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Policy Complementarities in the Promotion of Electric Vehicles

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**Policy Complementarities in the Promotion
of Electric Vehicles**

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Lavan T. Burra, Stephan Sommer, and Colin Vance¹

Policy Complementarities in the Promotion of Electric Vehicles

Abstract

To accelerate the electrification of the transport sector, many countries subsidize both the construction of public charging infrastructure and the purchase of electric vehicles (EVs). Possible complementarities between these measures raise the question of their optimal calibration. Drawing on county-level panel data from Germany spanning 2014–2021, this paper explores this question with an econometric model of EV uptake. Employing fixed effects- and instrumental variable estimators, we find that charging infrastructure has a positive and significant effect on the uptake, one whose magnitude increases with the subsidy level for car purchases. Simulations using the model estimates show how the predicted number of EVs for a given charging capacity level increase with higher consumer subsidies, allowing for a back-of-the-envelope calculation of the optimal expenditure of the two measures.

JEL-Codes: H23, L91, Q58

Keywords: Electric vehicles; charging capacity; consumer subsidy; calibration

April 2023

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1 Introduction

According to the Tinbergen principle, achieving a certain number of policy targets requires at least the same number of instruments (Tinbergen, 1952). If there are fewer instruments than targets, some policy goals will not be achieved. Conversely, if there are multiple instruments for a single target, complementarities between them may afford policymakers with opportunities to reach the target at lower expense, presuming that the instruments are appropriately calibrated.

This paper explores potential complementarities with respect to the effect of charging capacity on promoting electric vehicles (EVs) in Germany, and whether this effect varies according to the level of consumer subsidies extended for EV purchases. Since 2016, the German government has pursued a two-pronged approach to promote EV uptake that includes consumer subsidies and subsidies for the construction of public charging infrastructure. As of June 2020, the initial budget of €1.2 billion for both measures was more than doubled to €2.59 billion, with €2.09 billion allocated to consumer subsidies and the remaining €500 million to subsidies for charging infrastructure.

EV uptake in Germany has subsequently skyrocketed. According to statistics from the European Alternative Fuel Observatory (EAFO, 2022), the market share of new EV registrations reached 25.7% in 2021, compared to just 2.9% two years before. Given that EVs are increasingly considered to be instrumental in not only abating CO₂ emissions, but also in improving local air quality, the question arises as to the drivers of this growth. This especially applies to the respective roles played by consumer subsidies and subsidies for charging infrastructure, including their potential interaction and the extent to which their allocation is calibrated to maximize the return on public expenditure.

While a plethora of studies has focused on financial incentives for EV purchases and charging infrastructure individually (Coffman et al., 2017; Greene et al., 2020; Illmann and Kluge, 2020; Javid and Nejat, 2017; Jenn et al., 2018; Liao et al., 2017; Nazari et al., 2018; Sommer and Vance, 2021; Wee et al., 2018; Zambrano-Gutiérrez et al., 2018; Árpád Funke et al., 2019), relatively few have investigated them jointly. Exceptions include the

studies by Li et al. (2017), Springel (2021), and Li et al. (2022), all of which draw on panel data to investigate the determinants of EV uptake in the U.S., Norway, and China, respectively. A common conclusion reached by these studies is that subsidies for infrastructure are more cost-effective than those for EV purchases. Li et al. (2017) find that subsidizing charging stations is more than twice as effective as subsidizing consumer purchases on a per dollar basis in the U.S. Springel (2021) reaches a similar finding based on a structural equation model with Norwegian data, but she qualifies it by noting that the relation eventually inverts as government spending increases, because the marginal impact of infrastructure subsidies tapers off faster. Li et al.'s (2022) analysis of the Chinese market shows that investing in charging stations is nearly four times as effective as subsidizing consumer purchases in promoting EVs. A simulation analysis of the U.S. market by Cole et al. (2021) that evaluates different financial incentives corroborates these econometric results, pointing to the higher cost-effectiveness of charging infrastructure.

Our work builds on this small body of evidence by exploring complementarities in the German subsidization of EV purchases and charging infrastructure. We construct county-level panel data on monthly EV registrations from Germany covering the years 2014-2021, a period that straddles the introduction of the consumer subsidy in 2016 and two subsequent increases in 2019 and 2020. We specify an econometric model that allows for differential effects of charging infrastructure according to the subsidy level. To address the possible simultaneity of charging infrastructure and EVs, we employ two-stage least squares models using two instruments to account for endogeneity: the number of transformers along the electric grid at the county level, and the stock of subsidies allocated at the county level for charging infrastructure.

Among our key results, we find that charging infrastructure has a positive and statistically significant effect on the uptake of EVs, one that increases in magnitude with the increase in the subsidy level. Drawing on a technique suggested by King et al. (2000), we use the model estimates to simulate how the predicted number of EVs for a given charging capacity level increase with a higher consumer subsidy, which serves as a basis for calculating the optimal expenditure between these two measures. With reference to

the actual budget allocated between 2016 and 2021, this calculation reveals cost savings of up to 28% by shifting expenditures from consumer subsidies to subsidies for charging infrastructure.

