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

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For Online Publication

Appendix A Figures and Tables

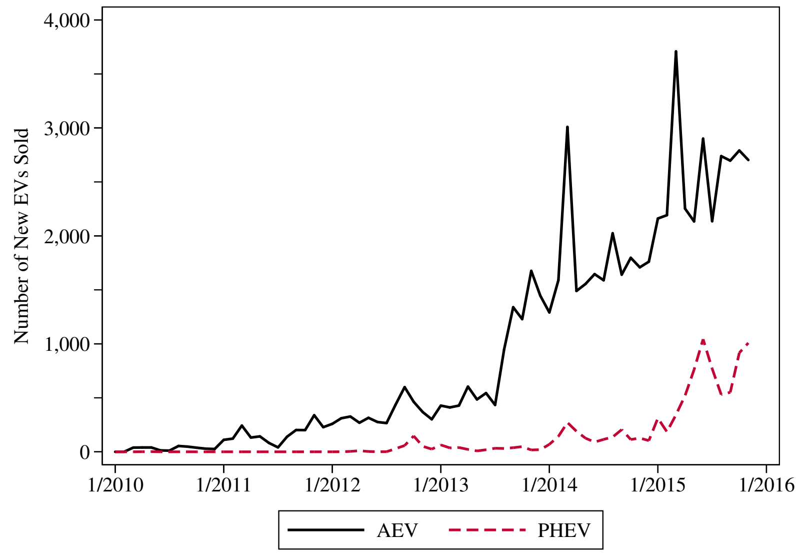
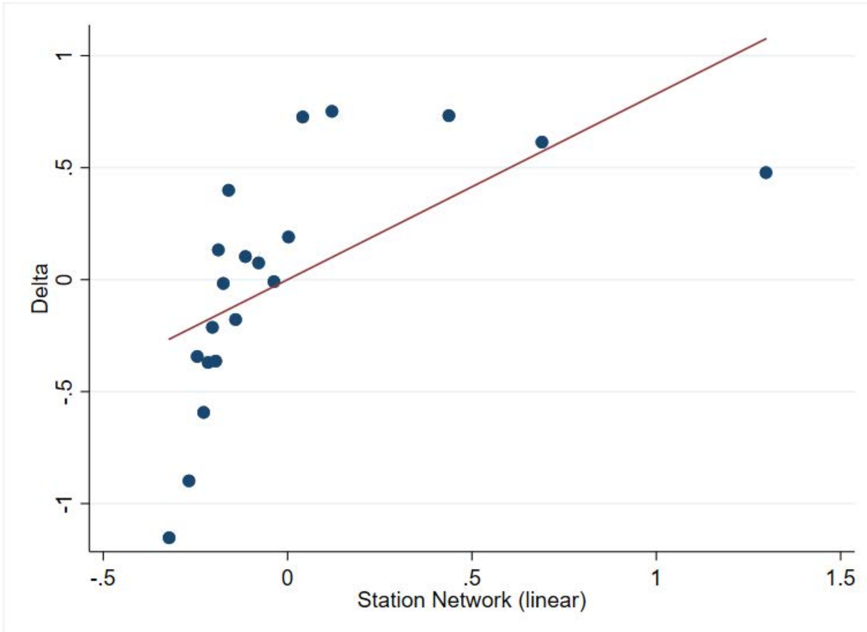
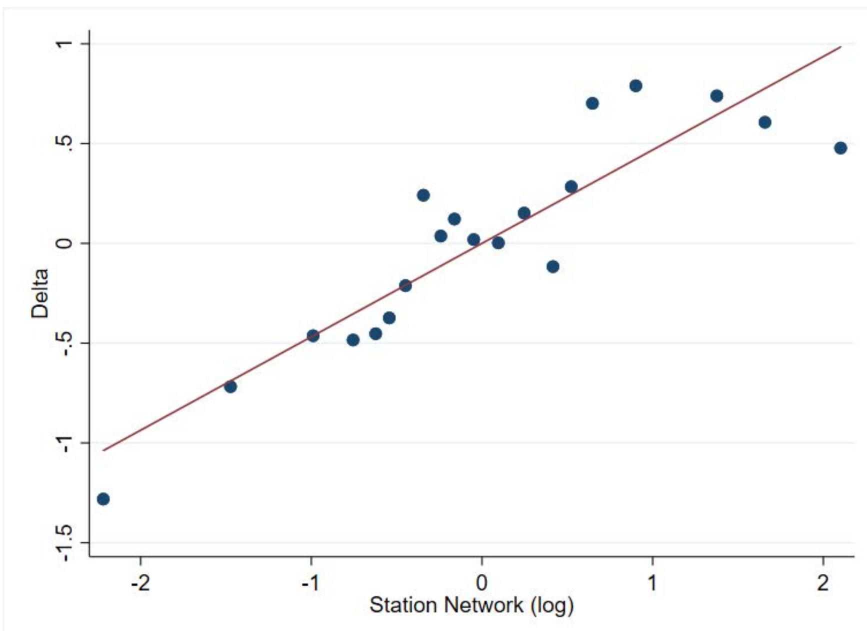


