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# Policy complementarities in the promotion of electric vehicles: Subsidies and charging infrastructure

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## Abstract

Over the last decade, the development and adoption of electric vehicles have increased significantly in many countries and are leading the way 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 electric vehicles (EVs) and charging infrastructure as well as their interaction. To this end, we use German panel data on vehicle registrations spanning from July 2016 to December 2020. Based on dynamic panel methods, we find that charging infrastructure has a positive impact on the uptake of electric vehicles and that the magnitude of the effect increases with the subsidy level. We use our model estimates to calculate the optimal balance of subsidies for charging infrastructure and EVs, and conclude that policy has over-subsidized the latter by a factor of about 2.5.

*JEL codes:* C54, H54, O18, Q58, R48

*Keywords:* Electric vehicle, charging infrastructure, subsidy, policy design, dynamic panel model

## 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, then some policy goals will not be achieved. Conversely, if there are multiple instruments for a single target, then complementarities between them may afford policy-makers with opportunities to reach a given target at lower expense, presuming that the instruments are appropriately calibrated.

The present paper explores this latter circumstance with reference to the promotion of electric vehicles (EVs) in Germany. As in many countries, the German government has stipulated subsidies for both the purchase of electric cars and for the deployment of charging infrastructure to foster the penetration of electric vehicles. We use panel data on EV registrations spanning from July 2016 to December 2020, a period during which the subsidy for EV purchases was increased from 1.2 billion to 2.09 billion Euros. Over this same time period, the number of electric charging points increased by 728%, partly driven by a subsidy program for

the installation of public charging stations. We aim to understand the impact of charging infrastructure on the uptake of electric cars and identify how this interacts with the subsidy for the purchase of an electric car.

A plethora of studies in the literature are focused on understanding factors affecting EV adoption. Among various external factors, the availability of charging stations has been found to play a key role in affecting consumers' decision to purchase EVs across countries (Coffman et al., 2017; Greene et al., 2020; Javid and Nejat, 2017; Li et al., 2017; Liao et al., 2017; Nazari et al., 2018; Schulz and Rode, 2022; Árpád Funke et al., 2019). Studies using observational data from Switzerland (Brückmann et al., 2021), the U.S. (Li et al., 2017; Zhou and Li, 2018), Norway (Schulz and Rode, 2022), and China (Li et al., 2021) all find positive effects of charging infrastructure on the diffusion of electric cars.

The evidence from Germany likewise reveals that charging infrastructure is a binding constraint on a more rapid uptake of EVs. Drawing on a panel data spanning 2012-2017, Illmann and Kluge (2020) investigate the effect of public charging infrastructure on private EV registrations, distinguishing between different measures of charging infrastructure (i.e. by count, overall capacity and average capacity). By adopting a dynamic heterogeneous panel approach, the study indicates that potential EV consumers attach more importance to charging speed rather than mere number of stations, along with a positive long-run relationship. A study by Sommer and Vance (2021) complements these results, finding that charging infrastructure has a positive and significant effect on EV sales in Germany by means of a panel-IV approach. Additionally, they distinguish between the effects of fast and normal chargers, and identify heterogeneity across space.

Notwithstanding the consensus concerning the positive role of charging infrastructure on EV uptake, few studies have questioned their effectiveness relative to that of subsidies for the purchase of EVs, or have explored complementarities between the two. The study by Li et al. (2017) takes up the former question, concluding that a policy of equal-sized spending on the subsidization of charging station deployment would have been more than twice as effective as one promoting EV adoption. Springel (2021) examines the purchase decisions of consumers and the installation decisions of charging stations estimating a structural equation model with Norwegian data. Like Li et al. (2017), she finds that subsidizing charging stations is more than twice as effective as subsidizing consumer purchases on a per dollar basis. In more recent work on the Chinese market, Li et al. (2021) find that the effect of charging stations increases with increases in purchase subsidies. They calculate that investing in charging stations is nearly four times as effective as

subsidizing consumer purchases in promoting EVs.

Our work takes a similar tact. We specify an econometric model that allows for differential effects of charging infrastructure according to the subsidy level. Recognizing the possible simultaneity of charging infrastructure and EVs, we employ a two-stage least squares model to account for endogeneity. Our results suggest a positive and statistically significant effect of charging infrastructure on the uptake in EVs, one that increases in magnitude with the introduction of a higher purchase subsidy. We use the model estimates to examine whether the subsidy levels for EVs and charging infrastructure is well-calibrated. Similar to the studies cited above, our results indicate an imbalance, with the purchase subsidy being roughly 2.5 times higher than the optimal level.

## 2 Data

In Germany, the EV market share remains a small percentage of the overall nation’s vehicle fleet. According to statistics from the European Alternative Fuel Observatory (EAFO, 2020), the market share of new EV registrations in Germany is 13.3% (6.4% BEVs and 6.9% PHEVs) in 2020 compared to just 2.9% (1.7% BEVs and 1.2% PHEVs) in the previous year. To accelerate the transition to electric mobility, Germany has offered generous subsidies for EVs and has invested heavily in charging infrastructure. Extending the electric car purchasing support that was launched in 2016, the federal share of subsidy was doubled from July 2020 for both BEV and PHEV that are priced below €65000. Since then, there has been a significant uptake in the number of new battery electric and plug-in hybrid electric vehicle registrations (figure 1).