The next section describes the data sets used for our analysis. Section 3 introduces the econometric model and identification strategy. Section 4 discusses the econometric estimates and results from the simulation. Section 5 uses the model estimates to calculate the optimal allocation of the government budget among the two subsidies to achieve the biggest budgetary return with respect to EV adoption in Germany. Section 6 concludes.

2 Data

The data is assembled from multiple sources that were merged via a Geographic Information System. Descriptive statistics are presented in Table 1. Data on the dependent variable, EV registrations, is obtained from the vendor IHS Markit, which provides counts of registrations by month and county. We consider all passenger EVs registered in Germany between January 2014 and October 2021. Given our focus on the impact of charging capacity, we limit the data to battery electric vehicles and exclude plug-in hybrids, owing to the latter’s partial reliance on fossil fuel and their flexibility in switching to an internal combustion engine (Illmann and Kluge, 2020; Sommer and Vance, 2021).

Figure 1 illustrates the uptake of EVs since 2014. In July 2016, the first iteration of the purchase-subsidy was introduced at €4000 per battery EV for cars priced under €60,000 (Table 2). In November of 2019, it was modified into a two-tier structure, with a subsidy of €6,000 for EVs priced under €40,000 and of €5,000 for those priced between €40,000 and €65,000. These two tiers were increased again in June of 2020 as part of the COVID-19 stimulus package, to €9,000 and €7,500, respectively. The number of registered EVs picked up momentum markedly over this time frame. An especially large jump in monthly registrations of 638% is seen by the outset of 2021, following the second increase in the subsidy six months prior.

Data on charging infrastructure is obtained by the Federal Network Agency BNetzA

Table 1: Summary statistics of the estimation sample

	Mean	St. dev	Min	Max
Monthly EV registrations	16.579	49.367	0.000	3454.000
Charging points (#)	38.859	84.322	0.000	1465.000
Total capacity (in 100 kW)	11.382	22.579	0.000	377.110
EV consumer subsidy (in €1000)	65.044	247.912	0.000	19551.3000
Infrastructure subsidy (in €1000)	7.3091	39.724	0.000	2561.823
No.of houses (# in 1000)	28.233	17.621	2.976	132.315
Purchase power pc (€1000)	23.161	2.885	16.880	36.737
Population density (persons/ km^2)	528.490	694.394	34.844	4806.476
Gasoline price (€/litre)	1.456	0.131	1.178	9.949
Age of population	44.983	1.956	40.200	51.200
No.of employees (# in 1000)	79.785	91.487	11.965	1413.970
Transformers (#)	15.180	26.211	0.000	445.000
New covid-19 cases	116.648	467.572	0.000	14550.000

Table 2: Consumer subsidies for battery electric vehicles in Germany

	EV price (in €)	Federal share of subsidy in €
Subsidy level-1 (Jul 2016 - Oct 2019)	<60,000	2000
Subsidy level-2 (Nov 2019 - Jun 2020)	<40,000 40,000-65,000	3000 2500
Subsidy level-3 (from Jun 2020)	<40,000 40,000-65,000	6000 5000