Figure A1: New Electric Vehicle Sales in Norway

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



(a) Linear Functional Form



(b) Log Functional Form

Figure A2: Consumer Utility and Station Network

Notes: Panel (a) plots the residualized values of consumer utility δ on the residualized values of the linear station variable under model (2) without random coefficients. The controls are: price/income, vehicle characteristics (fuel type, transmission, acceleration, size, consumption), and model, county and year fixed effects. Data are organized in 20 equal sized bins and their means are presented together with a linear fit line. Panel (b) shows an analogous plot where the station network variable is logged.

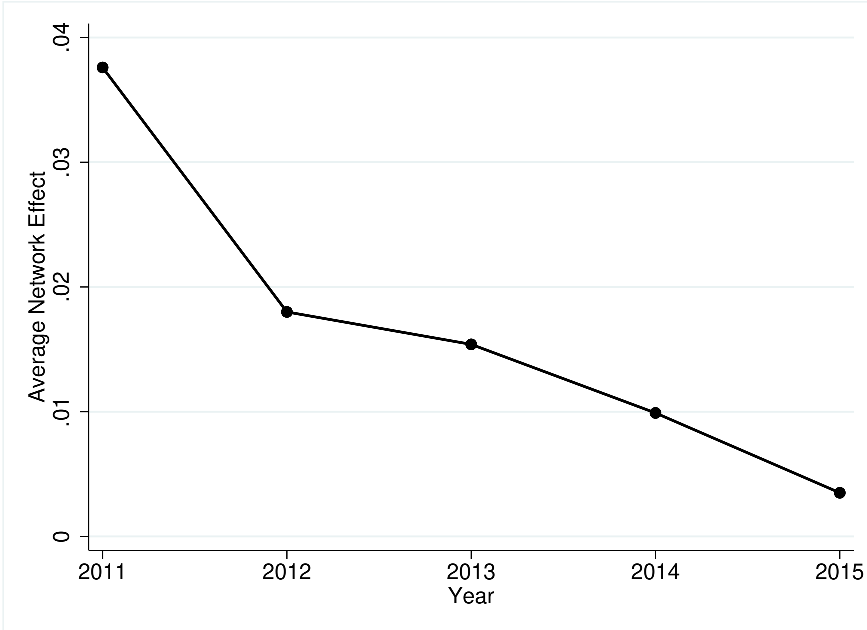


Figure A3: Estimated Network Effects Across Time

Notes: The figure shows the 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.

Table A1: Descriptive Analysis - Robustness Checks

	log(No. of Registered Cars)		
	[1]	[2]	[3]
EVSE Normal	-0.008		
	(0.001)		
EVSE Normal × Hybrid	0.041		
	(0.026)		
EVSE Fast	-0.001		
	(0.001)		
EVSE Fast × Hybrid	0.008		
	(0.008)		
Placebo EVSE Normal		0.000	
		(0.001)	
Placebo EVSE Normal × EV		-0.008	
		(0.010)	
Placebo EVSE Fast		-0.000	
		(0.000)	
Placebo EVSE Fast × EV		0.001	
		(0.001)	
Lead EVSE Normal × EV			-0.033
			(0.139)
Lagged EVSE Normal × EV			0.167
			(0.198)
Lead EVSE Fast × EV			0.006
			(0.014)
Lagged EVSE Fast × EV			0.016
			(0.015)
Observations	181,643	181,643	58,859
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 and Tax Incentives	Y	Y	Y
Macroeconomic Controls	Y	Y	Y

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

Table A2: Results from the IV Estimation: Vehicle Demand

Vehicle Demand	IV Logit
Price / Income	-2.008
	(0.230)
Log(Station Network)	0.664
	(0.111)
1st Stage	
Dep.var Price/Income	
F-statistic	550.87
p-value (F-statistic)	0.000
R-squared	0.966
Dep.var Log(Station Network)	
F-statistic	38.46
p-value (F-statistic)	0.000
R-squared	0.973

Notes: The table presents the coefficient estimates and standard errors from the IV Logit specification for the utility function. Unit of observation is model j in market m given by combination of county (c) and year (t). The dependent variable is $\log S_{jct} - \log S_{0ct}$. Based on 14,790 observations. County, model and time fixed effects are included. Standard errors are clustered by county. The instruments include electric vehicle supply equipment (EVSE) incentives, exogenous car characteristics and the cost-side instruments, as described in the text. Standard errors are reported in parentheses.

