivity to the EV price.

3.2 Supply of Charging Stations

The supply of charging stations N_t depends on their profitability. Per consumer profit at charging station k is $\pi_k = (r_k - c)D_k(r_1, \ldots, r_N)$. r_k is the price for charging, and c is the constant marginal cost of charging to the station owner which includes the cost of electricity and maintenance. Demand for charging $D_k(r_1, \ldots, r_N)$ depends on its price r_k. In the equilibrium, the price for charging is identical across all stations and depends on the overall number of charging stations $r_k = r(N)$. Thus, the profit function can be re-written as $\pi(N) = \frac{(r(N)-c)D(r(N))}{N}$. If the cost for building a charging station is C_t and investors expect an EV stock of Q^e_t, then the expected profit of a charging station is $\Pi^e_t = -C_t + Q^e_t \cdot \pi(N_t) + \delta \cdot Q^e_{t+1} \cdot \pi(N^e_{t+1}) + \ldots$. The profit per station can be transformed to indicate the number of charging stations in t:

$$N_t = \pi^{-1}\left(\frac{C_t - \delta C_{t+1}}{Q^e_t}\right) \tag{4}$$

Following a logarithmic transformation, one can recover a supply function for charging stations that depends on the electric vehicle stock Q, the change in cost of charging stations C, and a number of additional market conditions η_t:

$$ln(N_t) = \gamma_1 \cdot ln(Q_t) + \gamma_2 \cdot ln(C_t - \delta \cdot C_{t+1}) + \eta_t \tag{5}$$

γ_2 captures investors' sensitivity to investment costs while γ_1 measures indirect network effects. If $\gamma_1 > 0$ and $\beta_1 < 0$ from equation 3, there exist positive indirect network effects. In this case, a shock that increases N also increases the number of EVs, which in turn further increases the number of charging stations thereby generating a positive feedback loop.

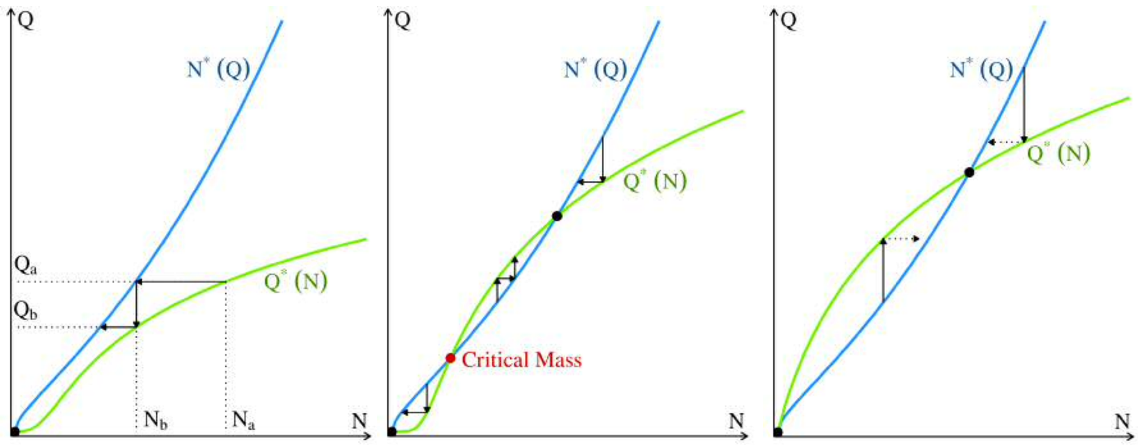
3.3 Market Equilibrium

In the steady state, the EV stock, the stock of charging stations, and their underlying determinants are fixed. This implies, for instance, that $Q_t = Q_{t-1} = Q^*$ and $N_t = N_{t-1} = N^*$, $\bar{q}_t = q$, $P_t = P$, $\bar{\theta}_t = \theta$, $\alpha_t = \alpha$, $\eta_t = \eta$, and $C_t = C$. Substitution of the steady state values into equations 2 and 4 returns

$$Q^*(N) = \left[1 - G\left(\frac{\alpha P}{v(N)}\right)\right]\frac{\bar{q}}{\rho} \tag{6}$$

Figure 3: *Market cases*

(a) *Case I: No adoption* **(b)** *Case II: Critical mass* **(c)** *Case III: Automatic adoption*



and

$$N^*(Q) = \pi^{-1}\left(\frac{(1-\delta)C}{Q}\right) \ . \tag{7}$$

Because $v(\cdot)$ increases monotonically while $\pi(\cdot)$ decreases monotonically in N, Q approaches zero if N approaches zero. Therefore, the solution $N^* = 0$ and $Q^* = 0$ is always a possible steady-state equilibrium in which neither EVs nor charging stations exist. Depending on market conditions, this could be the only equilibrium as shown in the left panel of Figure 3. In this case, a shock that increases N leads to the adoption of some electric vehicles. However, in the following periods, N and Q will decline until both have returned to zero. This is one of the three possible market equilibria, which we label Case I "no adoption."

The middle panel of Figure 3 highlights Case II which is subject to "critical mass" constraints. This case has two positive equilibria: one that is unstable at the critical mass, and one that is locally stable. Only if the market surpasses critical mass, it is set on a path to the locally stable equilibrium with high EV adoption. If below critical mass, the market is trapped on an inexorable path to the origin and zero adoption as in Case I. Finally, the right panel illustrates Case III with "automatic adoption." In this case it is only a matter of time before the market reaches the globally stable equilibrium with mass EV adoption.

Formally, the long-run equilibria are given by

$$\overbrace{(1-\rho Q^*/\bar{q})Q^{*-\beta_1\gamma_1}}^{LHS} = \overbrace{P^{\beta_2}C^{\beta_1\gamma_2}(1-\delta)^{\beta_1\gamma_2}e^{\xi+\beta_1\eta}}^{RHS} \ . \tag{8}$$

The right-hand side (RHS) is constant in Q. The left-hand side (LHS) reaches its maximum at $LHS_{max} = (1-\beta_1\gamma_1)^{\beta_1\gamma_1-1}(-\beta_1\gamma_1\bar{q}/\rho)^{-\beta_1\gamma_1}$, where Q^* is defined as $Q^* = \hat{Q} = \frac{-\beta_1\gamma_1\bar{q}}{(1-\beta_1\gamma_1)\rho}$. If all parameters have the expected signs, i.e. $\beta_1 < 0$, $\beta_2 > 0$, $\gamma_1 > 0$, $\gamma_2 < 0$, the three cases from Figure 3 can be differentiated.

Case I: No Adoption A municipality is in the "no-adoption" case if $LHS_{max} < RHS$. In this case, the number of charging stations and the EV stock are both $N = Q = 0$. Potential explanations for this outcome are that either the EV price P is too high or there are too few potential EV buyers with high preference for the public charging network θ.