Our analysis of the relationship between charging infrastructure and the uptake of electric vehicles draws on data extracted from multiple sources. We obtain information on EV registrations from the Federal Office for Economics and Export Control (BAFA). BAFA is responsible for the subsidy program for EV purchases and so the data includes only the purchase of subsidized EVs, which constitutes about 83% of total EVs sold in 2020 (KBA, 2020). For our analysis, we consider only private EVs registered from July 2016 until December 2020. Electric cars registered with companies and the public sector are excluded as their purchasing rationales may not be comparable to private households. Moreover, business and public sector might have their own charging outlets close to their operating regions and thus role played by public charging infras-

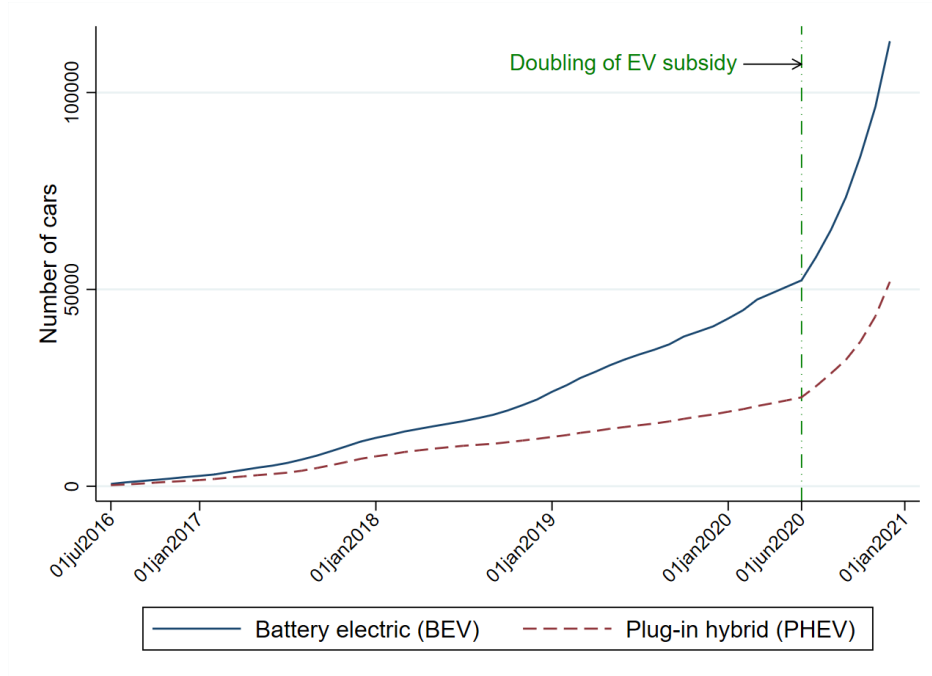


Figure 1: Evolution of electric cars

structure might differ<sup>1</sup>. Furthermore, the attention in this study is restricted to battery electric vehicles, as the rationale to purchase PHEV is different and their degree of dependence on public charging infrastructure has mixed evidence due to their flexibility of switching back to an internal combustion engine (Illmann and Kluge, 2020; Sommer and Vance, 2021).

Detailed information on the German public charging infrastructure is obtained from the Federal Network Agency (BNetzA, 2020). All charging stations are documented by exact spatial positions and provide detailed information on start date of operation, number of charging points, their type and capacity. BNetzA distinguishes between normal and fast chargers. Normal charging points (or level-2-chargers) have a maximum capacity of 22kW. These are the most common type of public charging points. In turn, fast charging points have a capacity ranging from 50 to 350 kW.

However, the range per hour of charging is subjective to size and state of battery, max charging rate of both vehicle and charge point, and environmental factors like temperature. The level-2 chargers may not be suitable for charging vehicles at an acceptable speed, thereby making frequent long-distance travel challenging. So, it is important to allow for nuances of charging points based on their capacity. Assuming that potential

<sup>1</sup>Sommer and Vance (2021) provide evidence that company owned electric cars rely less on public charging infrastructure

EV consumers would keep themselves informed about capacity of charging stations rather than just the mere number, we measure charging infrastructure by overall capacity in our estimation specifications. Nevertheless, we present models when charging infrastructure is measured by the count of charging points in the appendix.

We aggregate our data to the month and NUTS-3 level, yielding a balanced panel with  $N = 21,654$  observations, as Germany is divided into 401 NUTS3 regions (counties) and we observe data for 54 months between July 2016 and December 2020. Overall, we observe a total of 113,066 BEVs registered for eligible subsidies during our study period. Table 1 shows that a mean of 5.2 BEVs are purchased per county per month.

