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Abstract

Drawing on panel data from Germany, this paper estimates the relationship between charging infrastructure and the uptake of electric vehicles (EVs). We specify models with fixed effects and instrumental variables to gauge the robustness of our findings in the face of alternative channels through which endogeneity bias may emerge. We find that charging infrastructure has a statistically significant and positive impact on EV uptake, with the magnitude of the estimate increasing with population density. The evidence further suggests that although the incidence of charging points in Germany far exceeds the European Union's recommended minimum ratio of one point to ten EVs, inadequate infrastructure coverage remains a binding constraint on EV uptake. We use the model estimates to illustrate the relative cost effectiveness of normal and fast chargers by region, which supports a geographically differentiated targeting of subsidies.

JEL-Code: H54, H71, Q58, R40, R58

Keywords: Transport policy, electric vehicles, charging infrastructure, Germany

January 2021

1 Stephan Sommer, RWI; Colin Vance, RWI and Jacobs University Bremen. *- We are grateful for comments and suggestions by Manuel Frondel and Ken Gillingham as well as for the data provision by the Bundesamt für Wirtschaft und Ausfuhrkontrolle (BAFA). We acknowledge financial support of the German Federal Ministry of Education and Research (BMBF) within the project DIPOL (grant 01LA1809C).* *- All correspondence to: Colin Vance, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: colin.vance@rwi-essen.de*

1 Introduction

The European Union's (EU) progress in reducing CO2 emissions has long been impeded by the transportation sector. Transportation is the only sector in the EU in which CO2 emissions are on the rise, increasing by 28% between 1990 and 2017 (EEA, 2019). To buck this trend, several European governments have turned to the promotion of electric vehicles (EVs). In Germany, the government has set a particularly ambitious goal of registering one million EVs by the end of 2020, encouraged in part by a subsidy for EV purchases that was introduced in 2016. Total funding for the subsidy has been set at €1.2 billion, but progress has been sluggish. As of December 2018, there were only about 83,000 battery-electric (BEV) and 67,000 plug-in hybrids (PHEV) registered (KBA, 2019a), forcing Chancellor Merkel to concede that the goal would not be reached and igniting a debate about the reasons for the shortfall.

The aim of this paper is to assess the validity of one frequently cited impediment to the uptake of EVs: insufficient coverage of charging infrastructure. EU policy has prioritized guaranteeing a minimum ratio of one charge point to ten EVs (EC, 2014). To this end, the German government is providing €300 million towards expanding the charging infrastructure through a program that awards grants to the most competitive bids to construct charging stations. This program is complemented by directives that put binding rules in place to harmonize socket standards for publicly accessible charging stations as well as plans to harmonize authentication and payment at charging stations.

Between 2016 and 2018 the number of charging points in Germany increased over three-fold, from 4,561 to 16,085 (BNetzA, 2019), resulting in about one point for every five EVs, far exceeding the EU's recommended minimum. The question arises as to whether a saturation point has been reached, or whether insufficient infrastructure continues to pose a binding constraint on the uptake of EVs. Drawing on a panel of monthly county-level data from Germany spanning 2016-2018, we take up this question with an econometric analysis that quantifies the effect of charging points on EVs, distinguishing between normal and fast charging points as well as between battery-powered (BEVs) and plug-in hybrids (PHEVs).

Our work contributes to a growing body of research that has identified the accessibility of charging infrastructure to be among the most important determinants of EV purchases, alongside factors such as price and driving range (Axsen et al., 2009; Bobeth and Matthies, 2018; Coffman et al., 2017; Dagsvik et al., 2002; Hackbarth and Madlener, 2013; Langbroek et al., 2016; Liao et al., 2017; Nazari et al., 2018; Ziegler, 2012). Studies using revealed preference data include Li et al.'s (2017a) and Narassimhan and Johnson's (2018) analyses of regional data from the US, which both identify a positive effect of charging infrastructure on EVs. Likewise, Zhang et al. (2016) find significant positive effects of charging station density on a panel of Norwegian municipalities. Other revealed preference studies using county data from California (Javid and Nejat, 2017) and country-level panel data (Li et al., 2017b) provide additional supporting evidence.