Case II: Critical Mass A municipality is subject to critical mass constraints if $LHS(\underline{Q}) < RHS \leq LHS_{max}$. $\underline{Q}$ is the EV stock that corresponds to the minimal size of the charging network for which there is positive EV adoption. It is defined as $\underline{Q} = \frac{(1-\delta)C}{(P^{\beta_2}e^{\xi})^{1/(\beta_1\gamma_1)}e^{\eta/\gamma_1}}$. Case II arises for a municipality specific range of EV prices in combination with a small market size (q), weak preferences for EVs (α) or the public charging network (θ), and low benefits from public charging station investments (η).

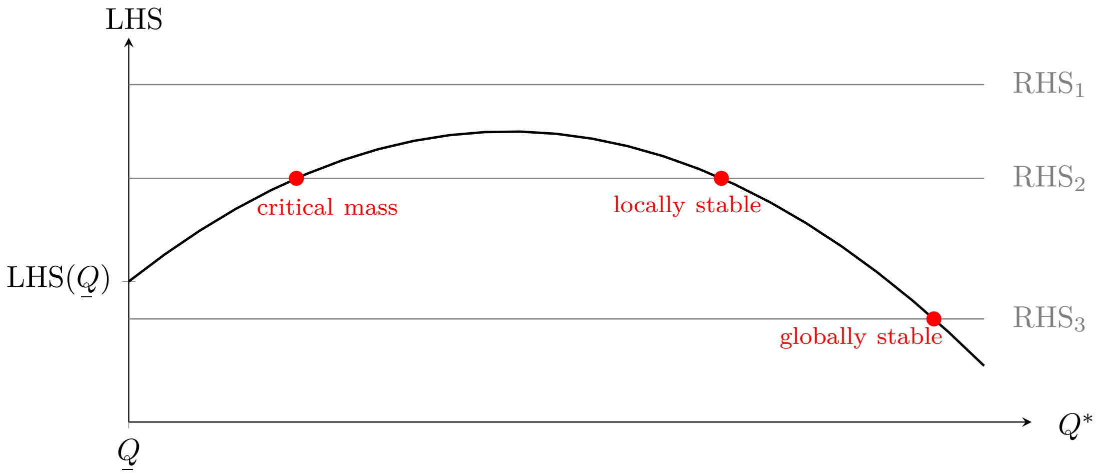
Case III: Automatic Adoption If $LHS(\underline{Q}) \geq RHS$, there is one globally stable, positive equilibrium. This case arises either because the EV price P is very low or because there are many potential EV buyers with high preference θ for the public charging network.

Figure 4 illustrates the three different cases under the condition that the number of charging stations exceeds the minimum number $\underline{Q}$ that allows EV adoption. When the curve described by LHS does not intersect with RHS, there is no equilibrium (Case I). A reduction of the EV price through subsidies shifts the RHS downward. If subsidies shift RHS_1 to either RHS_2 or RHS_3, Case I becomes Case II or III depending on the magnitude of the downwards shift.

4 Data

The Norwegian Road Federation provides annual registration data for new vehicles for the 422 municipalities in Norway. Among the 630 available vehicle models, 33 are mass-produced battery

Figure 4: *Policy impacts of EV subsidy on long-run equilibria*



Notes: This Figure shows the three equilibrium cases under the condition that the number of EVs exceeds the minimum number $\underline{Q}$ required for a charging network that supports positive EV adoption. Red dots highlight the intersections that describe the possible equilibria. RHS$_1$ describes Case I and the absence of equlibria. RHS$_2$ illustrates Case II with two possible equilibria. RHS$_3$ shows Case III with one global equilibrium. A reduction of the EV price through subsidies would shift the RHS downwards.

electric vehicles. We use this information to calculate the market share for each EV model by municipality over time. We collect data on the energy consumption of EVs from their respective manufacturers and calculate their gasoline equivalent fuel efficiency using a conversion factor of 33.705 kWh per gallon provided by the U.S. Environmental Protection Agency (EPA). Figure 6 in the Appendix provides an overview of new EV registrations by municipality.

NOBIL, Enova, and the Norwegian Electric Vehicle Association provide detailed information on the Norwegian charging station infrastructure. For instance, the data includes the latitude and longitude of each charging station, the date when it entered service, whether it received public funding, and the level of public subsidies for charging stations by municipality. Figure 7 in the Appendix shows the spatial distribution of charging stations in 2012 and 2019.

Statistics Norway[2] provides data on the number of EVs registered before 2012, the net median household income adjusted for the Norwegian consumer price index, the number of out-of-municipality commuting individuals between the ages of 20 and 66, the gasoline price, the length of roads by municipality, the total area of each municipality, and the deficit in the municipal accounts.

[2] See Appendix 9 for table codes from *ssb.no*.

The Norwegian Travel Survey of 2013-2014 provides information on the average travel time to work by municipality (Hjorthol et al., 2014). Finally, we obtain data on the number of supermarkets, fuel stations, malls, and stores from OpenStreetMap and Geofabrik. Comparisons with other sources confirm that the open source data is generally reliable.

Table 1 presents summary statistics for the data underlying our analysis. The upper panel holds the variables used in the estimation of EV demand, while the lower panel presents the variables used in the estimation of the charging station supply. The subscripts indicate the level at which we measure the individual variables in our data. j is the EV model, of which there are a total of 33, m indicates the municipality, of which there are a total of 422, and t indicates the year between 2012 and 2019.

5 Empirical Strategy

5.1 Demand for Electric Vehicles

This is how we estimate the empirical counterpart to the EV demand equation 3 from the theoretical model:

$$ln(1 - s_{jmt}) = \beta_1 \cdot ln(N_{mt}) + \beta_2 \cdot ln(P_{jt}) + \beta_3' \cdot X_{jmt} + \mu_{jm} + \lambda_t + \varepsilon_{jmt} \ . \tag{9}$$

s_{jmt} is the market share of EV model j in municipality m at time t. The dependent variable is the market share of vehicles other than the specific EV model. Therefore, $\beta_1 < 0$ indicates a positive elasticity of EV demand with respect to the combined number N_{mt} of slow and fast charging stations in municipality m and year t. Consequently, $\beta_2 > 0$ indicates a negative relationship between the market share and the price P_{jt} of a given EV model in a given year. The price includes cost, insurance, freight, taxes, and any importer or dealer profits.[3]

The model-municipality fixed effects μ_{jm} measure time invariant characteristics at the municipality level such as population size and density, specific preferences for EVs, and the prevalence of local incentives such as free toll-roads and parking, reduced fares, and access to bus lanes.[4] The fixed effects also absorb local preferences for and the local availability of certain EV models, and control for time-invariant model characteristics such as brand and model reputation. The year fixed effects λ_t control for national shocks that affect EV demand. The matrix X holds additional control variables, namely the real median household income per municipality, the share of commuters

[3] Please note that because of the occurrence of zero values we use the inverse hyperbolic sine transformation (Bellemare and Wichman, 2020) for some variables indicated in the table captions.