Table 1: Summary statistics of the estimation sample

	Mean	St. dev	Min	Max
Uptake of battery electric cars (#)	5.221	11.833	0.000	292.000
Uptake of plug-in hybrids (#)	2.399	6.182	0.000	229.000
Charging points (#)	42.565	80.923	0.000	1335.000
Total capacity (100kW)	11.852	19.821	0.000	309.510
No.of houses (# in 1000)	29.149	18.112	3.108	140.718
Purchase power pc (€1000)	23.631	2.785	13.756	35.382
Population density (1000/ $km^2$ )	0.533	0.700	0.035	4.702
Fuelprice (€/liter)	1.399	0.098	1.115	1.725
Grocery stores (#)	109.898	128.255	13.000	2054.000
Transformers (#)	15.180	26.211	0.000	445.000
Highway fuel stations (#)	0.868	1.414	0.000	8.000
No. of observations	21654			

By the end of 2020, Germany had a total of 38,627 public charging points under operation, among which 89% are normal chargers with an average capacity of 20 kW and the remaining are fast chargers with an average capacity of 107 kW. The average overall charging capacity available for EVs in a county was 2862 kW, the average charging capacity in a station is found to be 61 kW.

We illustrate the spatial distribution of EV registrations and the overall capacity of public charging infrastructure by county in Germany as of December 2020 in Figure 2. In general, we observe a higher concentration of electric cars towards western Germany, indicating the popularity of EVs in relatively dense areas. Highly dense cities like Berlin and Hamburg are observed to have higher overall charging capacity. Altogether, a positive association between EV registrations and charging infrastructure is visible from the

maps.

In addition, we use a large suite of further regional control variables that might affect the demand for electric vehicles. To this end, we use the RWI GRID Data, which entails rich information on a km<sup>2</sup> grid over Germany (Breidenbach and Eilers, 2018) and employ three variables. First, we use the number of one and two family homes in a county to proxy the possibility to charge an electric vehicle at home. Second, we use purchase power with the idea that higher incomes are more likely to afford an electric vehicle. Third, we control for population density, reflecting the idea that in urban areas the demand for electric mobility might be higher.

Further, we incorporate fuel prices in a county with the idea that higher fuel prices might be an incentive for potential car buyers to switch from a fossil-based engine to an electric one. The data is extracted from an online portal referred to as the Market Transparency Unit for Fuels which provides information on fuel price changes reported by owners of each fuel station in real time<sup>2</sup>. We aggregate this data across over panel dimensions and deflate it. The deflated mean petrol price in the sample is EUR 1.4. Finally, we control for total number of COVID-19 cases registered in each county to address for any shocks due to the recent pandemic.

### 3 Method

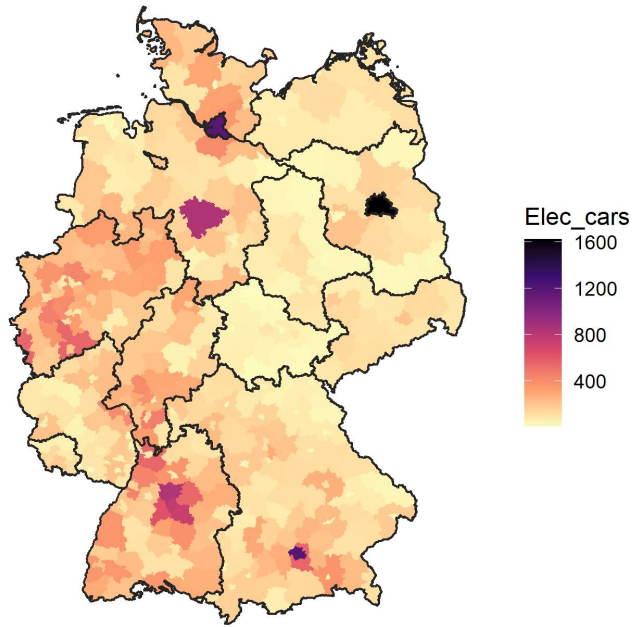
To analyze the effect of charging infrastructure on the uptake of electric cars, we exploit the panel dimension of our data set and use the following fixed-effects specification as our starting point:

$$ev_{it} = \beta_0 + \beta_c cap_{it} + \boldsymbol{\beta}_x \mathbf{X}_{it} + \theta_i + \mu_t + \lambda_{it} + \varepsilon_{it}, \quad (1)$$

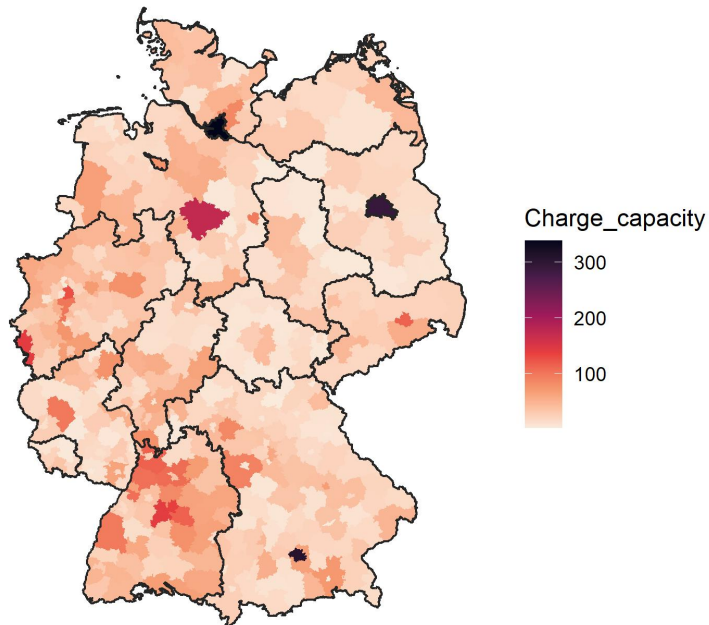
where  $ev_{it}$  is the number of electric vehicles purchased in county  $i$  in month  $t$  and  $cap$  is our main explanatory variable, namely the total capacity of the charging infrastructure. Vector  $\mathbf{X}$  contains our control variables from RWI GRID and the deflated fuel price. The vectors  $\theta_i$  and  $\mu_t$  denote county and year-month fixed-effects, respectively. Last, by including  $\lambda_{it}$ , we control for differential effects across states and years. The