Table A3: Results from the IV Estimation: Station Entry

Station Entry	IV
Log(EV base)	0.159
	(0.034)
EVSE normal (10,000 NOK)	0.149
	(0.033)
EVSE fast (10,000 NOK)	0.001
	(0.004)
1st Stage	
F-statistic	26.30
p-value (F-statistic)	0.000
R-squared	0.947

Notes: The table reports the coefficient estimates and standard errors from the IV specification for station entry. Unit of observation is county (c) by year (t). The dependent variable is the logarithm of the number of charging points, $\log N_{ct}$. Based on 114 observations. Excluded instruments include concurrent gas station density and one-year lagged gas station density, as described in the text. County fixed effects and a time trend are included. Standard errors are reported in parentheses.

Table A4: Station Entry IV Estimation - Robustness Checks

	Station Entry									
	OLS	IV	IV	IV	IV	IV	IV	IV	IV	IV
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Log(EV base)	0.144	0.184	0.179	0.357	0.159	0.185	0.099	0.160	0.114	0.171
	(0.020)	(0.014)	(0.072)	(0.068)	(0.034)	(0.022)	(0.034)	(0.051)	(0.020)	(0.051)
EVSE Normal (10,000 NOK)	0.126	0.163	0.139	0.249	0.149	0.163	0.126	0.138	0.121	0.085
	(0.028)	(0.030)	(0.028)	(0.051)	(0.033)	(0.033)	(0.025)	(0.033)	(0.027)	(0.031)
EVSE Fast (10,000 NOK)	0.006	0.001	0.005	-0.009	0.001	0.001	0.008	0.002	0.002	0.001
	(0.004)	(0.004)	(0.004)	(0.007)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
1st Stage										
F-statistic	-	8.47	28.41	11.25	26.30	62.83	61.52	16.79	65.36	29.48
p-value (F-statistic)	-	0.003	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	-	0.810	0.954	0.913	0.947	0.793	0.956	0.909	0.948	0.960
Instrument: Gas Station Density	-	Y	Y	Y	Y	N	N	N	N	Y
Instrument: Bus Lane Incentive	-	N	N	N	N	Y	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Trend	N	N	N	N	Y	N	N	N	Y	Y
Macroeconomic Controls	N	N	Y	N	N	N	Y	N	N	Y
Population Density Controls	N	N	Y	N	N	N	Y	N	N	Y
House Price Controls	N	N	N	Y	N	N	N	Y	N	Y
Road Network Controls	N	N	N	Y	N	N	N	Y	N	Y

Notes: The table reports the coefficient estimates and standard errors from re-estimating instrumental variable regressions for station entry adding further controls and using an alternative local EV policy instrument. The dependent variable is the logarithm of number of charging outlets. Unit of observations is county c by month t. Based on 114 observations. All regressions include county fixed effects. Standard errors (reported in parentheses) are clustered at the county level. Excluded instruments in Columns [2]–[5] include (concurrent and lagged) gas station density, in Columns [6]–[9] include (concurrent and lagged) local non-monetary incentive granting EV drivers full access to bus lanes and in Column [10] include both sets of instruments. To measure the benefit from the bus lane incentive, I use the fraction of public roads that are dedicated bus lanes in each county and year. First stage R-squared and F-statistics are reported for all IV regressions. Column [1] presents results from the OLS regression with no instrumental variables. Column [2] shows the estimates obtained from the same specification using the gas station density instruments for the endogenous cumulative electric vehicle term. Column [3] includes macroeconomic and population density controls (Statistics Norway, 2016b,d,e). The additional macroeconomics controls such as median household income and unemployment rates help alleviate concerns that time-varying macroeconomic factors affect both the density of gas stations and the growth of new charging stations within a county. Column [4] adds road characteristics such as the total length of state, provincial, local and private roads within a county in a given year and a price index for detached houses to control for unobserved locational characteristics (Statistics Norway, 2016f,g). Column [5] show the estimates obtained from estimating Equation (10). The estimates from using bus lane access policy instruments are displayed in Columns [6]–[9]. The specifications in these columns follow the exact same patterns as the ones using gas station density instruments reported in Columns [2]–[5]. Finally, Column [10] includes all discussed controls and both sets of instruments.

Table A5: Results from the GMM Estimation using Local Incentive as IV for Stock of EVs

	Variable	Parameter Estimate	Standard Error
Panel A: Vehicle Demand			
Means	Price / Income	-3.5777	0.3296
	Station Network	0.4566	0.0116
Std. Deviations	Price / Income	1.2409	0.0978
	Station Network	0.0451	0.1286
Panel B: Station Entry			
Means	log(EV base)	0.1237	0.0301
	EVSE normal (10,000 NOK)	0.1218	0.0315
	EVSE fast (10,000 NOK)	0.0017	0.0022

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 the concurrent and lagged version of a local incentive (free access to bus lanes), as described in the text. County-specific fixed effects and a time trend are included.