Studies using stated preference data generally concur with these findings. Achtnicht et al.'s (2012) choice experiment in Germany, for example, finds that inadequate expansion of alternative fuel stations represents a significant barrier to the adoption of alternative-fuel vehicles. Lebeau et al. (2012) similarly find that enhancing the charging infrastructure density would substantially increase the share of EVs based on a conjoint experiment from Belgium. More recently, Patt et al. (2019) employ a randomized controlled survey in Switzerland to focus on access to private charging infrastructure, finding this to be a potentially important factor influencing people's willingness to purchase EVs. Studies using Chinese (Sovacool et al., 2019) and Canadian (Miele et al., 2020) survey data present dissenting evidence that charging infrastructure plays a negligible role.

The question of causality is an issue that looms large in identifying the impact of charging infrastructure on EV uptake, particularly when using observational data as in the present study. To the extent that chargers are situated according to the prevalence of EVs, their estimated effect would be biased. We consequently present results from two estimators that address different channels from which such bias could emerge. The first includes county-level fixed effects to control for the influence of time-invariant unobservables, while the second additionally addresses potential bias from simultaneity and omitted variables by employing instrumental variables (IVs) in a two-stage least squares framework. We draw on three instruments. One follows Li et al. (2017a) by using a regional count of grocery stores. The other two are counts of transformers along the electricity grid and counts of interstate gasoline stations.

Our findings suggest that charging infrastructure remains a binding constraint on the adoption of electric vehicles in Germany. Specifically, our IV models indicate that each additional normal charging point installed in a month is associated with an increase of approximately 0.06 BEVs per county per month, while the effect of a fast charger is 0.27 BEVs. The corresponding effect sizes for PHEVs are about half the magnitude of BEVs, likely because PHEVs are partially powered by an internal combustion engine and therefore less dependent on charging infrastructure.

As a robustness check, we allow for non-linearities using a quadratic specification, thereby providing a test of whether a tipping point exists after which the effect of charging infrastructure levels off. We find no evidence for diminishing effects, suggesting that Germany – although exceeding the minimum recommendation of charging point density – has not reached saturation. We further undertake a systematic analysis that tests for heterogeneity in the effect of charging points according to regional socioeconomic conditions, finding that the estimate increases with population density and fuel prices. Taken together, these results indicate that the disappointing uptake of EVs in Germany since the implementation of the subsidy could be accelerated by an increase in charging infrastructure, particularly if it is regionally targeted to reflect the differential effects across rural and urban areas.

The next section presents the data set for our analyis. Section 3 introduces the methodology and Section 4 shows the results. Section 5 uses the model estimates to examine the relative cost-effectiveness of an ongoing subsidy program for normal- and fast chargers by county. The final Section 6 summarizes and provides policy implications.

2 Data

The data analyzed in this study is assembled from several sources that we merged via a Geographical Information System. Data on EV registrations, measured by month and county, is taken from the Federal Office for Economics and Export Control (BAFA, 2019), which is responsible for the subsidy program for EV purchases. The program has been effective since July 2016 and extends a subsidy of €4,000 for the purchase of a BEV and €3,000 for a PHEV. The subsidy applies to all cars that are priced under €60,000 and its cost is equally split between the government and the car manufacturers.[1] The data does not include the purchase of non-subsidized vehicles, which comprised about 12% of EVs sold in 2017 and 14% in 2018 (KBA, 2019b). Although our analysis thereby captures over 85% of the market, the absense of non-subsidized EVs is a potential caveat, particularly if such purchasers have a systematically different response to charging infrastructure than purchasers of subsidized EVs.

Between July 1, 2016 and December 31, 2018, we observe 91,456 subsidized purchases in total, which include subsidies to private customers, companies, and the public sector. As commercial and public customers most likely have their own charging points, we restrict the sample to private customers, excluding municipal companies (N=648), municipal associations (N=111), corporations (N=442), foundations (N=63), associations (N=360), and companies (N=50,172). In addition, we exclude cars with fuel cells (N=13), resulting in a final sample of 39,647 subsidized purchases that are summed by county. With a total of 400 counties – or NUTS3 regions – observed over 30 months from July 2016 until December 2018, the data forms a balanced panel comprising 12,000 observations.

Figure 1 illustrates the uptake of EVs since the start of the subsidy, which picks up momentum by the first quarter of 2017. Moreover, we observe substantial regional variation in the uptake of EVs (Figure 2), both across the East-West divide of the country and between rural and urban areas. The density of electric vehicles is higher in urbanized

[1] As part of a larger economic stimulus package in the aftermath of the Covid-19 pandemic, the German government stipulated an increase in the subsidy. Specifically, since June 2020, the purchase of EVs and PHEVs can be subsidized by up to €9,000 and €6,750, respectively.

areas, which are more prevalent in the West. In the East of Germany, which is largely rural, only the capital Berlin stands out as a hot spot of electric cars.