[4] Halse et al. (2021) quantify the impact of such incentives on local vehicle demand patterns.

Table 1: *Summary statistics*

EV demand	Mean	St. Dev.
Market Share$_{jmt}$	0.009	0.028
Price$_{jt}$ (NOK)	$283,853.996$	$255,734.448$
Charging Stations$_{mt}$	4.497	17.552
Net Median Household Income$_{mt}$ (NOK)	$504,972.407$	$55,842.250$
Shops$_{m}$	9.801	22.929
Share of Out-Commuters in 2011$_{mt}$	0.166	0.079
Average Commute Time$_{m}$ (Minutes)	45.018	23.204
Gasoline Price$_{t}$ (NOK)	14.702	0.673
Length of State Roads$_{m}$ (in km)	25.280	32.160
Number of Models$_{jt}{}^{Brand}$	12.335	8.627
Number of Models$_{jt}{}^{Other}$	339.238	29.452
Weight$_{jt}{}^{Brand}$ (kg)	$1,521.663$	256.740
Weight$_{jt}{}^{Other}$ (kg)	$1,570.378$	35.991
Length$_{jt}{}^{Brand}$ (cm)	447.228	28.864
Length$_{jt}{}^{Other}$ (cm)	453.198	3.426
Fuel Consumption$_{jt}{}^{Brand}$ (l/100km)	4.927	1.226
Fuel Consumption$_{jt}{}^{Other}$ (l/100km)	5.775	0.101
Charging station supply		
Charging Stations$_{mt}$	3.980	16.414
Station Cost$_{mt}$ (NOK)	$278,100.830$	$53,892.491$
Per Capita Deficit$_{mt}$ (NOK)	$1,363.117$	$2,290.848$
Lenght of State Roads$_{m}$ (in km)	25.280	32.160
EV Stock$_{mt}$	221.352	$1,496.306$
Average Fuel-Station Distance$_{m}$ (in km)	68.829	43.474
Out-Commuters in 2011$_{m}$	$1,927.436$	$4,034.423$

Notes: This table presents descriptive statistics across municipalities, years of observation, and vehicle models. Superscripts differentiate whether vehicle specific characteristics apply to the vehicles of a given brand or all others. All monetary units in prices of 2015. The average real cost of installing a charging station is $290,000$ NOK. To accommodate for public support, we divide the available public funds by the number of stations installed in a given year and subtract that amount from the real cost. Because funding cannot exceed the average real cost, any remaining funds are passed on to the next period.

interacted with a linear time trend and fuel prices interacted with the average travel time to work. ε is an error term.

Because the number of charging stations and the size of the EV stock are determined simultaneously, we instrument for $ln(N_{mt})$ using two shift-share (or "Bartik") instruments. First, similar to Zhou and Li (2018) and Delacrétaz et al. (2020), we instrument the stock of slow charging stations with the interaction of the total number of shops, supermarkets, malls, and department stores at the level of that municipality and the national stock of slow charging stations in the preceding period in all other municipalities. According to Figenbaum (2018), charging infrastructure is often located at malls and retail stores. Chains like McDonald's, IKEA, and Kiwi food-stores install charging stations to attract patrons. Therefore, our IV strategy's intuition is that the municipalities with more sales points have a better endowment of good sites for charging and will be more affected by national shocks than others.

Second, we instrument the stock of fast charging stations in a municipality with the interaction of the total length of state roads in that municipality and the national stock of fast charging stations in the preceding period in all other municipalities. Because the government aims for at least one fast charger on every 50 km segment of major road, fast charging stations are mainly located along major roads (Figenbaum, 2018). Thus, the intuition of our shift-share instrument is that municipalities with more state roads will be more affected by national shocks to fast charging station investments than others.

Because the demand for vehicles and their prices are determined simultaneously, we also instrument the price of EV models P_{jt}. To this end, we construct an instrument from automakers' price setting behavior. According to Berry et al., automakers set the price for each of their models based on the attributes of their competitors' models and their own brand's other models. With K observed exogenous vehicle characteristics, the set of instruments comprises the aggregate values of attributes of a brand's other vehicles z_k^{Brand} and the aggregate values of other brand's vehicles z_k^{Other}.[5] For model j of brand b at time t with a set of brand models $\mathscr{S}_{bt}$, and the number of models sold by a given brand at a given time N_{bt}, the vector of instruments includes $2 \cdot K$ instruments with

$$z_{jkt}^{Brand} = \frac{\sum\limits_{r \neq j, r \in \mathscr{S}_{bt}} z_{rkt}}{N_{bt} - 1} \quad \text{and} \quad z_{jkt}^{Other} = \frac{\sum\limits_{r \neq j, r \notin \mathscr{S}_{bt}} z_{rkt}}{\sum\limits_{d \neq b} N_{dt}} \ . \tag{10}$$

The attributes we use are length, curb weight, and fuel consumption in liters per 100km or their equivalent for EVs. Our identifying assumption is that our instruments are independent of unobserved product characteristic in the error term after controlling for the model-municipality and year

[5] Because we take logarithms, our setup is identical to using means as in Bresnahan et al. (1997).

fixed effects. We present summary statistics for our instruments in Table 1.

5.2 Supply of Charging Stations

This is the empirical counterpart of the theoretical charging station supply in equation 5:

$$ln(N_{mt}) = \gamma_1 \cdot ln(Q_{mt}) + \gamma_2 \cdot ln(C_{mt} - \delta \cdot C_{mt+1}) + \gamma_3' X_{mt} + \upsilon_m + \varsigma_t + \vartheta_{mt} \ . \qquad (11)$$

γ_1 indicates the elasticity of the total number of charging stations N_{mt} with respect to the stock of EVs Q_{mt}. γ_2 does the same for the change in the cost of installing a charging station C_{mt}. We include municipality fixed effects υ_m and year fixed effects ς_t. ϑ_{mt} is an error term. Matrix X holds control variables, including the length of the state road network by municipality times a linear time trend and the deficit per capita in a given year to capture local government expenditure.

To address concerns regarding the endogeneity from simultaneity, we also use instruments for the EV stock Q_{mt}. We construct two instruments. For the first, we follow Zhou and Li (2018) and use a proxy for the municipality-specific fuel price. The intuition for this instrument is that higher local fuel prices increase the total cost of ownership of conventional vehicles, which is likely to induce more consumers to purchase an EV. Also, it is reasonable to assume that the fuel price only affects the number of charging stations via its effects on the EV stock. We follow Springel (2019) and multiply the fuel price with the average density of fuel stations at the municipal level to approximate the level of local competition.[6] We expect that a lower fuel station density leads to higher and less volatile prices (Loy et al., 2018) and, hence, to a higher EV stock.