Table A6: Robustness Check: Dynamic Model

	Vehicle Demand	
	Static	Dynamic
	[1]	[2]
Price/Income (-α)	-1.961	-2.015
	(0.192)	(0.209)
Station Network (γ)	0.648	0.669
	(0.092)	(0.088)
Annual Discount Factor (β)		0.000
		(0.001)
Observations	12,220	12,220

Notes: The table presents the coefficient estimates and standard errors from the De Groote and Verboven (2019) specification of the model. The unit of observation is model j in market m given by combination of county (c) and year (t). The dependent variable is $\log s_{jct} - \log s_{0ct}$. In column [1], the static version of the model is estimated ($\beta = 0$). In column [2], the discount factor β is estimated. The model also includes the vehicle characteristics: EV dummy, transmission, acceleration, size and consumption. The instruments include electric vehicle supply equipment (EVSE) incentives, exogenous car characteristics and the cost-side instruments, as described in the text. Standard errors are reported in parentheses.

Appendix B Electric Vehicle Charging Stations

All-electric vehicles (AEVs), sometimes referred to as battery-electric vehicles (BEVs), use onboard rechargeable batteries to store energy to power their electric motors. AEV batteries are charged by plugging the car in to an off-board electric power source. Drivers primarily charge their cars at home and sometimes use workplace or fleet charging, if available. In addition, AEV drivers also have access to the public charging station network with charging equipment installed at various places such as shopping centers, airports, hotels, restaurants, grocery stores and parking garages (Institute of Transport Economics, 2013).

Charging equipment is classified by the maximum amount of electric power the charger provides to the battery. There are three major categories: Level 1, Level 2, and DC fast charging (Institute of Transport Economics, 2013). Level 1 chargers provide charging through a 120 volt alternating current (AC) plug and do not require the installation of additional charging equipment as most AEVs are sold with a Level 1 cord set. Level 2 chargers provide charging through 240 volt for residential or 208 volt for commercial applications. Level 2 chargers, also referred to as normal chargers, require the installation of additional charging equipment. Based on the applications for support between 2009 and 2011 in Norway, Transnova estimated that on average the cost of equipment and installation for a Level 2 charger was around 20,000 NOK during this period of time (Transnova, 2014a). Level 1 and Level 2 chargers provide AC to the vehicle, which the car's onboard charging equipment converts to direct current (DC) and then feeds it into the vehicle's onboard battery.

DC Fast charging equipment, typically providing 480 volt AC three-phase input, provide DC directly to the car's onboard battery and offer the fastest charging speeds available today. DC fast chargers require highly specialized, high-powered equipment, significantly increasing equipment and installation costs. Transnova (2014a) estimated that the typical cost of establishing a fast charger ranges between 500,000–700,000 NOK, but costs can vary considerably depending on local conditions such as the site location, necessary excavation and foundation work, and whether grid reinforcement contributions are required. There are three main types of DC fast charging systems, commonly referred to as fast chargers, available today based on the type of charging outlet on the vehicle: SAE Combined Charging System (CCS), CHAdeMO, and Tesla.

Charging times vary substantially based on not just the type of the charging equipment but also the type of the vehicle's battery, how depleted the battery is, how much energy does the battery hold, and weather conditions (U.S. Department of Energy, 2015). Level 1 chargers can deliver 2 to 5 miles of range per hour of charging and they are typically used for residential charging purposes. Level 2 chargers can deliver 10 to 20 miles of range per hour of charging and are widely used for home, workplace and publicly accessible charging. DC Fast chargers can deliver 60 to 80 miles of range with just 20 minutes of charging. Given the substantial equipment, installation and maintenance costs involved, DC Fast chargers are typically used for publicly accessible charging options.

While the terms "charging station," "charger," and "charging point" are often times used interchangeably in the literature and in this paper, it is important to clarify the difference between them. A charging point, also called charging outlet or charging port, is the actual cord and plug used to charge a single AEV. The charger is the installation to which one or more charging outlets are attached. A charging station is a physical location consisting of one or more chargers. Unless otherwise stated, herein all references to "charging stations" or "chargers" refer to charging points.

Appendix C Estimation Methodology

GMM estimation The equilibrium for the model is defined by the number of operating charging stations N^* and the vector of vehicle market shares s^* that simultaneously satisfy the system of equations in (5) and (10).[1] I jointly estimate this system using the Generalized Method of Moments (Hansen, 1982), since some of the parameters enter in a nonlinear fashion. I construct a matrix of exogenous variables (Z_S and Z_D) where matrices Z_S and Z_D contain the exogenous variables and the instruments for the station and the consumer side, respectively. The instruments include the ones discussed before for the endogenous price variable (p), the endogenous station network term ($\log N$), and the endogenous cumulative electric vehicle base $\left(\log Q^{EV}\right)$.

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

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

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

[1] Note that in a two-sided market setting with network externalities, multiple equilibria are typical. The multiplicity of equilibria does not pose a challenge in the estimation of the system as long as market share data on both sides are observed and valid instruments are available. However, it can complicate the analysis of counterfactual policies. Nevertheless, there exist sufficient conditions that researchers can check to determine if multiplicity is posing an issue. For a more detailed discussion on the multiplicity issue in two-sided markets, see Song (2015).