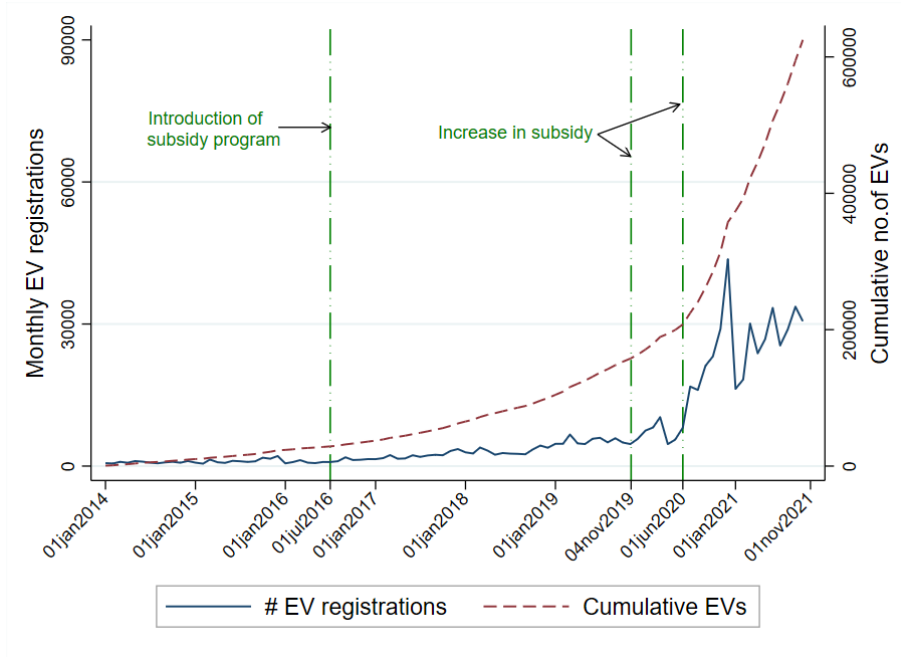


Figure 1: Evolution of electric cars in Germany

(BNetzA, 2021). All charging stations are documented by exact geographical locations and with detailed information on start date of operation, number of charging points, their type, and capacity. The Federal Ministry for Digital Affairs and Transport (BMDV) supports construction, modernization, and the associated grid connection of publicly accessible charging infrastructure by providing funding of up to a maximum of €20,000 per charging point depending on the capacity and a maximum of €100,000 for the grid connection per location, which is allocated through a competitive tendering process. By the end of October 2021, Germany had a total of 49,955 public charging points under operation, among which 84% are normal chargers with an average capacity of 21 kilowatts and the remaining are fast chargers with an average capacity of 100 kilowatts. In this study, we measure public charging infrastructure by the overall power capacity, following evidence that consumers value the rate at which they can charge their EVs more than the mere number count of these stations (Illmann and Kluge, 2020). Moreover, this serves to consolidate normal and fast charging stations, and is consistent with the capacity-based allocation of the subsidy. Figure 2 depicts the total capacity of the charging stock in kilowatts (kW) along with the cumulative subsidies extended for its construction.

The data is completed by several regional, time-varying control variables assembled

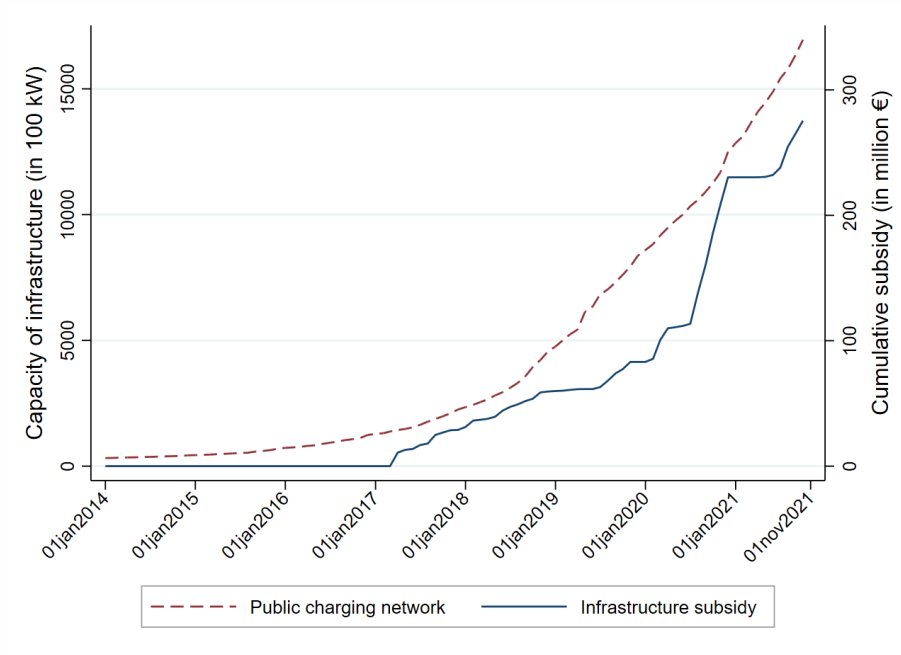


Figure 2: Temporal development of charging infrastructure

from different sources. The RWIGEO-GRID km^2 raster data (Breidenbach and Eilers, 2018) provides measures of the number of one and two family homes in a county, which proxies for the possibility of charging an EV at home. Two other demand side variables from this source are purchasing power and population density. Controls for the average age of the population and the number of employees are drawn from the GENESIS (2021) database. Last, we control for the deflated petrol price using data from the Market Transparency Unit for Fuel, which records fuel prices for each of Germany’s roughly 15,000 gas stations (see Frondel et al., 2020), as well as the 7-day-incidence rate of COVID-19 cases (RKI, 2022).

The data covers 94 months between January 2014 and October 2021. With 401 NUTS3 regions (counties), yield inga balanced panel with $N = 37,694$ observations.

3 Methodology

Our point of departure is a fixed effects model specified as:

$$EV_{it} = \beta_0 + \beta_c charge_{it} + \beta_{cs} charge_{it} \cdot sub_t + \mathbf{X}'_{it} \boldsymbol{\beta}_x + \lambda_{sy} + \mu_i + \rho_t + \varepsilon_{it}, \quad (1)$$

where EV_{it} is the number of electric vehicle registrations in county i and month t , $charge_{it}$ measures the total capacity (in kilowatts) of the charging infrastructure available for public use, and sub_t is the average subsidy a consumer would receive for purchasing an EV. By including an interaction between subsidy level and charging capacity, $charge_{it} \cdot sub_{it}$, we distinguish between the effect of public charging infrastructure at different subsidy levels. Vector \mathbf{X} contains the time-varying control variables. State-by-year fixed effects (λ_{sy}) control differential effects across states and years, while month fixed effects (ρ_t) control for differential effects across time, and county fixed effects (μ_i) capture time-invariant unobservable characteristics at the county level. The idiosyncratic error term ε_{it} captures unobserved shocks.