Second, we also use the number of out-of-municipality commuters to instrument for the EV stock. According to Figenbaum (2018), the average EV owner is more likely to drive to work and has a longer commute than owners of conventional vehicles. In Norway, electricity is considerably cheaper than fossil fuels (Lévay et al., 2017). Moreover, EVs are exempt from most road tolls and parking fees. It is reasonable to assume that the number of commuters only affects the number of charging stations via their influence on the EV stock. To rule out concerns that better charging infrastructure incentivizes commuting, we multiply the EV stock in the previous year in all other municipalities by the local number of out-of-municipality commuters in 2011, to obtain another shift-share instrument.

[6] Note that data on municipality-level fuel prices over time is unavailable.

6 Estimation Results

Table 2 presents our results for the demand for EVs using OLS and IV. The conditional F-statistics (Sanderson and Windmeijer, 2016) indicate a strong first stage. Table 7 in the Appendix holds the results for the first stage. Only our IV elasticity estimates have the expected signs.

First, the coefficient for the number of charging stations N is insignificant with OLS but turns negative and highly significant with IV. The negative coefficient estimate based on IV implies that a larger charging station network increases EV demand. Our results suggest that OLS underestimates the effect of charging station availability on consumers' EV adoption decisions. This bias in OLS may stem from an unobserved demand shock that is negatively correlated with the size of the charging network, such as the introduction of incentives for home charging from local governments or utilities in response to the limited number of public charging stations in select municipalities. With -0.004 the magnitude of our IV estimate is of considerably smaller magnitude compared to the -0.012 in Zhou and Li (2018) for the nascent US market. This suggests that Norwegian consumers are less sensitive to the supply of charging station than early U.S. consumers. One potential explanation is that home charging is by far the most dominant charging mode in the mature Norwegian market (Figenbaum, 2018).

Second, the coefficient for the price of EVs P is negative in the OLS specification but turns a positive sign in the IV approach. The positive IV coefficient implies that EV consumers are sensitive to the purchase prices. The difference in the estimates between OLS and IV suggests that vehicle prices are positively correlated with unobserved time-varying local demand conditions, such as time-varying tastes for specific EV models in given municipalities.

To evaluate the economic magnitude of feedback effects on the consumer side, we calculate the EV purchase price reduction that is needed to compensate for one fewer charging station. Given our estimates for β_1 and β_2, we calculate that one fewer charging station in a given municipality has to be compensated by a reduction in the price of EVs by about $18,939$ NOK or about $1,900$ EUR on average to hold the EV stock constant.[7] The magnitude of these positive feedback effects on the demand side is of considerably higher magnitude compared to the 355 USD in Zhou and Li (2018) for the nascent U.S. market. This is mainly driven by the lower EV price elasticity that we find for Norwegian consumers.

Table 3 holds the results from estimating the supply of charging stations using OLS and IV. Using instruments leads to considerably different results. First, the coefficient for the EV stock Q

[7] This calculation relies on the sample mean price $\bar{P} = 283,853$ NOK, the average number charging stations $\bar{N} = 4.5$, and the estimated coefficients $\hat{\beta_1}$ and $\hat{\beta_2}$. Let x denote the price change needed to compensate for one fewer charging station: $x = \frac{\hat{\beta_1}\bar{P}}{\hat{\beta_2}\bar{N}}$.

Table 2: *EV demand*

Dependent variable	$ln(1-S_{jmt})$	
	OLS	IV
$ln(N_{mt})$	0.000	-0.004^{***}
	(0.000)	(0.001)
$ln(P_{jt})$	-0.012^{***}	0.012^{***}
	(0.001)	(0.002)
$ln(\text{Income}_{mt})$	-0.008^{*}	-0.008^{*}
	(0.004)	(0.004)
$\text{Commuters}_m \cdot \text{Time Trend}_t$	-0.002^{**}	-0.002^{***}
	(0.001)	(0.001)
$ln(\text{Gasoline Price}_t) \cdot ln(\text{Commute Time}_m)$	-0.002	-0.001
	(0.002)	(0.002)
Observations	55,290	55,290
1st stage conditional F-stat (N_{mt})		53
1st stage conditional F-stat (P_{jt})		11,893
Year FEs	Y	Y
Model-Municipality FEs	Y	Y

Notes: This table presents the OLS and IV regression results for EV demand. Please note that we use an inverse hyperbolic sine transformation instead of $ln(N_{mt})$ because there are many zero values in this variable. Standard errors are clustered at the model-municipality and year level. $^{***}(^{**},^{*})$ indicates statistical significance at the 1% (5%, 10%) level. Conditional F-statistics based on Sanderson and Windmeijer (2016) are reported for the first stage. They are both larger than the critical value of 10.58 suggested by Stock and Yogo (2005) for a model with two endogenous variables, ten instruments, and maximum accepted bias of the IV estimator relative to OLS equal to 10%.

increases nearly threefold compared to OLS. Second, the standard error increases roughly sixfold. Yet, the IV estimate remains highly significant. With an F-statistic of 22, the first stage is strong. Altogether, there is again clear evidence that OLS results are biased because of endogeneity. Table 6 in the Appendix holds the results for the first stage.

In the IV specification, the positive coefficient for Q indicates that a 1% increase in the EV stock Q increases the number of charging stations N by 0.331%.[8] This coefficient is markedly smaller than the elasticity of 0.671 from Zhou and Li for the nascent U.S. market. This suggests that the indirect network effects of the EV stock to the charging station supply are weaker in more mature

[8] We follow Bellemare and Wichman (2020) to calculate this elasticity based on the coefficient estimate in Table 3, which is only an approximation of the elasticity because of the inverse hyperbolic sine transformation.

markets, e.g. because in a market environment, in which the large majority of newly sold vehicles are electric, investors face considerably less uncertainty about the demand side and therefore may be more concerned about other investment conditions, such as building costs. The statistically significant coefficient for the change in charging station costs suggests that future reductions in installation costs reduce the number of concurrent installations.

Table 3: *Charging station supply*

Dependent variable	$ln(N_{mt})$	
	OLS	IV
$ln(Q_{mt})$	0.124***	0.321***
	(0.021)	(0.121)
$ln(C_{m,t} - \delta \cdot C_{m,t+1})$	−0.013***	−0.013***
	(0.001)	(0.001)
$ln(\text{Per Capita Deficit}_{mt})$	−0.004**	−0.004**
	(0.002)	(0.002)
$ln(\text{Length of State Roads}_m) \cdot \text{Time Trend}_t$	0.020***	0.018***
	(0.003)	(0.003)
Observations	3,376	3,376
1st stage F-statistic		22
Year FEs	Y	Y
Municipality FEs	Y	Y

Notes: This table presents the OLS and IV regression results for the supply of charging stations. Please note that we use an inverse hyperbolic sine transformation instead of $ln(N_{mt})$, $ln(Q_{mt})$, and $ln(C_{m,t} - \delta C_{m,t+1})$ because there are many zero values in these variables. Standard errors are clustered at the municipality and year level. ***(**,*) indicates statistical significance at the 1% (5%, 10%) level.