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<sup>2</sup>More information on the Market Transparency Units for Fuels can be found at [https://bundeskartellamt.de/EN/Economicsectors/MineralOil/MTU-Fuels/mtufuels\\_node](https://bundeskartellamt.de/EN/Economicsectors/MineralOil/MTU-Fuels/mtufuels_node).



(a) Number of Electric cars



(b) Total capacity of charging infrastructure (100kW)

Figure 2: Dispersion of EVs and capacity of charging infrastructure across counties by December 2020.

time-specific intercepts ( $\theta_t$ ) control for any demand shocks at the national level, while the county fixed effects ( $\mu_i$ ) capture time-invariant unobservable characteristics at the county level. The idiosyncratic error term  $\varepsilon_{it}$  captures unobserved shocks.

We are particularly interested in the differential effect of the subsidy across time. To this end, we augment the above specification by an interaction between a dummy variable  $S$ , which equals unity after the amount of the subsidy was increased in June 2020 and zero otherwise, and charging capacity, i.e.  $cap_{it} \cdot S_{it}$ , yielding:

$$ev_{it} = \beta_0 + \beta_c cap_{it} + \beta_s S_{it} + \beta_{cs} cap_{it} \cdot S_{it} + \beta_x \mathbf{X}_{it} + \theta_t + \mu_i + \lambda_{it} + \varepsilon_{it}. \quad (2)$$

The reviewed literature (Illmann and Kluge, 2020; Li et al., 2017; Sommer and Vance, 2021) has shown that endogeneity issues loom large when analyzing the relationship between charging infrastructure and the uptake of electric vehicles. It is plausible that charging infrastructure is built where the prevalence of electric cars is high, in which case the estimates of  $\beta_c$  and  $\beta_{cs}$  would be biased. To address this, we pursue a two-stage-least-squares (2SLS) strategy, in which we first model the decision to install charging infrastructure ( $cap_{it}$ ) and subsequently estimate the above equations with an estimate for the endogenous variable. Estimating the first stage requires the use of an instrumental variable  $z_{it}$ .

There are two underlying assumptions an instrument needs to fulfill: First, an instrumental variable needs to be correlated with the endogenous variable, in our case the charging capacity, i.e.  $cov(z_{it}, cap_{it}) \neq 0$ . Second, the instrument should not bear on the dependent variable via other channels. Put differently, it should be uncorrelated to the error term,  $cov(z_{it}, \varepsilon_{it}) = 0$ . We follow Sommer and Vance (2021) and use the number of transformers along the electric grid at the county level as an instrumental variable<sup>3</sup> for charging infrastructure, since they act as a regulator to bring down the transmission voltages that can be supported by charging points.

Thus, we use one instrumental variable to instrument for the endogenous variable, yielding a model that is just identified. Yet, when we use the interaction term between charging infrastructure and the subsidy, beside the main effect, we also need to instrument the interaction. Thus, to estimate model (2) in the 2SLS version, we instrument the interaction term  $cap_{it} \cdot S_{it}$  by  $z_{it} \cdot S_{it}$  as recommended by Wooldridge (2001).

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<sup>3</sup>Since the count of transformers do not vary over time, we interact them with a linear year-month trend to allow for differential effects over time. Refer to Sommer and Vance (2021) for a more detailed explanation of the validity of the instrument.

Subsequently, we estimate a dynamic panel model to capture both short-run and long-run relationship between charging infrastructure and EV adoption. Under the assumption that future EV registrations do not influence past values, we introduce a lagged dependent variable that represents EV registrations observed in the previous time period. This implies that time-varying errors are uncorrelated with current and lagged values of the regressor but may be correlated with future values. Let  $ev_{i,t-1}$  be the count of BEVs in a county  $i$  at time  $t - 1$ , then equation (1) would be transformed to:

$$ev_{it} = \beta_0 + \beta_l ev_{i,t-1} + \beta_c cap_{it} + \beta_x \mathbf{X}_{it} + \theta_t + \mu_i + \lambda_{it} + \varepsilon_{it}. \quad (3)$$