While the specification in Model (1) affords broad coverage of unobserved influences that could otherwise lead to omitted variable bias, endogeneity may nevertheless emerge given potential simultaneity in the relationship between charging infrastructure and the uptake of electric vehicles. To the extent that charging infrastructure is built where the prevalence of electric cars is high, for example, the estimates of β_c and β_{cs} would be biased. We address this potential source of simultaneity by instrumenting the measure of charging capacity and employing two-stage-least squares techniques to estimate Model (1). We draw on two instruments, denoted Z , employing these individually in separate models.

The first follows Springel’s (2021) analysis of the Norwegian EV market, which uses the volume of subsidies for the development of infrastructure at a regional level to instrument the charging station network. Correspondingly, we use the cumulative subsidy allocated for charging stations in each county and month as an instrument (denoted *station subsidies*). The second IV follows Sommer and Vance (2021) by using a measure of transformers along the electric grid at the county level, since they act as a regulator to bring down the transmission voltages that can be supported by charging points. As the number of transformers, which is obtained from georeferenced data provided by Geofabrik (2016), does not vary over time in our sample, we introduce temporal variation by interacting it with the lagged charging capacity in all counties other than the county cor-

responding to the given observation (denoted *transformers*), following a similar approach as Li et al.’s (2017) analysis of the US EV market.

The potential endogeneity of charging capacity also necessitates an instrument for its interaction with the subsidy, *sub*. Following Wooldridge (2001), we create instruments from the multiplication of *sub* with *transformers* and *station subsidy*. Model (1) is thus specified with two endogenous variables and two instruments, making it just identified.

The validity of the instruments rests on two assumptions pertaining to their covariance: (i) they are correlated with charging capacity, i.e. $cov(z_{it}, charge_{it}) \neq 0$, while (ii) they are not correlated with the error term, $cov(z_{it}, \varepsilon_{it}) = 0$. The first assumption, which is tested below for each instrument, comports with intuition. It is expected that more subsidies for charging infrastructure would be positively correlated with charging capacity. A positive correlation of charger capacity with transformers is also expected since they are used to step down the voltage from the distribution grid to the level supported by charging outlets (Brinkel et al., 2020; Khan et al., 2019).

The second assumption – the IV has no direct causal effect on the outcome – cannot be formally tested, but is plausible. There is no evident pathway through which transformers, of which most people are unaware, would affect EV purchases. Similarly, it is unlikely that subsidies for charging infrastructure would directly bear on EV purchases since these received scant press coverage and were generally known only to industry interests through government publications.

4 Results

Our discussion focuses on the relationship between charging capacity and the adoption of EVs, with the first stage IV estimates presented in the appendix. We turn first to Panel A of Table 3, which presents estimates of the average effect of charging capacity on the adoption of EVs, omitting its interaction with the subsidy level. The FE model in the first column indicates that deploying an additional capacity of 100 kW is associated with the adoption of one additional EV per county in the month of the deployment. Models (2) and

(3) instrument charging capacity using *Station subsidy* and *Transformers*, respectively, yielding estimates that are roughly double that of the FE model but that are similar to each other. The first stage F-statistics, at 32 and 9.8, respectively, provide some support for the strength of the instruments based on the conventional reference of 10, though they fall well below the threshold of 104.7 recently suggested by Lee et al. (2021). We consequently calculate the 95% confidence interval of the estimate of *Total capacity* based on the tF adjustment procedure proposed by the authors, which is robust to weak IVs. For Model (2) the estimates range between 1.317 and 2.918, while they cross zero for Model (3), ranging between -0.186 and 4.720.

Panel B of Table 3 presents models that account for the differential affects of charging infrastructure according to the EV subsidy levels using the interaction term as specified in Equation (1).¹ The findings across all models confirm a positive association of charging capacity with EV uptake, and one that increases with increases in the level of the consumer subsidy. As in Panel A, the estimated coefficients of the two IV models are higher than the FE model but are again similar to each other. The use of *Station subsidy* instrument is again seen to yield higher first stage F-statistics, but further application of the tF procedure is in this case precluded by the two endogenous variables in the specification, for which critical values have not been calculated. Moreover, with respect to the remaining control variables, most have expected signs or are statistically insignificant.

To glean more insights into the coefficient estimates, Figure 3 presents the corresponding marginal effects of charging infrastructure for each of the three subsidy levels for EV purchases. While the estimates using IVs are somewhat larger in magnitude than the standard FE estimate, the confidence intervals of all three estimates overlap. Moreover, the IV estimates differ only negligibly. Focusing on the differential effect of the consumer-subsidy, we note that during the first subsidy level, the FE estimates indicate that an increase of 100 kW in the charging capacity is associated with an increase of 1.08 EVs in the month following its deployment, with the effect roughly doubling to 2.15 EVs

¹Recognizing that including an interaction of two variables that vary within units in a FE regression may yield biased estimates, we follow a “double demeaning” approach as suggested by Giesselmann and Schmidt-Catran (2022).