7 Policy Simulation

Having recovered the parameters of the underlying theoretical structural model, we use equation 8 to determine in which of the three possible equilibrium cases each municipality is (see Section 3.3). This allows us to evaluate whether critical mass constraints remain binding in the relatively mature Norwegian EV market. Relatedly, we are interested in the number of local markets that will eventually reach a high-adoption equilibrium even without further policy support. To this end, we run simulations for two different policy regimes for 2012 and 2019 that mark the beginning and the end of our sample period.

First, we run a simulation with the current policy support that subsidies EV purchase prices. In particular, EVs are exempt from the 25% value added tax (VAT) and the vehicle registration tax, which was, on average, about $1,155$ EUR in 2019.[9] Second, we run a simulation in which EV purchase prices do not benefit from VAT and vehicle tax exemptions. For both simulations, we assume that the cost of building and operating a charging station is $C = 290,000$ NOK or about $29,000$ EUR. In addition, we assume a scrappage rate of $\rho = 0.044$ (Statistics Norway) and a discount factor of $\delta = 1/1.06$.

Table 4: *Policy simulation*

Year	2012		2019	
EV Subsidies	no	yes	no	yes
Municipalities by Case				
I	361	309	336	264
II	40	77	50	100
below critical mass	7	32	0	0
above critical mass	33	45	50	100
III	21	36	36	58

Notes: This table shows into which of the three equilibrium cases the 422 Norwegian municipalities fall. The left panel is for 2012 while the right panel is for 2019. In both cases, results are reported for the prevailing policy regime that offers subsidies as well as a counterfactual scenario without. For Case II, the table also returns the number of municipalities below or above the critical mass constraint.

Table 4 shows the results of our simulations of the long-run equilibria by subsidy regime for the years 2012 and 2019. Irrespective of the subsidy regime, we find that the large majority of municipalities are Case I because they have no positive equilibrium. This is particularly true in the early stage of the market in 2012 but also holds true in the more mature stage in 2019. Subsidies can effectively shift some municipalities out of the no adoption equilibrium and are more effective at this in the later market stage. In 2019, 63% of all municipalities have no positive equilibrium in the presence of subsidies compared to 80% in the absence of subsidies.

Depending on the year of interest and the subsidy regime, between 10% and 24% of municipalities are classified as Case II municipalities. These municipalities face two possible equilibria and are

[9] The curb-weight based registration tax is the only relevant criteria for taxing EVs. We calculate the average benefit according to registration tax exemption figures from Fridstrøm (2019) and annual vehicle registration data from Statistics Norway (`https://www.ssb.no/en/statbank/table/12906`).

therefore subject to critical mass constraints, which imply convergence towards non-adoption if the vehicle stock falls short of the critical mass. Table 4 shows that under early market conditions in 2012 between 18% and 42% of affected municipalities fall below critical mass so that their EV stock will decrease to zero eventually. In sharp contrast, under late market conditions in 2019, all Case II municipalities have overcome critical mass and are en route to the high-adoption equilibrium. This holds true even in the absence of subsidies.

Finally, Table 4 shows that across subsidy regimes and market maturity, only between 5% to 14% municipalities fall into the high-adoption Case III. Nevertheless and irrespective of market maturity, subsidies effectively increase the number of Case III municipalities that automatically transition to a long-run equilibrium with mass EV adoption.

Table 5 returns demographic statistics at the municipality level that may be correlated with consumer preferences for EVs or investors' expectations regarding profits from charging stations. We report mean values for characteristics by equilibrium case for the policy simulation in 2019 with and without subsidies. Most importantly, the table shows that with subsidies 75% of the Norwegian population lives in Case II & III municipalities that all reach a high-adoption equilibrium. Without subsidies this share is 61%, indicating that a large share of municipalities could maintain a sustainable long-term equilibrium without policy support. While there are many Case I municipalities in absolute numbers, only a small fraction of the overall population lives there. Population density is on average almost six times higher in Case II than in Case I municipalities and more than twenty times higher in Case III than in Case I municipalities. Finally, Table 5 also demonstrates that the urbanized Case III municipalities are home to households with higher average incomes, higher education levels, and higher shares of foreigners.

Figure 5 shows that the municipalities classified as either Case II or III are mainly concentrated in the populated coastal areas of southern Norway. Oslo, Bergen, Stavanger, and Trondheim stand out as Case III municipalities. Case I municipalities are instead concentrated in the rural heartland. The comparison between the two subsidy regimes reveals that the removal of subsidies in 2019 would mainly hit Case II municipalities that are less populated and less urbanized than the average Case II municipality but more affluent and more dependent on commuting than the average Case I municipality.

Our findings inform ongoing academic and policy debates about the design of subsidy schemes to promote EV adoption in the long run. First, they suggest that critical mass is a constraint during the launch stage of EV markets, which can be overcome by purchase subsidies to facilitate a higher EV adoption in the long-run.

However, second, the observation of critical mass no longer constraining the Norwegian EV

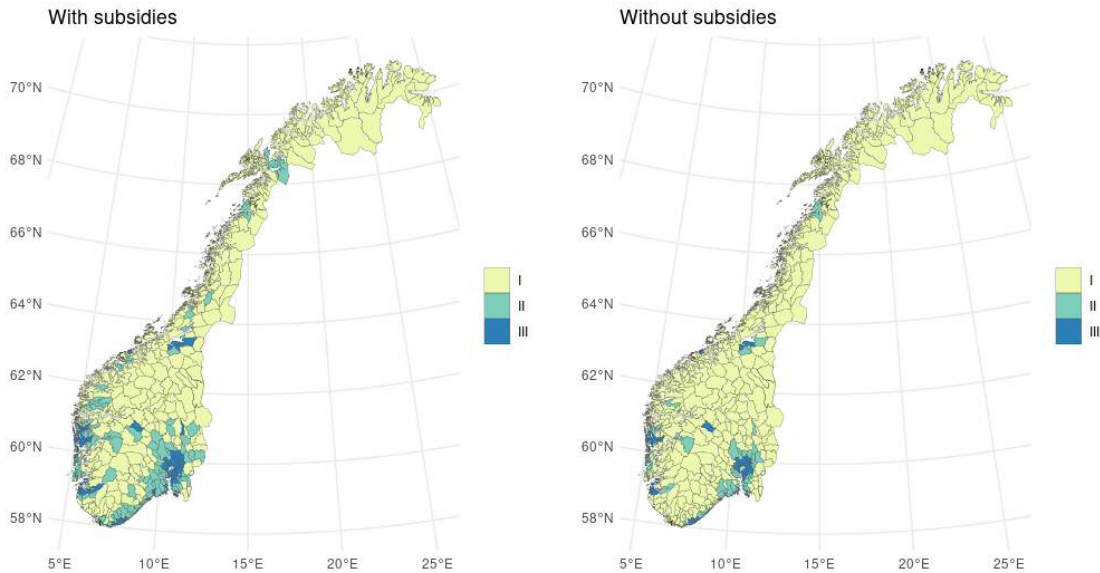
Table 5: *Municipality characteristics by equilibrium case*