Including a lag dependent variable would raise the issue of correlation between  $ev_{i,t-1}$  and fixed-effects in the error term, resulting in dynamic panel bias (Nickell, 1981) and thus violating one of the assumptions of classical linear regression estimation. However, Roodman (2009) suggest that for a panel data model with sufficiently large T, dynamic panel bias becomes insignificant with sufficiently large N. So, we use a straightforward fixed-effects estimator with a lagged dependent variable by assuming the bias to be negligible since we utilize a panel data with reasonably large N (=401) and T (=54) <sup>4</sup>. The instantaneous or short-term effect of charging infrastructure on EV registrations is captured by  $\beta_c$ . Since  $cap_{it}$  has an effect on  $ev_{it}$ ,  $cap_{it}$  will also have an effect on  $ev_{it+1}$  through the lagged dependent variable. Summing up all the short-term and delayed effects all the way to the infinite future, the cumulative effect of  $cap_{it}$  on  $ev_{it}$  will be  $\frac{1}{1-\beta_l} * \beta_c$ .

## 4 Results

This section presents estimates of equation (1) and (2) that investigate the effect of charging infrastructure on the uptake of EVs with and without accounting for the influence of purchase subsidy. Further, using equation (3) and thus by including a lagged dependent variable we distinguish between the short- and long-run relationship between charging infrastructure and EV adoption. All model specifications are estimated using standard FE model and FE model coupled with IVs to control for simultaneity and omitted variables.

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<sup>4</sup>According to Nickell (1981), the limit of  $(\hat{\beta}_l - \beta_l)$  as N tends to  $\infty$  can be approximated to  $\frac{-(1+\beta_l)}{(T-1)}$ : a negligible value for T=54. Even if  $\beta_l = 1$ , the bias will be -0.037 or about 1/27 of the true value.

Starting from a model with capacity of charging infrastructure and a set of time-varying macroeconomic controls, we then estimate a dynamic model. In the case of IV regression, we only report the second-stage results<sup>5</sup>. The findings across all models indicate that capacity of charging infrastructure has a statistically significant and positive effect on the uptake of BEVs (see Table 2). The FE estimates indicate that an increase of 100 kW in the charging capacity is associated with an increase of 0.187 BEVs in the month following its inclusion, with the estimate tripling to 0.566 in the instrumented case. Thus, it would take 177 additional kilowatts in order to observe one additional BEV per month. This is equivalent to roughly one fast charger or eight normal chargers. With regard to the strength and validity of instruments, Kleibergen-Paap rk Wald F statistic presented at the bottom of the corresponding model provide supportive evidence against the test for weak instruments.

Table 2: FE and IV estimation results for the impact of total charging capacity on the uptake of BEVs

	(1) FE		(2) IV - Transformers		(3) Dynamic FE		(4) Dynamic IV	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
L(Electric cars)	–	–	–	–	0.898***	(0.024)	0.844***	(0.040)
Total capacity (100kW)	0.187***	(0.032)	0.566***	(0.058)	0.057***	(0.010)	0.175***	(0.040)
Purchase power pc	0.574***	(0.147)	0.446***	(0.092)	0.184***	(0.047)	0.173***	(0.054)
Population density	2.061	(14.685)	32.178***	(12.347)	0.955	(4.871)	10.549	(6.896)
No.of houses	0.365***	(0.119)	-0.038	(0.090)	0.114***	(0.035)	0.016	(0.055)
Fuelprice	5.923**	(2.957)	-2.725	(2.515)	1.777	(1.361)	-0.470	(1.696)
New covid-19 cases	0.011***	(0.001)	0.008***	(0.001)	0.003***	(0.001)	0.003***	(0.001)
Constant	-25.163**	(10.672)	–	–	-8.722**	(3.741)	–	–
Year-month fixed effects	Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes	
Year * Bundesland	Yes		Yes		Yes		Yes	
Kleibergen-Paap rk								
Wald F statistic	-		164.536		-		133.245	
No. of observations	21654		21654		21253		21253	

Notes: Robust standard errors are reported in parenthesis. \*\*\*, \*\*, and \* denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

The coefficient on charging infrastructure gets relatively smaller when we include the autoregressive term. Moreover, we observe a significant effect of previous month's number of BEVs, indicating that visibility could have a strong influence in shifting behaviors towards electric cars. Along these lines, Illmann and Kluge (2020) speculate that consumers' decision to shift to electric mobility might be linked to some general factors like the presence of high enough peer pressure or when they encounter more electric cars in their

<sup>5</sup>Refer to tables A1 & A2 in the appendix for first-stage results.

neighbourhood or in the media.

Table 3: FE and IV estimation results for the impact of subsidy and total charging capacity on the uptake of BEVs