Table 3: FE and IV estimation results for the uptake of EVs

	(1) FE		(2) FE-IV: <i>Station subsidy</i>		(3) FE-IV: <i>Transformers</i>	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Panel A. Models without interaction between infrastructure and EV subsidy						
Total capacity (100kW)	1.038***	(0.175)	2.118***	(0.347)	2.267***	(0.691)
Purchase power pc	4.500**	(2.222)	3.596*	(2.059)	3.471	(2.137)
Population density	0.128	(0.107)	0.219**	(0.100)	0.232**	(0.111)
Fuelprice	3.889	(2.702)	3.011	(2.123)	2.890	(2.167)
No.of houses	-0.259	(0.752)	-1.170	(1.260)	-1.296	(1.407)
Avg age of population	1.237	(5.287)	1.309	(4.729)	1.319	(4.752)
No.of employees	0.333	(0.561)	-1.734**	(0.798)	-2.019	(1.395)
New covid-19 cases	0.020***	(0.003)	0.010**	(0.004)	0.009	(0.007)
Constant	-222.126	(241.461)	-314.996	(235.557)	-330.687	(240.405)
Weak identification test	-		32.97		9.42	
No. of observations	37293		37293		37293	
Panel B. Models with interaction between infrastructure and EV subsidy						
Total capacity (100kW)	0.478***	(0.181)	0.809***	(0.251)	0.893	(0.602)
Total capacity \times EV subsidy	0.305***	(0.037)	0.470***	(0.095)	0.483***	(0.169)
Purchase power pc	5.095**	(2.289)	4.885**	(2.086)	4.821**	(2.180)
Population density	0.038	(0.074)	0.044	(0.057)	0.049	(0.077)
Fuelprice	3.618	(2.638)	2.958	(2.195)	2.860	(2.150)
No.of houses	-0.879	(0.987)	-1.747*	(0.986)	-1.863*	(1.097)
Avg age of population	1.091	(5.353)	1.055	(4.828)	1.056	(4.772)
No.of employees	1.561***	(0.402)	1.011*	(0.608)	0.857	(1.201)
New covid-19 cases	0.015***	(0.003)	0.007	(0.004)	0.005	(0.007)
Constant	-263.981	(243.076)	-194.094	(194.205)	-145.441	(254.113)
Weak identification test:	-		10.61		8.01	
First-stage:Charging capacity						
Weak identification test:	-		29.75		14.38	
First-stage:Capacity \times EV subsidy						
No. of observations	37293		37293		37293	

Notes: The dependent variable is monthly EV registrations in all model specifications. For IV models, measure of the cumulative subsidy amount granted for charging stations was used as an instrument for model specification in column (2), and count of transformers interacted with the lag of national charging points as an instrument for model specification in column (3). EV subsidy is expressed in €1000. All models include the same set of fixed effects: year-month FEs, county level FEs, and year-bundesland FEs. The Sanderson-Windmeijer multivariate F-statistic is reported for each of the first-stage regressions in panel-B. Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

by the third subsidy period. A similar increase is indicated by the IV models.

Moving beyond the coefficient estimates, Figure 4 presents the predicted outcomes and associated 95% confidence intervals using a statistical simulation approach suggested by King et al. (2000). The method employs a sampling procedure akin to Monte Carlo