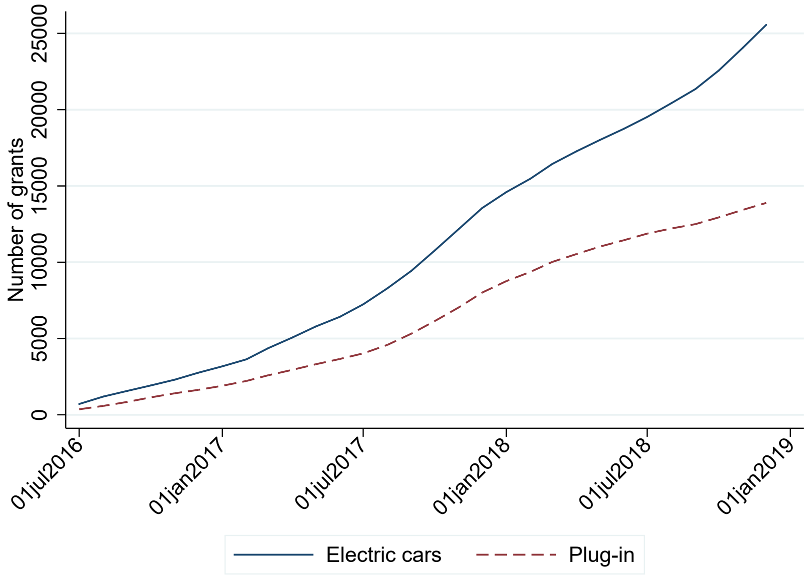

Figure 1: Temporal development of uptake of electric cars

Data on charging infrastructure is obtained by the Federal Network Agency BNetzA (2019), which provides a list of registered charging stations, including their start date of operation and their geographical coordinates. The data additionally includes the number of charging points at each station, distinguishing between normal- and fast charging points. Normal charging points have a maxmimum capacity of 22kW, while fast charging points reach up to 350 kW. There are a total of 7,988 charging stations having an average of two charging points that were put in operation until December 31, 2018. The majority of these, about 88%, is normal charging points, which, as in the case of EVs, saw a more rapid growth in the recent past than fast charging points (Figure 3). Moreover, a spatial pattern similar to that of EVs is evident, with charging points clustering in big cities, in particular Berlin and Hamburg (Figure 4).

Table 1 presents descriptive statistics on the dependent and explanatory variables used in the models. Overall, we observe a mean of 2.260 BEVs purchased per county and month as well 1.157 PHEVs. In about 31% of the month-county combinations, we do not observe any purchase of an BEV, whereas this share increases to 46% in the case