$\hat{\xi}$ are estimates of ε and ξ based on the estimates of the parameters θ and λ, and

$$m = \begin{bmatrix} Z'_S & \hat{\varepsilon} \\ Z'_D & \hat{\xi} \end{bmatrix}$$

The difficulty in identifying and estimating the variances of the random coefficients is well-known (e.g. see the discussions in Gandhi and Houde (2019) and Conlon and Gortmaker (2019)). In this paper, I use the optimal instruments described in Reynaert and Verboven (2014) based on Chamberlain (1987) to address this issue. The Chamberlain (1987) optimal set of instruments are the expected value of the derivatives of the structural error term ξ with respect to the parameter vector θ that are evaluated at the initial estimate of the parameter vector $\hat{\theta}$. Reynaert and Verboven (2014) show that the use of this set of instruments greatly decreases bias and improves the efficiency and stability of the estimated parameters, in particular for the variances of the random coefficients. I implement the optimal instruments with a two-step procedure. First, I estimate the model using the standard inefficient instruments Z. Second, using the first-stage estimates, I derive the optimal set of instruments by evaluating the Jacobian of the mean utilities with respect to the parameter vector at the first-stage estimates. I then re-estimate the model with the optimal set of instruments. I repeat this process an additional time to ensure stability of the estimates.

In the estimation, I account for a variety of computational issues to which recent work has drawn attention (see Knittel and Metaxoglou, 2014) to ensure that my estimates are not stuck at a local minimum. First, I approximate the market share integral for each market using 200 draws of a Halton sequence, a quasi-random number sequence, as suggested by Train (2000).[2] Second, for the contraction mapping that equates observed to predicted market shares in the inner loop within the GMM objective function, I use a strict tolerance level of $1e^{-14}$. Third, the termination tolerance level on the GMM objective function value is fixed at $1e^{-6}$. Fourth, I use a very robust optimization method, the Nelder-Mead non-derivative simplex search algorithm. Fifth, I use a number of starting values to search for a global minimum, I document the presence of other local minima and I check that the GMM objective function value is higher at each of these local minima than at the global minimum. Finally, I verify the solution by checking the first-order and second-order conditions.

Counterfactuals In this section, I discuss issues relating to the existence and uniqueness of the equilibrium when conducting counterfactual simulations.

As discussed in the main text, the methodology to compare the effects of counterfactual incentive structures is as follows. First, either the subsidies for EV purchases or for charging

[2] Train (2000) finds that the simulation variance in the estimation of mixed logit parameters is lower with 100 Halton draws than with 1,000 random draws.

station entry are altered to a counterfactual level. Second, the parameter estimates from the GMM estimation are used to jointly determine the equilibrium number of charging stations and market shares in each county for each year. More precisely, recall that the equilibrium for a market is defined by the number of operating charging stations N^* and the vector of vehicle market shares s^* that simultaneously satisfy the system of equations in (5) and (10).

To establish the uniqueness of the equilibrium, one can combine the system of equations to define the following function:

$$s^* = T(s^*)$$

on the domain $[0,1]^J$, where for each $j = 1, ..., J$:

$$s_j^* = \int \frac{e^{u_{ij}(N(s^*))}}{1 + \sum_{l \in J} e^{u_{il}(N(s^*))}} dP$$

where u_{ij} is the utility consumer i receives from choosing model j. Since T is a combination of continuous functions, T is continuous on $[0,1]^J$. Therefore it follows by the fixed-point theorem that T has a fixed point on $[0,1]^J$, which establishes the existence of the equilibrium.

However, this does not necessarily imply uniqueness of the equilibrium. Since multiplicity of equilibria is a common issue in two-sided markets, I check for multiple equilibria when conducting the counterfactual simulations. Across the wide range of simulations, I did not find cases where there were multiple equilibria for a given set of subsidies. Therefore, conditional on each simulated set of subsidies, I simply report the results from the unique equilibrium that I find which solves the system of Equations (5) and (10).

Appendix D Subsidy Non-Neutrality in Two-Sided Markets

The EV market can be considered within the framework of two-sided markets, that is, a market in which one or several platforms facilitate interactions between two set of end-users.[3] The platform tries to get the two sides on board by appropriately charging each side, where the decisions of agents on one side affect the participation and welfare of agents on the other, typically through usage and/or membership externality (Rochet and Tirole, 2006). In the context of the EV industry, the platform can be thought of as the technology for EVs or the EV manufacturer like Tesla Motors or Nissan, while the two sides consist of buyers of EVs and electric charging station providers like Fortum Charge & Drive. The interaction between the two sides is the actual charging of an

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

automobile, a transaction not observed (in most cases) by the platform.[4]

Following the work of Armstrong (2006), the framework that best applies to the EV market is the pure membership externality model. Sometimes referred to as the indirect network effects model. Membership externalities are generated by membership decisions insofar as the benefits enjoyed by end-users on one side depend upon how well the platform does in attracting customers from the other group (Rochet and Tirole, 2006). This model is associated with the existence of transaction-insensitive end-user costs (or membership charges). There are no usage charges in this setting as the platform is not likely to observe transactions between the two sides of the EV market.[5] For other application of this model see Rysman (2004) or Argentesi and Filistrucchi (2007). Rysman (2004) estimates the importance of network effects in the market for Yellow Pages. Argentesi and Filistrucchi (2007) estimate market power in the Italian newspaper industry.