Case	I	II	III
With subsidies:			
Aggregates			
Number of municipalities	264	100	58
Share of population in %	25	28	47
Characteristics			
Population	4,941	15,121	43,300
Density	12	69	261
Net household income	52,396	54,935	60,017
Bachelor degrees in %	18	21	24
Foreigners in %	11	12	15
Commuters in %	13	20	24
Without subsidies:			
Aggregates			
Number of municipalities	336	50	36
Share of population in %	39	21	40
Characteristics			
Population	6,232	22,033	59,243
Density	20	122	343
Net household income	52,867	56,680	61,381
Bachelor degrees in %	19	22	25
Foreigners in %	11	13	16
Commuters in %	15	23	24

Notes: This table presents aggregate and average demographics by equilibrium case at the municipality level for the simulation in 2019 with and without subsidies. Included variables are the average population, the population density per km^2, the average household income in EUR, and the shares of individuals holding bachelor degrees, foreign nationals, and self-reported commuters in the population. Municipality-level characteristics are provided by Statistics Norway.

market in its later stages suggests that concerns about critical mass can no longer justify subsidies. All major markets in urbanized regions in 2019 appear to be securely locked onto a path towards a high-adoption equilibrium. This raises the question how municipalities overcome their critical

Figure 5: *Spatial distribution of municipality by equilibrium case*



Notes: This map shows into which of the three equilibrium cases the 422 Norwegian municipalities fall in 2019. The panel on the left shows the situation with subsidies, while the panel on the right shows the counterfactual situation in the absence of subsidies.

mass over time. According to our theoretical framework, this succeeds if the number of consumers with strong preferences for either EVs (α) or the public charging infrastructure (θ) increase over time. While we do not observe these preferences directly, we are able to scrutinize the factors that affect them. Tables 8 and 9 in the Appendix show that the number of EV models increased from 10 in 2012 to 28 in 2019. Hence, consumers might find EVs that better suit their needs. Moreover, popular models like the Nissan Leaf, the Citroen C-Zero, the Peugeot iOn, and the Mitsubishi I-MiEV already available in 2012 became cheaper over time. In contrast, the new models in 2019 tend to be heavier and more expensive, which suggests that they offer higher battery capacity and longer driving ranges in addition to more comfort. These observations are consistent with an upward shift in α and θ.

Yet, third, we have also shown that subsidies in the more mature market stage trigger positive feedback loops in Case I municipalities (i.e. those local markets that would otherwise not adopt EVs in the absence of any policy intervention), for reasons other than critical mass constraints. We have shown that subsidies effectively shift a meaningful share of Case I municipalities to the locally stable equilibrium of EV adoption. Relative to the average Case I municipality, the positively affected municipalites are more populous and more densely populated, with households receiving higher incomes and demonstrating a higher propensity to commute. Thus, the continuation of the current subsidies can be justified if long-term EV market penetration in these regions is a distinctive policy goal.

Finally, it is worth noting that beneficiaries of the continuation of current nation-wide subsidies are consumers in high adoption regions likely to adopt EVs even in absence of any policy support. Thus, shifting towards a localized scheme may allow policy makers to reduce windfall profits and to increase public spending efficiency by redirecting funds to those municipalities where subsidies have a noticeable and positive impact on long-term equilibrium attainment.

8 Conclusion

In this paper, we investigate whether the world's most mature EV market in Norway has overcome the critical mass hurdles that impede the large-scale adoption of EVs and that justify policy interventions. Our empirical analysis is guided by a structural model developed by Zhou and Li (2018) that features both high-adoption and no-adoption equilibria emerging from the interdependence between the demand for EVs and the supply of complementary charging stations. We estimate these indirect network effects for consumers' EV adoption decisions and investors' charging station investment decisions using an instrumental variable approach and municipality-level panel data from 2012 to 2019.

We find that in 2012 when the EV market was in its infancy, almost 20% of the Norwegian municipalities faced critical mass constraints despite subsidies. About half of them were effectively trapped in a zero-adoption equilibrium. In stark contrast, under mature market conditions in 2019, all municipalities subject to critical mass surpass their constraints and are on a stable path to EV adoption. Importantly, this holds true even when subsidies are abolished. This is particularly notable because the exemptions from value added and vehicle registration taxes can be up to half or as much as the full vehicle purchase price (IEA, 2021a). Thus, the goal to move markets beyond critical mass constraints does not justify the current level of subsidies. Without subsidies, about 60% of the Norwegian population in 2019 would have already lived in municipalities securely locked into high-adoption equilibria. Finally, we show that the continuation of EV subsidies may be justified if a long-term EV market penetration is a distinctive policy goal in semi-urban municipalities that would otherwise not adopt EVs.

We conclude by discussing some limitations of our study and by indicating directions for future research. First, we assume that consumers' utility is only affected by the local supply of charging stations. Therefore, we neglect potential spatial interactions. However, EV owners who cross municipal borders may take into account the supply of charging infrastructure in surrounding municipalities as well. Similarly, charging station investors may consider the EV stock in an area that exceeds the municipality where they plan to invest. Overall, the role of spatial spillovers is an important policy question for future research.

Second, our study focus is on the existence of critical mass constraints in a mature EV market. Policy makers would greatly benefit from follow-up analyses that investigate alternative EV subsidy designs in more depth. Our findings suggest that switching from the current, nation-wide subsidy to localized schemes may allow for better targeting and less windfall profits. We hope that future research makes progress regarding optimal policy design.

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Appendix A: Tables and figures

Table 6: *Charging Station Supply: First Stage*

Dependent variable	$ln(Q_{mt})$
ln(Distance between fuel stations$_m$) $\cdot$ ln(Fuel Price$_t$)	1.208***
	(0.226)
ln(Commuters$_m$) $\cdot$ ln(EV stock$_{-m,t-1}$)	0.067***
	(0.015)
ln(Δ Station Costs$_{mt}$)	-0.001
	(0.002)
ln(Per capita deficit$_{mt}$)	0.000
	(0.003)
ln(Length of state roads$_m$) $\cdot$ time trend$_t$	0.006
	(0.004)
Observations	3,376
F-Stat	22.01
Controls	Y
Year and Municipality FEs	Y

Notes: This table presents the first stage results for the IV regression in Table 3. Please note that we use inverse hyperbolic sine transformations instead of $ln(Q_{mt})$, ln(Fuel Station Distance$_m$) $\cdot$ ln(Fuel Price$_t$), and ln(Commuters$_m$) $\cdot$ ln(EV Stock$_{-m,t-1}$), and ln(ΔStation Costs$_{mt}$) because there are many zero values in the respective variables. Standard errors are clustered at the model-municipality and year level. ***(**,*) indicates statistical significance at the 1% (5%, 10%) level.