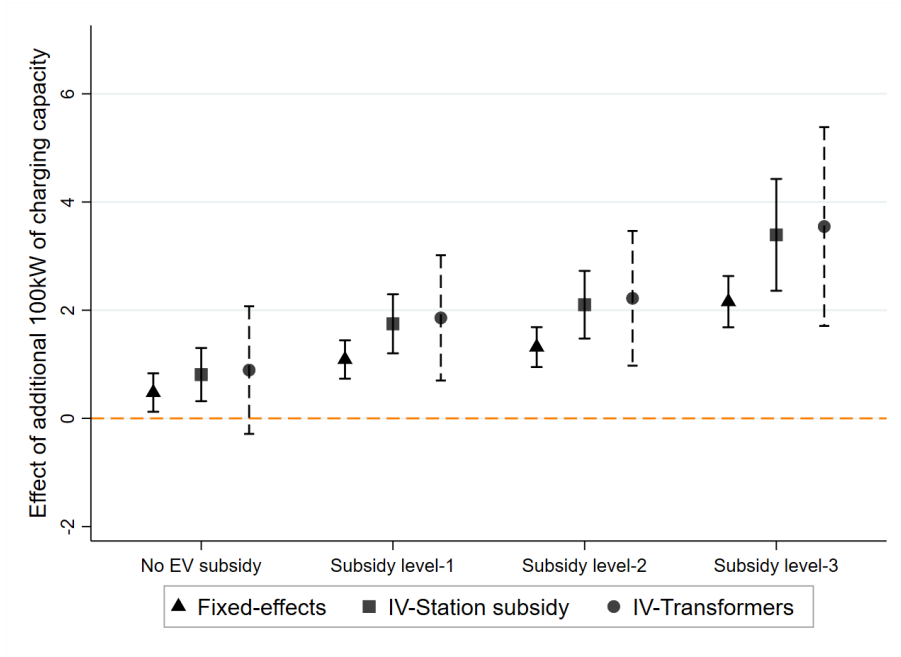


Figure 3: Marginal effect of charging infrastructure on the uptake of EVs in various subsidy periods

simulation in which a large number of values — say 1000 — of each estimated parameter is drawn from a multivariate normal distribution. Taking the vector of coefficient estimates from the model as the mean of the distribution and obtaining the variance from the variance–covariance matrix, each of the 1000 simulated parameter estimates can be multiplied by corresponding predetermined values of the explanatory variables to generate 1000 expected values. Ordering these values from lowest to highest and then referencing the 5th and 95th positions in the array yields the point estimates and confidence intervals plotted in the figure.

The figure presents predicted EVs for the range of charging capacity observed in the data over three levels of the subsidy, evaluated at the mean of the other explanatory variables. For a given level of charging capacity, the predicted number of EVs is seen to increase substantially as the subsidy increases. Moving from the zero purchase-subsidy level to a subsidy of €5,500 results in a nearly fourfold increase in EVs for any given level of charging capacity².

The trade-offs inherent in balancing consumer subsidies with subsidies for charging

²The subsidy of €2,000 per car and €5,500 per car correspond to the average subsidy for purchasing an EV in the subsidy periods 1 and 3 as reported in Table 2.

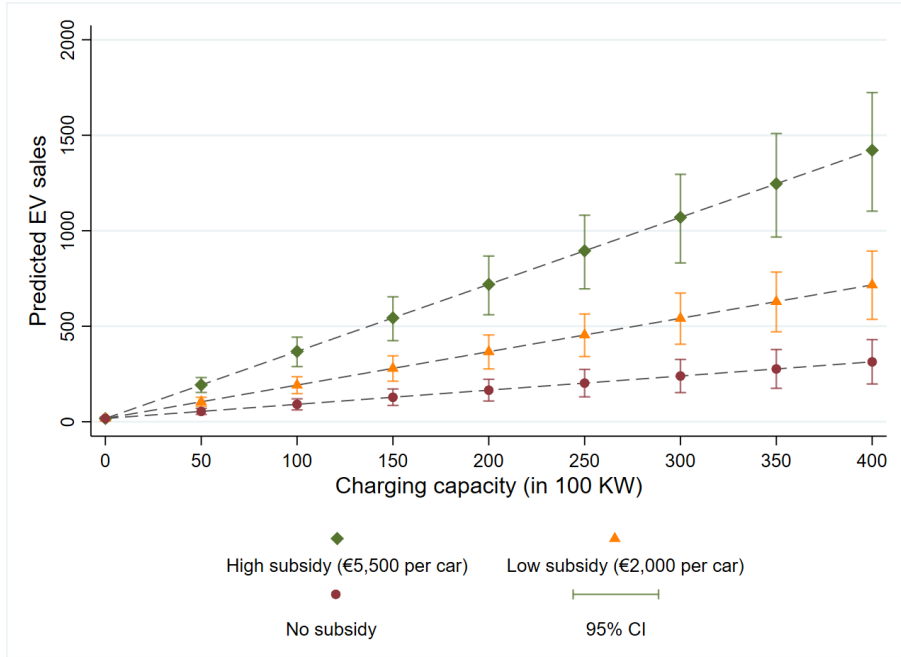


Figure 4: Predicted effect of charging infrastructure on the uptake of EVs by subsidy level

capacity can be illustrated by a simple optimization exercise that assumes a target level of 75 EVs per county, which corresponds to the sample average in the final month of the data. We further assume spending of €175/kW for charging infrastructure subsidies, which is estimated by dividing the total construction of charging infrastructure (1,557,500 kW) between 2017 and 2021 by the total spending on subsidies (€275 million). With these figures in hand, coupled with the estimated relationship between charging capacity and EVs, it is possible to estimate the total outlay per EV for different levels of consumer-subsidy and charging capacity. Generating such estimates is, of course, an approximate undertaking for which caveats abound. Aside from the uncertainty underpinning the econometric estimates, these caveats include the neglect of general equilibrium effects. Nevertheless, the simulated predictions suggest a reasonable basis for obtaining an indicative measure of total costs per EV.