	(1) FE		(2) IV - Transformers		(3) Dynamic FE		(4) Dynamic IV	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
L(Electric cars)	—	—	—	—	0.785***	(0.021)	0.616***	(0.071)
Total capacity (100kW)	0.037**	(0.018)	0.337***	(0.055)	-0.001	(0.007)	0.144***	(0.036)
Total capacity*Subsidy	0.387***	(0.049)	0.557***	(0.097)	0.190***	(0.020)	0.330***	(0.091)
Subsidy	8.534***	(1.556)	15.845***	(1.713)	4.585***	(0.777)	8.846***	(1.125)
Purchase power pc	0.547***	(0.144)	0.412***	(0.090)	0.220***	(0.057)	0.228***	(0.061)
Population density	3.705	(13.384)	33.532***	(12.524)	1.772	(5.569)	17.606**	(8.586)
No.of houses	0.376***	(0.114)	-0.008	(0.084)	0.150***	(0.043)	0.020	(0.057)
Fuelprice	6.009**	(2.573)	-2.311	(2.259)	2.355*	(1.350)	-0.787	(1.659)
New covid-19 cases	0.007***	(0.001)	0.003*	(0.001)	0.002***	(0.000)	0.001	(0.001)
Constant	-25.794**	(9.983)	—	—	-11.045**	(4.361)	—	—
Year-month fixed effects	Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes	
Year * Bundesland	Yes		Yes		Yes		Yes	
Kleiberger-Paap rk	-		84.742		-		57.155	
Wald F statistic								
No. of observations	21654		21654		21253		21253	

Notes: Robust standard errors are reported in parenthesis. \*\*\*, \*\*, and \* denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

We subsequently estimate models that interact the EV purchase subsidy with the capacity of charging infrastructure, allowing for differential affects according to the subsidy by adopting the functional form as specified in equation (2). We find evidence for a statistically significant coefficient estimate on the interaction term, increasing the effect of total capacity of chargers in supporting EV adoption (see Table 3). From column (2), for example, it would take 297 kW of additional capacity without a subsidy, whereas, it would just need 111 kW of additional capacity to observe one additional EV per month when the purchase subsidy is implemented. Finally, we estimate equation (3), where we also include one-month lagged number of BEVs. A statistically significant coefficient estimate on the interaction term between the subsidy policy and charging infrastructure is seen, but the magnitude is smaller than the estimates without an autoregressive term.

Further, by adopting the model estimates from column (4), we explore the short- and long-run effects of local charging infrastructure with and without the interaction effects of subsidy and charging infrastructure.

The long-run effect of charging infrastructure is 2.6 (*i.e.*  $\frac{1}{1-0.616}$ ) times that of the short-run effect. Long-run increase in the uptake of BEVs resulting from an additional capacity of charging stations without a subsidy would still be less when compared to the uptake of BEVs resulting in the short run with the subsidy.

Table 4: Short- and long-run relationship between charging capacity and the uptake of BEVs

	Without subsidy	Subsidy is in effect
Short-run	0.144	0.474
Long-run	0.375	1.234

## 5 Optimal subsidy allocation

The estimation results provide an understanding on the impact of charging infrastructure and its interaction with purchase subsidy in influencing EV registrations. We now turn to the question of what should be the optimal allocation of government budget subsidies for EV purchases and for charging stations that would result in the biggest bang for the buck with regard to the EV adoption in Germany. Using the estimates from our econometric model, we determine the optimal allocation of EV budget among both types of subsidies for a given amount of government spending.

In 2016, the German government declared a budget of €1.2 billion to encourage EV car purchases via subsidies and €300 million for public charging infrastructure. We consequently take the total available government budget to be €1.5 billion in promoting electric cars. An optimal allocation is one that equalizes the marginal return per Euro spent on subsidies for charging infrastructure and EV purchases:

$$\text{Objective: } \frac{MR_{price\ sub}}{\epsilon_{price\ sub}} = \frac{MR_{charge\ sub}}{\epsilon_{charge\ sub}}$$

Recognizing that the total budget is given by:

$$\epsilon_{price\ sub} + \epsilon_{charge\ sub} = budget$$

and the marginal returns by:

$$MR_{price\ sub} = \frac{\partial EV}{\partial subsidy} = \beta_s + \beta_{cs}Cap_i$$

$$MR_{charge\ sub} = \frac{\partial EV}{\partial charge} = \beta_c + \beta_{cs}\epsilon_{price\ sub}$$

we can rewrite the optimizing equation as:

$$\text{Objective: } \frac{\beta_s + \beta_{cs}Cap_i}{\epsilon_{price\ sub}} = \frac{\beta_c + \beta_{cs}\epsilon_{price\ sub}}{\epsilon_{charge\ sub}}$$

We assume that, during our data period, the average subsidy for a normal charging point is set at €4000 and for a fast charging point at €12000<sup>6</sup>. Based on the information from government response to concerns raised online, as of August 2018, a total of 17000 charging points (14500 are normal and remaining 2500 are fast chargers) were approved for subsidy by the government which corresponds to €80 million of subsidy money. Using this relation between subsidy allocation and charging infrastructure, we assume a 6:1 split between normal and fast chargers over the study period. By the end of 2020, the capacity of charging infrastructure in a county can be expressed as a function of the station subsidy allocated by assuming the average capacity of normal and fast chargers would remain constant over the study period<sup>7</sup>.

Solving the above optimization problem results in an allocation of €417 million for EV purchase subsidy and €1.083 billion for charging station subsidy, a near reversal of the actual funding announced by the government. Put differently, the subsidy amount spent on charging infrastructure was in practice 0.25 times the amount spent on subsidies EV purchases, when an optimal allocation would have been 2.6 times that amount.