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

The baseline model presents the analysis for a monopoly platform with constant marginal cost serving both sides of the market. End-users on both sides (buyers and electric charging stations) are price takers in their relation to the platform who set the prices (EV manufacturer). I assume a simultaneous-move static game.[6] Network effects are only across (intergroup externalities) and not within (intragroup externalities) the two sides. This means that agents on one side only care about the number of users on the other.[7] In addition, I assume linear network effects.[8] Agents are

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

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

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

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

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

assumed to choose only one platform, the so-called "single-homing" assumption.

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

Each agent i on side $\mathcal{I}$ derives an inherent fixed benefit or cost $B_{\mathcal{I}}$, called membership value, from joining the platform, independently from the number of agents on the other side. Users are assumed to have heterogeneous membership values; this is the only source of heterogeneity allowed. $B_{\mathcal{B}}$ can be thought of as a fixed benefit obtained from owning an EV, it will depend on individual characteristics and product attributes.[9] $B_{\mathcal{S}}$ is the fixed cost stations on side $\mathcal{S}$ incur, thus it is likely that $B_{\mathcal{S}} < 0$ will hold. Furthermore, each agent i on side $\mathcal{I}$ enjoys a net transaction benefit $b_{\mathcal{I}}$ for every agent that joins the platform on side $\mathcal{J}$.[10] I assume that users have homogeneous interaction values ($b^i_{\mathcal{I}} = b_{\mathcal{I}}$ for each side $\mathcal{I}$).

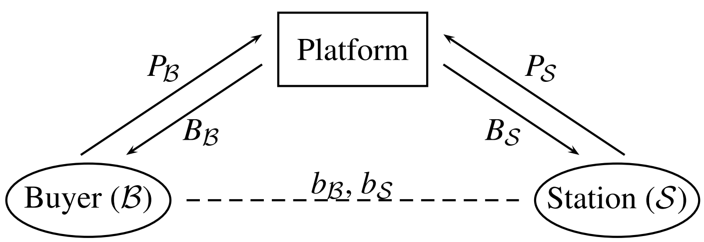

Figure D4: Graphical representation of the baseline model

End-users on side $\mathcal{I}$ pay a fixed membership fee $P_{\mathcal{I}}$ to the platform. These prices are assumed to be independent of the number of participating agents on side $\mathcal{I}$ or $\mathcal{J}$. $P_{\mathcal{B}}$ can be thought of as the purchase price for an EV. $P_{\mathcal{S}}$ is akin to a fixed fee that the car manufacturer might pay to the charging station providers to attract them, thus it is likely that $P_{\mathcal{S}} \leq 0$ holds. Turning to the cost side, the platform incurs a constant marginal cost $C_{\mathcal{B}}$ on side $\mathcal{B}$ (marginal cost of car manufacturing), while the marginal cost on side $\mathcal{S}$, denoted by $C_{\mathcal{S}}$, is assumed to be zero. Figure D4 highlights the discussed relationships between the end-users and the platform in this model.

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

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

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

are given by

$$U_{\mathcal{B}} = b_{\mathcal{B}} \times N_{\mathcal{S}} + B_{\mathcal{B}} - P_{\mathcal{B}} \tag{13}$$
$$\pi_{\mathcal{S}} = b_{\mathcal{S}} \times N_{\mathcal{B}} + B_{\mathcal{S}} - P_{\mathcal{S}}$$

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

$$N_{\mathcal{B}} = Pr(U_{\mathcal{B}} \geq 0) = \phi_{\mathcal{B}}(b_{\mathcal{B}}N_{\mathcal{S}} - P_{\mathcal{B}}) = \phi_{\mathcal{B}}(N_{\mathcal{S}}, P_{\mathcal{B}}) \tag{14}$$
$$N_{\mathcal{S}} = Pr(\pi_{\mathcal{S}} \geq 0) = \phi_{\mathcal{S}}(b_{\mathcal{S}}N_{\mathcal{B}} - P_{\mathcal{S}}) = \phi_{\mathcal{S}}(N_{\mathcal{B}}, P_{\mathcal{S}})$$

where I assume that the ϕ functions are continuously differentiable.