Table 7: *EV demand: First stage*

Dependent variable	$\ln(\mathrm{N}_{mt})$	$\ln(\mathrm{P}_{jt})$
$\ln(\text{State Roads}_m) \cdot \ln(\text{Fast Chargers}_{-m,t-1})$	0.031^{***}	0.000
	(0.002)	(0.000)
$\ln(\text{Shops}_m) \cdot \ln(\text{Slow Chargers}_{-m,t-1})$	0.035^{**}	0.000
	(0.016)	(0.003)
$\ln(\text{Income}_{mt})$	−0.083	−0.001
	(0.137)	(0.025)
$\text{Commuters}_m \cdot \text{Time Trend}_t$	-0.082^{***}	0.000
	(0.019)	(0.004)
$\ln(\text{Fuel price}_t) \cdot \ln(\text{Commute Time}_m)$	0.048	−0.001
	(0.055)	(0.016)
ln(Weight (other brands))	−0.025	-13.914^{***}
	(4.309)	(0.848)
ln(Length (other brands))	0.330	48.448^{***}
	(14.222)	(2.073)
ln(Fuel Cost (other brands))	0.041	−0.237
	(1.389)	(0.258)
ln(Models (other brands))	0.003	-2.400^{***}
	(0.785)	(0.124)
ln(Weight (own brand))	−0.003	-0.433^{***}
	(0.130)	(0.032)
ln(Length (own brands))	0.020	2.175^{***}
	(0.369)	(0.082)
ln(Fuel cost (own brands))	0.001	0.232^{***}
	(0.046)	(0.009)
ln(Models (own brands))	0.0001	-0.072^{***}
	(0.020)	(0.003)
Observations	55,290	55,290
Conditional F-Stat	53	11,893
Model-Municipality FEs	Y	Y
Year FEs	Y	Y

Notes: This table presents the first stage results for the IV regression in Table 2. Please note that we use inverse hyperbolic sine transformations instead of $ln(N_{mt})$, $ln(\text{State Roads}_m) \cdot ln(\text{Fast Chargers}_{-m,t-1})$, and $ln(\text{Shops}_m) \cdot ln(\text{Slow Chargers}_{-m,t-1})$ because there are many zero values in the respective variables. Standard errors are clustered at the model-municipality and year level. $^{***}(^{**},^{*})$ indicates statistical significance at the 1% (5%, 10%) level.

Table 8: *Available EV Models, 2012*

Model	Sales	Price	Weight	Length
500	184	201,095	903	3.55
C-Zero	511	205,538	1,114	3.48
C30	36	266,360	1,263	4.27
Focus	3,661	267,068	1,280	4.46
I-MiEV	659	205,005	1,110	3.48
iOn	406	203,898	1,116	3.48
Leaf	2,268	271,565	1,525	4.45
Mini	169	243,535	1,111	3.72
Partner	19	285,248	1,410	4.38
SLS AMG	1	3,041,214	1,660	4.64
Weighted average		**254,330**	**1,305**	**4.23**

Notes: This table presents the EV models sold in Norway in 2012 according to the data from the Norwegian Road Federation. We report total sales per year, together with average price (in 2015 NOK), average curb weight (in kilograms) and average length of the car (in meters).

Table 9: *Available EV Models, 2019*

Model	Sales	Price	Weight	Length
500	17	170,487	936	3.58
Ampera-e	1,057	295,939	1,616	4.16
Berlingo	1	284,606	1,424	4.50
C-Zero	122	130,307	1,065	3.48
DS 3 Crossback	6	291,629	1,304	4.12
e-Golf	9,197	287,274	1,540	4.27
e-Niro	719	334,477	1,737	4.38
e-NV200	575	296,787	1,613	4.56
EQ ForFour	44	169,946	1,125	3.50
EQ ForTwo	68	163,087	1,023	2.70
EQC	84	545,126	2,420	4.77
e-Soul	302	315,645	1,663	4.20
e-tron	5,377	579,043	2,489	4.90
e-up!	769	173,285	1,153	3.60
Focus	1,589	297,736	1,319	4.54
i3	4,851	255,325	1,274	4.01
I-MiEV	79	135,289	1,090	3.48
iOn	114	147,653	1,065	3.48
IONIQ EV	3,037	220,217	1,437	4.47
I-PACE	3,080	532,446	2,133	4.68
Kona electric	3,450	269,856	1,685	4.18
Leaf	6,127	245,487	1,542	4.49
Mini	72	254,394	1,207	3.90
Model 3	15,682	340,271	1,838	4.69
Model S	1,148	598,285	2,172	4.98
Model X	1,966	669,811	2,430	5.05
Soul EV	208	205,866	1,539	4.15
Zoe	2,090	221,119	1,498	4.09
Weighted average		**341,890**	**1,740**	**4.48**

Notes: This table presents the EV models sold in Norway in 2019, according to the data from the Norwegian Road Federation. We report total sales per year, together with average price (in 2015 NOK), average curb weight (in kilograms) and average length of the car (in meters).

Figure 6: *EV sales by municipality per 1,000 households (Norwegian Road Federation).*