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<sup>6</sup>For more information on subsidy allocation for charging stations with different capacity levels, see [https://www.bav.bund.de/SharedDocs/Downloads/DE/LIS/Vierter\\_Aufruf\\_zur\\_Antragseinreichung.pdf?\\_\\_blob=publicationFile&v=4](https://www.bav.bund.de/SharedDocs/Downloads/DE/LIS/Vierter_Aufruf_zur_Antragseinreichung.pdf?__blob=publicationFile&v=4)

<sup>7</sup>We find an average capacity of 20 kW among normal charging points with more than 3.7 kilowatts and less than 22 kilowatts; 107 kw among fast charging points with more than 22 kilowatts.

## 6 Conclusion

Using extensive panel data from Germany, we have analyzed the effect of public charging infrastructure on the uptake of EVs. We use data on a subsidy program for the purchase of EVs that was implemented in July 2016 to foster the adoption of electric mobility. Initially, the program granted a subsidy of up to €4000 for the purchase of an EV. In July 2020, the subsidy was increased to €9000.

Our analysis suggests that there is a positive impact of charging capacity on the uptake of EVs. Moreover, we detect an increasing effect of charging capacity on the adoption of EVs. Consequently, both policies seem to be complements as the positive effect of charging infrastructure increases with the subsidy level. At the lower subsidy of €4000, the short-run elasticity of additional capacity amounts to 0.144, i.e. a 10% increase in capacity would increase the uptake of EVs by 1.44%. As expected, the long-run elasticity is much larger and amounts to 0.375. Both elasticities are substantially larger at the higher subsidy level. To be precise, the corresponding short-run elasticity amounts to 0.474 and the long-run elasticity to 1.234. Hence, a 10% increase in capacity would result in an increase of EV of 12.34%.

We can use our empirical results to provide some an insightful policy implication: Therefore, we assume that the government keeps the budget, which is currently channeled to the promotion of electric mobility fix at €1.5bn (€300m for charging infrastructure and €1.2bn for the uptake of cars). From a cost-effectiveness perspective this budget should be spent such that the marginal return per € spent on charging infrastructure equals the marginal return per € spent on EV subsidies. Yet, our calculations reveal that the optimal allocation is almost reverse to the current policy: Roughly €400m should be allocated for EV purchase subsidy and the remainder of €1.1bn should be used to subsidize charging infrastructure. Consequently, policymakers could get the biggest “bang for the buck” if they allocated more money to support the deployment of charging infrastructure.

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## APPENDIX

Table A1: First stage estimation results - charging infrastructure is measured by total capacity

	Dynamic IV - Without subsidy		Dynamic IV - With subsidy			
	(1) Charging capacity		(2) Charging capacity		(3) Charging capacity×Subsidy	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Transformers	0.002***	(0.000)	0.002***	(0.000)	-0.002***	(0.000)
L(Electric cars)	1.389***	(0.137)	1.419***	(0.146)	2.164***	(0.244)
Purchase power pc	-1.021**	(0.487)	-1.034**	(0.488)	-0.963*	(0.503)
Population density	-323.548***	(107.444)	-323.447***	(107.324)	-81.923	(96.161)
No.of houses	0.903**	(0.367)	0.891**	(0.368)	-0.032	(0.395)
Fuelprice	42.814***	(8.704)	42.631***	(8.710)	-3.692	(7.993)
New covid-19 cases	0.013***	(0.003)	0.013***	(0.003)	0.025***	(0.006)
Transformers×Subsidy	—	—	-0.000	(0.000)	0.000***	(0.000)
Subsidy	—	—	-46.395***	(6.124)	-35.078***	(9.932)
No. of observations	21253		21253		21253	

*Notes:* This table reports the first-stage regression results for model (4) of table 2 & 3. The dependent variable is charging capacity in column (1) & (2), and the interaction between charging capacity and subsidy in column (3). All models include the same set of fixed effects: year-month FEs, county level FEs, and year-bundesland FEs. Robust standard errors are reported. \*p<0.10; \*\*p<0.05; \*\*\*p<0.01.

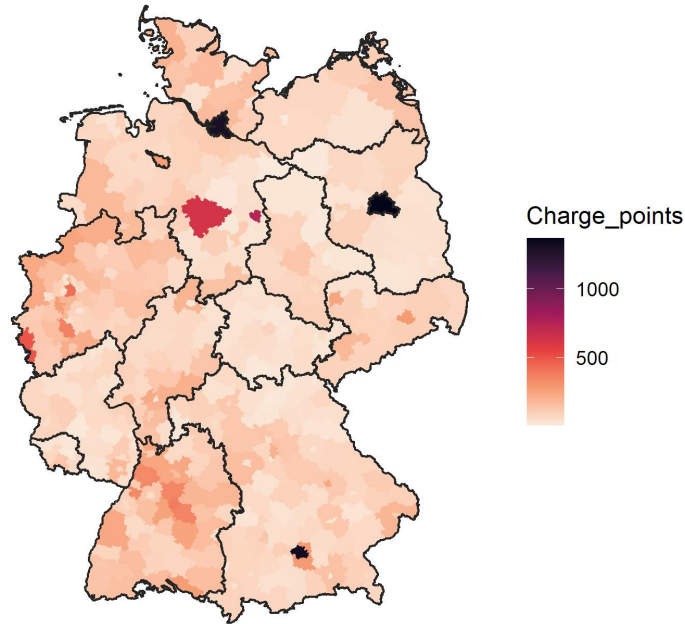


Figure A1: Dispersion of charging points across counties by December 2020.