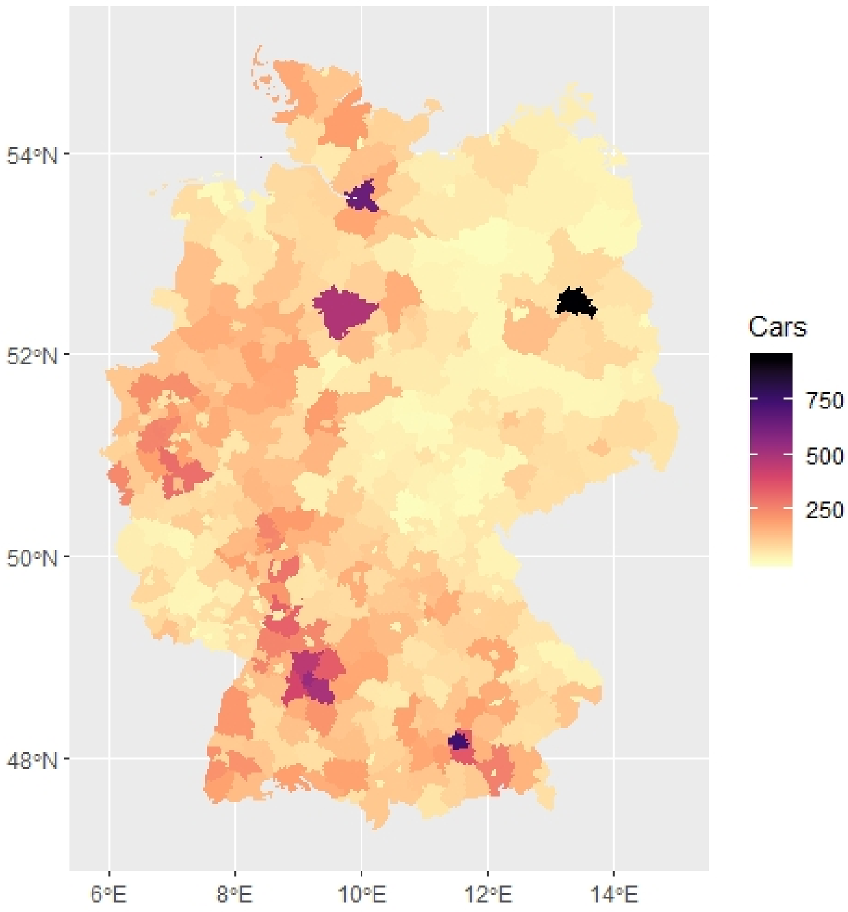

Figure 2: Dispersion of electric vehicles across counties by December 2018

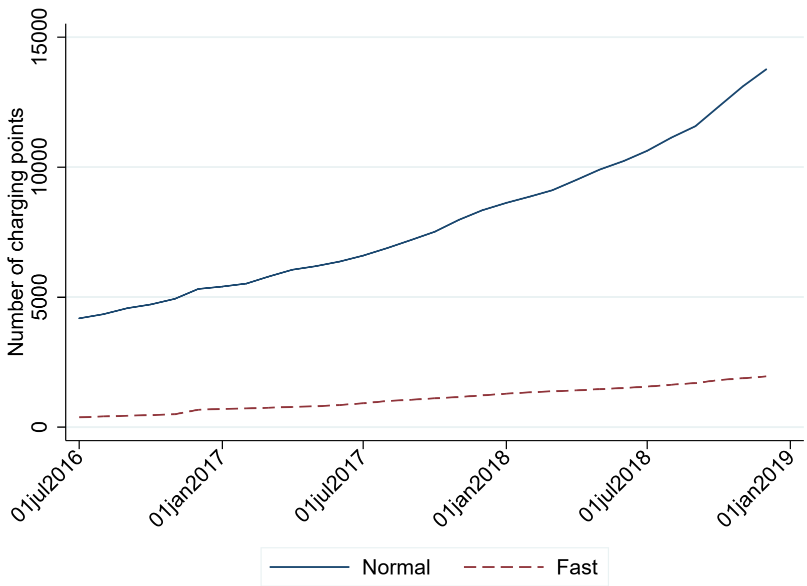

Figure 3: Temporal development of charging points

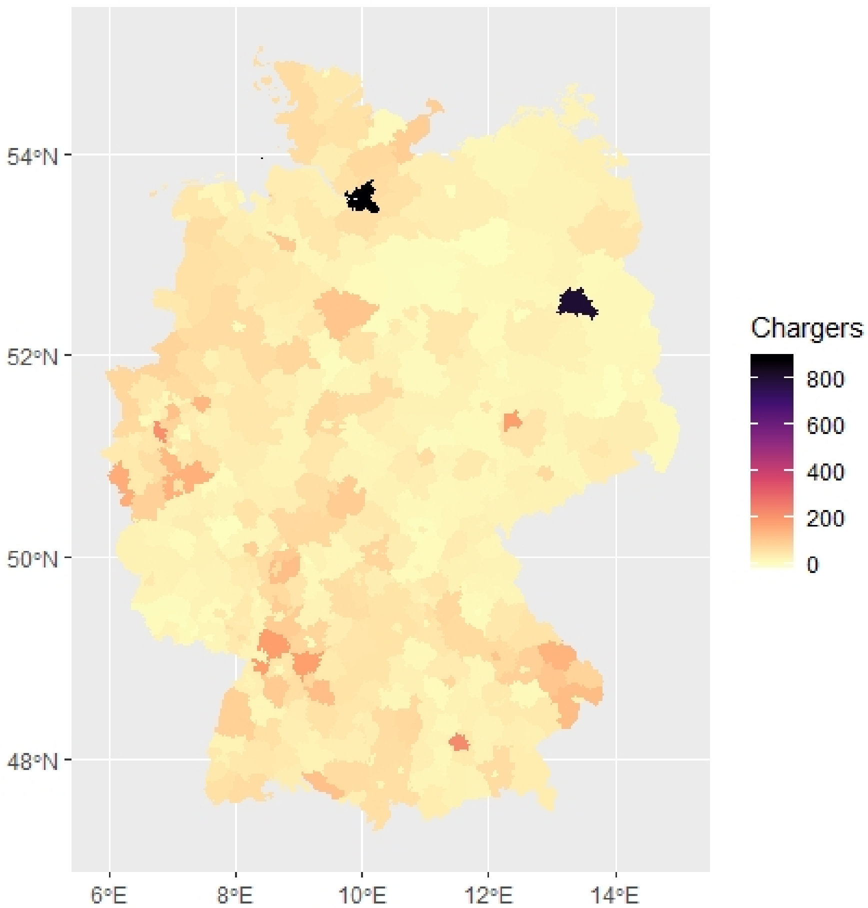

Figure 4: Dispersion of charging stations (normal and fast) across counties in December 2018

of PHEVs. On average, in a given month a county has about 20 normal charging points and three fast charging points. In 14% of the observations, no normal charging point is installed and in 53% no fast charging point is installed. Given the presence of zeros in the measurements of cars and chargers, we maintain measurement in levels rather than logs to avoid missing values.

Table 1: Summary statistics of the estimation sample

	Mean	St. Dev.	Min	Max
Electric cars (#)	2.260	3.091	0.000	45.000
Plug-in hybrids (#)	1.157	1.795	0.000	28.000
Normal charging points (#)	19.727	46.765	0.000	776.000
Fast charging points (#)	2.736	5.997	0.000	128.000
Family houses (#)	27.789	17.440	1.983	116.868
Purchase power pc (€1,000)	22.933	2.504	18.111	34.758
Population (1,000 / km^2)	0.529	0.694	0.036	4.678
Fuel price (€/ liter)	1.291	0.055	1.201	1.492
Supermarkets (#)	84.805	89.504	11.000	1375.000
No. of observations		12,000		

The data is completed by a suite of regional, time-varying control variables taken from the RWI-GEO-GRID km^2 raster data (Breidenbach and Eilers, 2018), including purchasing power per capita, which we aggregate to the county level. Moreover, we control for regional characteristics, such as population density and the number of one- and two-family homes. The latter variable captures home-readiness to recharge, which has been shown to be a particularly important determinant of BEV uptake (Patt et al., 2019).

Last, we control for the deflated fuel price in the county by drawing on data from an online portal called the Market Transparency Unit for Fuel, which records the petrol and diesel price at three minute intervals for each of Germany's roughly 15,000 gas stations (LeSage et al., 2017). We aggregated this data by calculating the mean petrol price by county over the month directly preceding the observation month.

3 Methodology

Our empirical point of departure is a fixed effects regression specified as