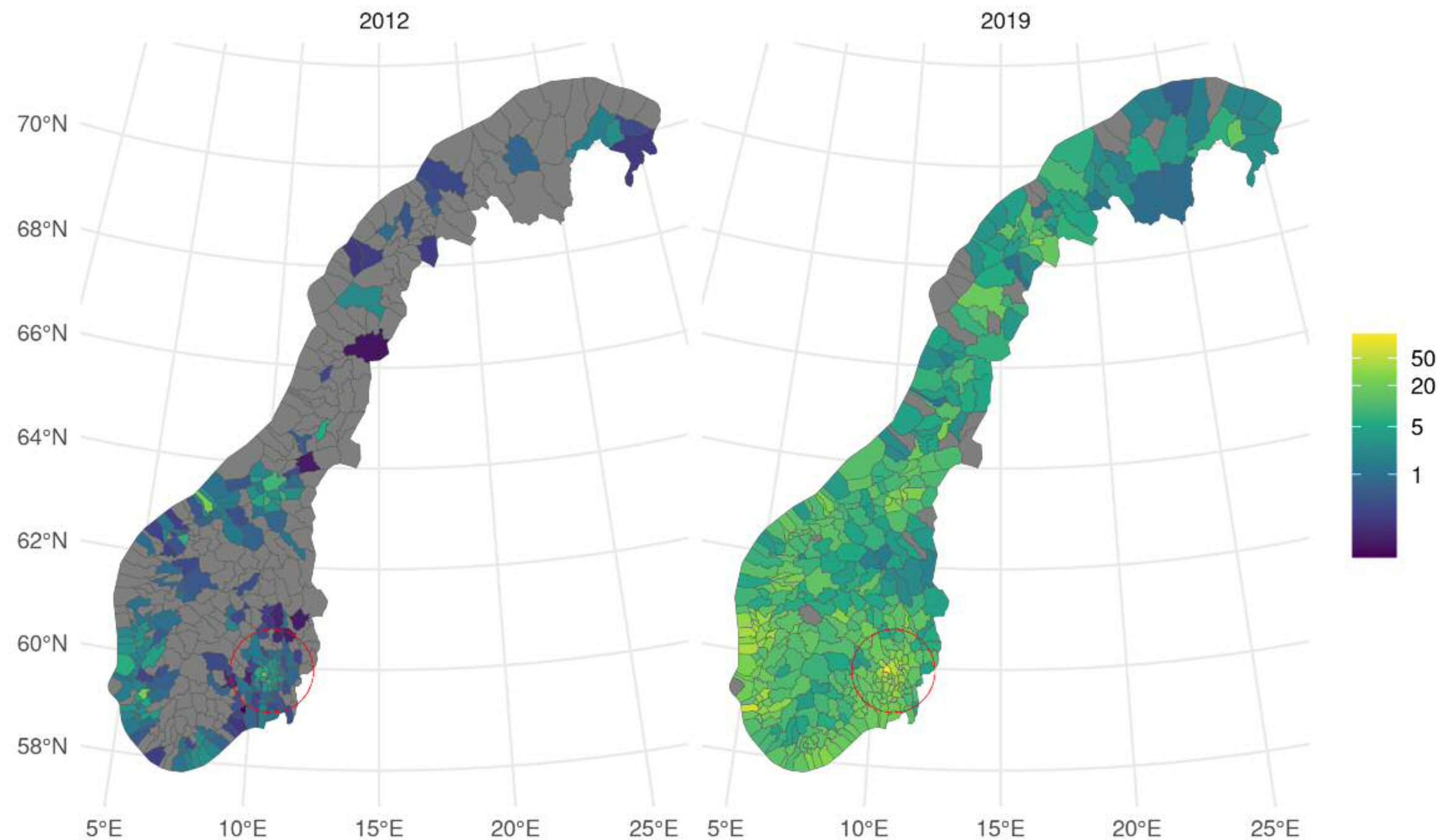
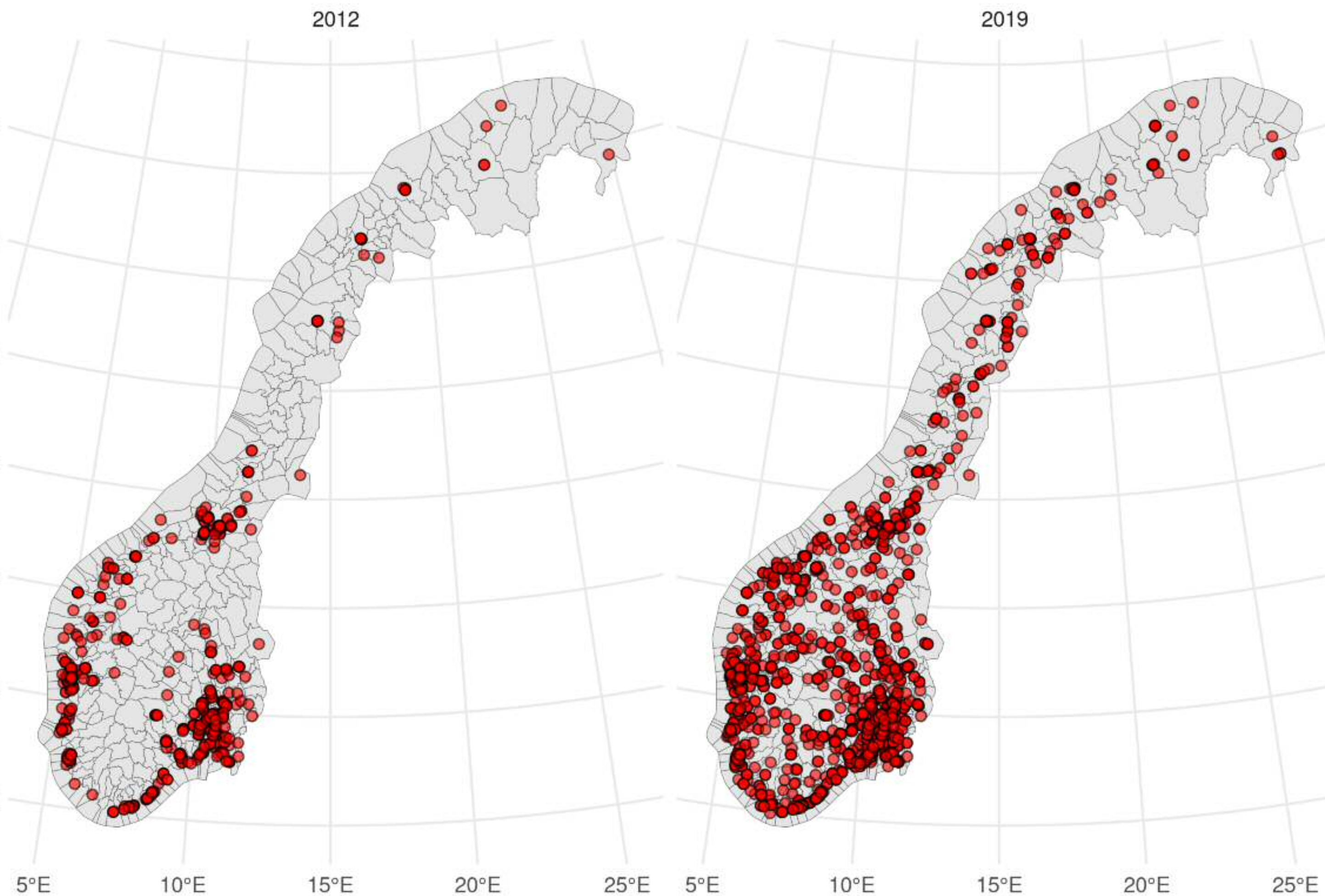


Figure 7: *Charging Stations across Norway (NOBIL)*



Appendix B: Data from Statistics Norway

Table 10: *Table codes of used variables*

Variable	Code
Scrapped vehicles	05522
Median household disposable income	06944
Stock of circulating electric vehicles and fleet share	07832
Number of EVs registered before 2012	07849
Consumer Price Index	08183
Electricity production in Norway	08308
Municipal size	09280
Average gasoline price	09654
Residents aged 20-66 who commute out of the municipality	11616
Kilometers of road per municipality	11845
Financial key figures for municipalities	12134