Table A2: First stage estimation results - charging infrastructure is measured by quantity

	Dynamic IV - Without subsidy		Dynamic IV - With subsidy			
	(1) Charging points		(2) Charging points		(3) Charging points×Subsidy	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Transformers	0.001***	(0.000)	0.001***	(0.000)	-0.000***	(0.000)
L(Electric cars)	0.415***	(0.033)	0.423***	(0.035)	0.612***	(0.054)
Purchase power pc	0.095	(0.110)	0.092	(0.111)	-0.104	(0.108)
Population density	-92.579***	(23.501)	-92.550***	(23.470)	-30.468	(20.735)
No.of houses	0.508***	(0.093)	0.505***	(0.093)	0.081	(0.093)
Fuelprice	17.171***	(2.792)	17.118***	(2.792)	3.313	(2.265)
New covid-19 cases	0.003***	(0.001)	0.003***	(0.001)	0.006***	(0.001)
Transformers×Subsidy	—	—	-0.000	(0.000)	0.000***	(0.000)
Subsidy	—	—	-11.484***	(1.385)	-2.934	(2.082)
No. of observations	21253		21253		21253	

*Notes:* This table reports the first-stage regression results for model (4) of table A3 & A4. The dependent variable is the number of charging points in column (1) & (2), and the interaction between charging points and subsidy in column (3). All models include the same set of fixed effects: year-month FEs, county level FEs, and year-bundesland FEs. Robust standard errors are reported. \*p<0.10;\*\*p<0.05;\*\*\*p<0.01.

Table A3: FE and IV estimation results for the impact of charging points on the uptake of BEVs

	(1) FE		(2) IV - Transformers		(3) Dynamic FE		(4) Dynamic IV	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
L(Electric cars)	—	—	—	—	0.900***	(0.024)	0.838***	(0.041)
Charging points	0.053***	(0.016)	0.179***	(0.019)	0.016***	(0.005)	0.057***	(0.013)
Purchase power pc	0.646***	(0.146)	0.669***	(0.102)	0.205***	(0.045)	0.247***	(0.057)
Population density	1.728	(16.429)	36.727**	(16.218)	0.854	(5.418)	12.624	(7.841)
No.of houses	0.421***	(0.140)	0.080	(0.093)	0.132***	(0.040)	0.054	(0.052)
Fuelprice	7.015**	(2.919)	-0.637	(2.401)	2.098	(1.372)	0.118	(1.651)
New covid-19 cases	0.011***	(0.001)	0.007***	(0.001)	0.003***	(0.001)	0.003***	(0.001)
Constant	-29.814**	(12.287)	—	—	-10.114**	(4.179)	—	—
Year-month fixed effects	Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes	
Year * Bundesland	Yes		Yes		Yes		Yes	
Kleibergen-Paap rk	-		129.017		-		100.754	
Wald F statistic								
No. of observations	21654		21654		21253		21253	

*Notes:* Robust standard errors are reported in parenthesis. \*\*\*, \*\*, and \* denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table A4: FE and IV estimation results for the impact of subsidy and charging points on the uptake of BEVs

	(1) FE		(2) IV - Transformers		(3) Dynamic FE		(4) Dynamic IV	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
L(Electric cars)	—	—	—	—	0.790***	(0.021)	0.665***	(0.060)
Charging points	0.016**	(0.007)	0.131***	(0.017)	0.002	(0.002)	0.055***	(0.012)
Charging points*Subsidy	0.096***	(0.014)	0.113***	(0.021)	0.047***	(0.006)	0.063***	(0.018)
Subsidy	10.342***	(1.562)	20.934***	(1.733)	5.371***	(0.779)	10.965***	(1.341)
Purchase power pc	0.627***	(0.145)	0.646***	(0.104)	0.250***	(0.057)	0.324***	(0.069)
Population density	1.300	(16.313)	34.778**	(16.327)	0.585	(6.947)	17.003*	(9.648)
No.of houses	0.428***	(0.140)	0.102	(0.089)	0.169***	(0.051)	0.073	(0.055)
Fuelprice	7.824***	(2.661)	0.630	(2.147)	3.113**	(1.423)	0.686	(1.593)
New covid-19 cases	0.007***	(0.001)	0.003**	(0.001)	0.002***	(0.000)	0.001	(0.001)
Constant	-30.294**	(12.670)	—	—	-12.688**	(5.463)	—	—
Year-month fixed effects	Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes	
Year * Bundesland	Yes		Yes		Yes		Yes	
Kleibergen-Paap rk	-		65.329		-		47.048	
Wald F statistic								
No. of observations	21654		21654		21253		21253	

Notes: Robust standard errors are reported in parenthesis. \*\*\*, \*\*, and \* denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table A5: Short- and long-run relationship between charging points and the uptake of BEVs

	Without subsidy	Subsidy is in effect
Short-run	0.055	0.118
Long-run	0.163	0.351