Figure 5 presents the resulting plot, with the points along the line indicating different combinations of consumer subsidy and charging capacity that correspond to an uptake of 75 EVs per county. In this example, the minimum total cost per EV is €8,300, which occurs at a capacity of 2000 kW and a purchase-subsidy of €4,155³. The figure thus

³The optimization calculation is carried out with an objective of minimizing the overall spending per

highlights how the overall effectiveness of the two types of subsidies changes depending the budget allocation.

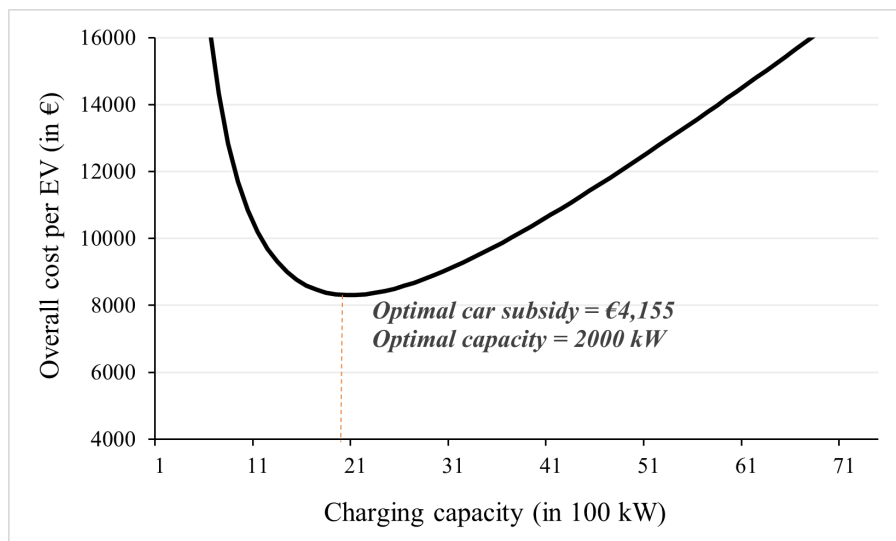


Figure 5: Relation between money spent per car and charging capacity for a given number of EVs (in this case 75 per month)

5 Optimal Calibration of Subsidies

The complementarity between subsidies for charging infrastructure and EVs evidenced by the econometric results raises the question of the optimal budget allocation between these two subsidies to minimize the overall spending and thereby yield the biggest ‘bang for the buck’ for policymakers in reaching a target EV market. Using the optimization logic underpinning Figure 5, we pursue this question with respect to the period between 2016 and 2021, when approximately 600,000 EVs were registered in Germany and €2725 million was expended in subsidies for charging infrastructure and EV purchases. In doing so, we assume that 85% of the EVs will receive the price subsidy, consistent with the current proportion of EVs that are subsidized in Germany (Sommer and Vance, 2021).

Table 4 shows the breakdown of this spending, with €2450 million allocated to the consumer subsidy and €275 million allocated to the infrastructure subsidy, resulting in a 90/10 split in favor of consumer subsidies. Recognizing the complementarity of this

EV using the excel solver.

measure with charging capacity, we calculate that the same number of EVs could have been reached with a total expenditure of €1944 million, a savings reduction of 28%. Achieving this would have required a 318% increase in spending on the infrastructure subsidy coupled with a 67% decrease in spending on the consumer subsidy, resulting in a roughly 40/60 split in favor of the latter.

Table 4: Calibration of optimal consumer and station subsidies

	Actual money spent by the government (in million €)	Cost-effective mix of subsidies (in million €)
EV consumer subsidy	2450 (90%)	794 (40%)
Infrastructure subsidy	275 (10%)	1150 (60%)
Total amount	2725	1944

It bears noting that this calibration likely reflects a conservative estimate of the effectiveness of the public charging infrastructure because the installed capacity will continue to contribute to future EV sales that are not accounted for in the calculation. Overall, this finding is in line with the studies of Li et al. (2017), Springel (2021), and Li et al. (2022), all of which suggest that subsidizing charging infrastructure is more effective than consumer subsidies on a per dollar basis in promoting electric vehicle adoption.

6 Conclusion

Over the last decade, the development and adoption of electric vehicles have increased significantly in many countries, being widely seen as a key pathway to a low-carbon future. To facilitate the acceleration of electric vehicle adoption, governments have implemented various subsidy programs. This paper explores the promotion of electric mobility via subsidies for charging infrastructure and electric vehicles (EVs), as well as their interaction. To this end, we use German panel data on vehicle registrations spanning January 2014 to October 2021 to quantify the effect of public charging capacity on the uptake of EVs, allowing differential estimates according to the level of the consumer subsidy. Due to the potential endogeneity of charging capacity, we implement fixed effects estimators coupled with two-stage least squares.

Using two distinct instruments, we obtain a tight range of estimates that suggest a positive impact of charging capacity on the uptake of EVs, one that increases in magnitude as the consumer subsidy increases. Between 2016 and 2021, when 600,000 EVs were registered, roughly 90% of the budget of €2725 million was allocated to consumer subsidies, with the remaining 10% allocated to infrastructure subsidies. Using the model estimates, we calculate total cost savings of €780 million, or an 28% reduction, given a budgetary split of 40/60. These findings point to the complementarity between the two measures, which if recognized in budgetary planning, can lead to substantial cost savings.