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

$$\pi_{\text{platform}} = \underbrace{(P_{\mathcal{B}} - C_{\mathcal{B}})N_{\mathcal{B}}}_{\text{profit from Buyers/Drivers}} + \underbrace{P_{\mathcal{S}}N_{\mathcal{S}}}_{\text{profit from Sellers/Stations}} \tag{15}$$

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

$$\overbrace{\underbrace{P_{\mathcal{I}}}_{\text{price}} - \underbrace{\frac{D_{\mathcal{I}}(N_{\mathcal{J}}, P_{\mathcal{I}})}{D'_{\mathcal{I}}(N_{\mathcal{J}}, P_{\mathcal{I}})}}_{\text{market power}} + \underbrace{b_{\mathcal{J}}N_{\mathcal{J}}}_{\text{external benefit}}}^{\text{marginal revenue}} = \underbrace{C_{\mathcal{I}}}_{\text{marginal cost}} \tag{16}$$

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

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

$$T = \tau_{\mathcal{B}}N^*_{\mathcal{B}}(\tau_{\mathcal{B}}, 0) = \tau_{\mathcal{S}}N^*_{\mathcal{S}}(0, \tau_{\mathcal{S}}) \tag{17}$$

Then buyer utility and station profits can be re-written as shown in (18) while the monopolist platform's profit function stays the same.

$$
\begin{aligned}
U_{\mathcal{B}} &= b_{\mathcal{B}} \times N_{\mathcal{S}} + B_{\mathcal{B}} - P_{\mathcal{B}} + \tau_{\mathcal{B}} \\
\pi_{\mathcal{S}} &= b_{\mathcal{S}} \times N_{\mathcal{B}} + B_{\mathcal{S}} - P_{\mathcal{S}} + \tau_{\mathcal{S}}
\end{aligned} \tag{18}
$$

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

$$
\begin{aligned}
B^i_{\mathcal{B}} &\sim_{iid} U[\mu_{\mathcal{B}}, \upsilon_{\mathcal{B}}] \\
B^i_{\mathcal{S}} &\sim_{iid} \pi[\mu_{\mathcal{S}}, \upsilon_{\mathcal{S}}]
\end{aligned} \tag{19}
$$

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

$$
\begin{aligned}
N_{\mathcal{B}} &= \hat{\phi}_{\mathcal{B}}(P_{\mathcal{B}}, P_{\mathcal{S}}, \tau_{\mathcal{B}}, \tau_{\mathcal{S}}) = \frac{1 + b_{\mathcal{B}} - P_{\mathcal{B}} - b_{\mathcal{B}} P_{\mathcal{S}} + \tau_{\mathcal{B}} + b_{\mathcal{B}} \tau_{\mathcal{S}}}{1 - b_{\mathcal{B}} b_{\mathcal{S}}} \\
N_{\mathcal{S}} &= \hat{\phi}_{\mathcal{S}}(P_{\mathcal{B}}, P_{\mathcal{S}}, \tau_{\mathcal{B}}, \tau_{\mathcal{S}}) = \frac{1 + b_{\mathcal{S}} - P_{\mathcal{S}} - b_{\mathcal{S}} P_{\mathcal{B}} + \tau_{\mathcal{S}} + b_{\mathcal{S}} \tau_{\mathcal{B}}}{1 - b_{\mathcal{B}} b_{\mathcal{S}}}
\end{aligned} \tag{20}
$$

In principle, participation rates need not be unique for given prices, however, under a set of regularity conditions, the system of equations above has a unique solution. Next, we can solve for the prices $\left(P^*_{\mathcal{B}}, P^*_{\mathcal{S}}\right)$ set by the monopolist platform by substituting in the expressions for participations rates given by (20) into the first order conditions of the monopolist platform. Once I obtain the prices I can express the equilibrium participation rates as

$$
\begin{aligned}
N^*_{\mathcal{B}}(P^*_{\mathcal{B}}(\tau_{\mathcal{B}}, \tau_{\mathcal{S}}), P^*_{\mathcal{S}}(\tau_{\mathcal{B}}, \tau_{\mathcal{S}})) &= \frac{2 + b_{\mathcal{B}} + b_{\mathcal{S}} - 2C_{\mathcal{B}} + 2\tau_{\mathcal{B}} + b_{\mathcal{B}}\tau_{\mathcal{S}} + b_{\mathcal{S}}\tau_{\mathcal{S}}}{4 - b^2_{\mathcal{B}} - 2b_{\mathcal{B}} b_{\mathcal{S}} - b^2_{\mathcal{S}}} \\
N^*_{\mathcal{S}}(P^*_{\mathcal{B}}(\tau_{\mathcal{B}}, \tau_{\mathcal{S}}), P^*_{\mathcal{S}}(\tau_{\mathcal{B}}, \tau_{\mathcal{S}})) &= \frac{2 + b_{\mathcal{B}} + b_{\mathcal{S}} - b_{\mathcal{B}} C_{\mathcal{B}} - b_{\mathcal{S}} C_{\mathcal{B}} + 2\tau_{\mathcal{S}} + b_{\mathcal{B}}\tau_{\mathcal{B}} + b_{\mathcal{S}}\tau_{\mathcal{B}}}{4 - b^2_{\mathcal{B}} - 2b_{\mathcal{B}} b_{\mathcal{S}} - b^2_{\mathcal{S}}}
\end{aligned} \tag{21}
$$