$$ev_{it} = \beta + \beta_c charge_{it} + \boldsymbol{\beta}_x^T \mathbf{X}_{it} + \theta_i + \mu_t + \nu_{it}, \tag{1}$$

where ev_{it} denotes either the number of BEVs or PHEVs in county i in period t, $charge_{it}$ measures the corresponding number of normal or fast charging points, vector $\mathbf{X}_{it}$ contains time-varying control variables, and the β are the corresponding parameters to be estimated. In additon, we control for county fixed effects θ_i and a set of year-month fixed effects μ_t. The term ν_{it} is an idiosyncratic error that captures unobserved shocks.

One of the assumptions required for identifying the causal effect using the above model is the absence of simultaneity, which would emerge if the number of electric vehicles was simultaneously a determinant of charging points. We address this potential source of endogenity by instrumenting our measure of charging points and employing two-stage-least squares (2SLS) to estimate Model (1). We draw on three instruments.

The first follows Li et al.'s (2017a) analysis of the electric vehicle market in the United States, which instruments charging stations using a measure of the number of grocery stores and supermarkets in a Metropolitan Statistical Area (MSA). As this measure does not vary over time, the authors multiply it with the one-quarter lagged number of existing charging stations in all MSAs other than the MSA corresponding to a given observation. The variable so constructed thereby allows differential effects of grocery stores according to national shocks in charging station investment, as measured by the lagged number of stations in other MSAs. We apply the same procedure here, drawing on the RWI-GEO regional database to construct counts of grocery stores for each county, which does not vary over the time interval of the data. We then interact this with the one-month lagged count of charging points in all remaining counties, denoting the resulting instrument as *groceries*.

The second instrument is a measure of the count of transformers along the electric grid (denoted *transformers*), while the third is a count of the number gasoline stations located along the interstate (denoted *interstate stations*). Both variables are measured at the county level. As both are static, we interact them with month-year dummies to allow for differential effects over time.