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APPENDIX

Table A1: First stage estimation results of models omitting interaction

	(1) IV = <i>Station subsidy</i>		(2) IV = <i>Transformers</i>	
	Coeff.	Std. Err.	Coeff.	Std. Err.
<i>Station subsidy</i>	0.025***	(0.004)	-	-
<i>Transformers</i>	-	-	2.60e ⁻⁵ ***	(8.47e ⁻⁶)
Purchase power pc	1.137	(0.805)	0.904	(0.877)
Population density	-0.084**	(0.036)	-0.077**	(0.039)
Fuelprice	0.393	(1.536)	0.797	(1.770)
No.of houses	-0.120	(0.929)	0.278	(0.821)
Avg age of population	-0.433	(2.143)	0.643	(2.305)
No.of employees	1.405***	(0.256)	1.811***	(0.263)
New covid-19 cases	0.005***	(0.002)	0.009***	(0.002)
No. of observations		37293	37293	
Weak identification test: F-statistic		32.97	9.42	
Endogeneity test		12.00	3.96	

Notes: This table reports the first-stage regression results for model (2) & (3) of panel-A in Table 3. The dependent variable is charging capacity in both models. All models include the same set of fixed effects: year-month FEs, county level FEs, and year-bundesland FEs. Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A2: First stage estimation results of interaction model: $IV = Station\ subsidy$

	(1) Charging capacity		(2) Capacity×EV subsidy	
	Coeff.	Std. Err.	Coeff.	Std. Err.
<i>Station subsidy</i>	0.020***	(0.006)	0.004	(0.006)
<i>Station subsidy</i> ×EV subsidy	0.003	(0.002)	0.033***	(0.003)
Purchase power pc	1.163	(0.816)	0.817	(1.132)
Population density	-0.090**	(0.037)	0.064	(0.127)
Fuelprice	0.321	(1.491)	0.660	(2.516)
No.of houses	-0.082	(0.952)	1.276*	(0.715)
Avg age of population	-0.555	(2.183)	-2.238	(3.628)
No.of employees	1.513***	(0.249)	-0.619	(0.706)
New covid-19 cases	0.004**	(0.002)	0.013**	(0.005)
No. of observations	37293		37293	
Sanderson-Windmeijer multivariate F test	10.61		29.75	
Endogeneity test			9.02	

Notes: This table reports the first-stage regression results for model (2) of panel-B in Table 3. The dependent variable is charging capacity in column (1) and the interaction between charging capacity and subsidy in column (2). All models include the same set of fixed effects: year-month FEs, county level FEs, and year-bundesland FEs. Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A3: First stage estimation results of interaction model: $IV = Transformers$

	(1) Charging capacity		(2) Capacity×EV subsidy	
	Coeff.	Std. Err.	Coeff.	Std. Err.
<i>Transformers</i>	$1.52e^{-5}$ **	$(7.43e^{-6})$	$-8.70e^{-6}$	$(1.02e^{-5})$
<i>Transformers</i> ×EV subsidy	$5.70e^{-6}$ **	$(2.23e^{-6})$	$4.37e^{-5}$ ***	$(8.27e^{-6})$
Purchase power pc	0.883	(0.874)	-0.380	(1.130)
Population density	-0.081**	(0.040)	0.130	(0.163)
Fuelprice	0.675	(1.668)	1.395	(2.798)
No.of houses	0.361	(0.818)	2.599**	(1.155)
Avg age of population	0.478	(2.302)	1.105	(3.939)
No.of employees	1.857***	(0.258)	-0.450	(0.901)
New covid-19 cases	0.008***	(0.002)	0.029***	(0.007)
No. of observations	37293		37293	
Sanderson-Windmeijer multivariate F test	8.01		14.38	
Endogeneity test			2.72	

Notes: This table reports the first-stage regression results for model (3) of panel-B in table 3. The dependent variable is charging capacity in column (1) and the interaction between charging capacity and subsidy in column (2). All models include the same set of fixed effects: year-month FEs, county level FEs, and year-bundesland FEs. Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A4: Placebo estimation results

	EV registrations	
	Coeff.	Std. Err.
<i>Transformers</i>	$1.70e^{-5}$	$(1.56e^{-5})$
<i>Transformers</i> × EV subsidy	$-1.39e^{-6}$	$(1.4e^{-6})$
Purchase power pc	0.158	(0.276)
Population density	0.008	(0.008)
Fuelprice	0.782	(3.306)
No.of houses	0.193	(0.162)
Avg age of population	-0.141	(0.322)
No.of employees	-0.272	(0.177)
Constant	10.979	(20.353)
No. of observations	6126	

Notes: The dependent variable is the number of electric vehicle registrations. The model include the year-month FEs, county level FEs, and year-bundesland FEs. Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.