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

$$
\tau_{\mathcal{B}} N^*_{\mathcal{B}}(P^*_{\mathcal{B}}(\tau_{\mathcal{B}}, 0), P^*_{\mathcal{S}}(\tau_{\mathcal{B}}, 0)) = \tau_{\mathcal{S}} N^*_{\mathcal{S}}(P^*_{\mathcal{B}}(0, \tau_{\mathcal{S}}), P^*_{\mathcal{S}}(0, \tau_{\mathcal{S}})) \tag{22}
$$

Neutrality of the government subsidies holds if for *all pairs* $(\tau_{\mathcal{B}}, \tau_{\mathcal{S}})$ that satisfy Equation (22) it is true that $N^*_{\mathcal{B}}(\tau_{\mathcal{B}}, 0) = N^*_{\mathcal{B}}(0, \tau_{\mathcal{S}})$. By solving Equation (22) I find that there are always exactly two pairs of revenue equivalent subsidies for which neutrality is true (the degenerate case of zero subsidies and a non-degenerate case shown below) in this setting, for all other subsidy pairs neutrality fails.

$$\tau_{\mathcal{B}} = \frac{1}{4}(-2 - b_{\mathcal{B}} - b_{\mathcal{S}} + 2C_{\mathcal{B}}) + \frac{1}{4}\left(\sqrt{(2 + b_{\mathcal{B}} + b_{\mathcal{S}} - 2C_{\mathcal{B}})^2 + 8\tau_{\mathcal{S}}(2 + b_{\mathcal{B}} + b_{\mathcal{S}} - b_{\mathcal{B}}C_{\mathcal{B}} - b_{\mathcal{S}}C_{\mathcal{B}} + 2\tau_{\mathcal{S}})}\right) \tag{23}$$

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

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

Appendix E Consumer Effects of Subsidies (Details)

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

Denote the object of interest, the partial effect of the price of j on the cumulative all-electric vehicle base, by $\partial s^{EV}/\partial \tilde{p}_j$, where s^{EV} is the total share of EVs and $\tilde{p}_j$ denotes the price of the vehicle (without dividing by consumer income y_m) . Let I denote the number of households in the market, and EV denote the set of models which are all-electrical vehicles. Differentiating s^{EV} with respect to p_j and simplifying, I obtain

$$\frac{\partial s^{EV}}{\partial \tilde{p}_j} = \sum_{k \in EV} \eta_{kj} + \frac{\lambda_1}{Q^{EV}} \frac{\partial Q^{EV}}{\partial \tilde{p}_j} \sum_{k \in EV} \gamma_k \tag{24}$$

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

$$\eta_{kj} = \begin{cases} \int \frac{-\alpha_i s_{ij}(1-s_{ij})}{y_m} dP_v^*(v) & \text{if } j = k, \\ \int \frac{\alpha_i s_{ij} s_{ik}}{y_m} dP_v^*(v) & \text{otherwise.} \end{cases} \tag{25}$$

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

$$\gamma_j = \int \beta_i^N s_{ij}(1 - s_{ij}) dP_v^*(v) \tag{26}$$

Thus, Equation (24) shows the decomposition of cumulative all-electric vehicle sales into two terms. The first term is due to standard price elasticities of demand which would exist in a world without network effects, while the second term is due to the change in the size of the charging station network. Finally, isolating $\partial s^{EV} / \partial \tilde{p}_j$, I obtain the expression

$$\frac{\partial s^{EV}}{\partial \tilde{p}_j} = \frac{\sum_{k \in EV} \eta_{kj}}{1 - \sum_{k \in EV} \gamma_k \lambda_1 / s^{EV}} \tag{27}$$

Hence, the effectiveness of electric vehicle price subsidies is tied to the own- and cross-price elasticities of demand captured by η_{kj}, which, importantly, is not the case for charging station subsidies. Furthermore, the effectiveness of price subsidies is amplified by the network externalities, which are captured by the terms λ_1 and $\gamma_k(\beta_i^N)$.

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

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

$$\frac{\partial s^{EV}}{\partial EVSE} = \sum_{k \in EV} \gamma_j \lambda_2 + \frac{\lambda_1}{Q^{EV}} \frac{\partial Q^{EV}}{\partial EVSE} \sum_{k \in EV} \gamma_k \tag{28}$$

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

$$\frac{\partial s^{EV}}{\partial EVSE} = \frac{\sum_{k \in EV} \gamma_k \lambda_2}{1 - \sum_{k \in EV} \gamma_k \lambda_1 / s^{EV}} \tag{29}$$

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