The validity of the instruments, denoted Z_{it}, rests on two assumptions: they are correlated with charging points, i.e. $cov(Z_{it}, charge_{it}) \neq 0$, while they are not correlated with the error term ν_{it}, $cov(\nu_{it}, Z_{it}) = 0$. The first assumption, which is tested below for each instrument (Table A1), comports with intuition. As in the US, grocery stores in Germany commonly host charging points to attract EV motorists who can combine charging with shopping excursions. Hence, a positive correlation is expected between grocery stores and chargers. A positive correlation of chargers with transformers and interstate gas stations is also expected: Transformers are required to reduce transmission voltages for end uses such as charging stations, while interstate gas stations serve as a convenient location for recharging, particularly in the case of fast chargers.

The second assumption – that the IV has no direct causal effect on the outcome – cannot be formally tested, but receives further scrutiny below.

4 Results

We focus our analysis on BEV uptake, beginning with separate models for normal and fast chargers that ignore heterogeneity.[2] Figure 5 presents point estimates and 95% confidence intervals from four models that either employ standard fixed effects (FE) or that additionally couple FE with instrumental variables to control for simultaneity and omitted variables (see Table A1 and Table A2 for the regression tables of the first and second stage, respectively). For normal chargers, we explored the use of two alternative instruments: *groceries* and *transformers*. Noting that they yield virtually identical point estimates, Figure 5 presents results using the *transformers* instrument, which has a slightly narrower confidence interval. For fast chargers, we use the instrument *interstate stations*.

Across all models, the estimates of normal and fast chargers are positive and sta-

[2] To request access to the data and code used in the analysis, please contact the corresponding author.

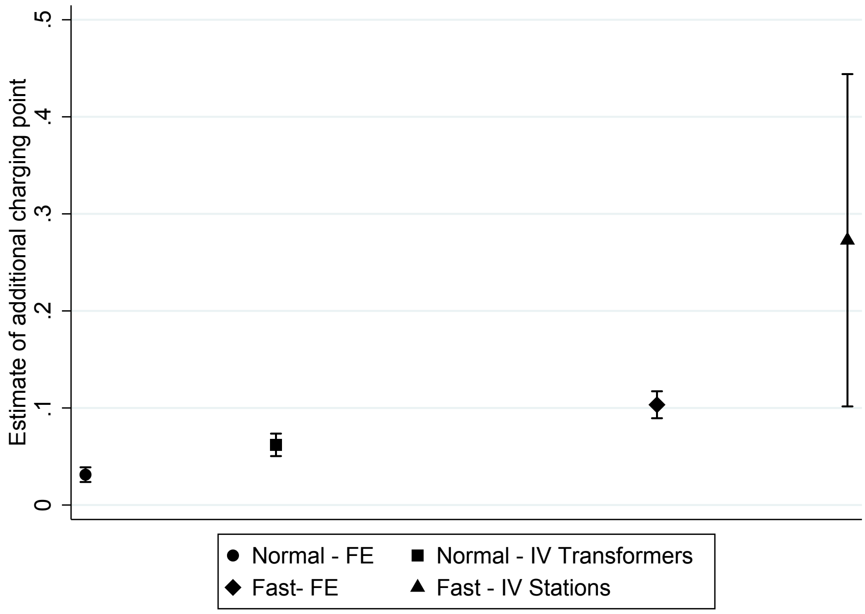

Figure 5: Coefficient estimates for norma and fast charging points

tistically significant. The FE estimate indicates that each additional normal charger is associated with an increase of 0.03 BEVs in the month following its installation, with the estimate doubling to 0.062 in the instrumented case. Multiplying this coefficient with the ratio of mean normal charging points to mean electric vehicle purchases yields an elasticity estimate of 0.54. Thus, a 10% increase in normal charging points is associated with a 5.4% increase in BEVs, which is somewhat lower than the 8.4% estimate reported by Li et al. (2017a) from their generalized method of moments model.

Fast chargers are seen to have a considerably stronger influence on BEV uptake, with an FE estimate of 0.103.[3] The instrumented model suggests an even higher point estimate that reaches 0.273. However, its wide confidence interval renders it statistically indistinguishable from the FE estimate.

With regard to the strength and validity of the instruments, diagnostic checks presented in the appendix are generally supportive. The first stage F-statistics, ranging

[3]The stronger effect found for fast chargers parallels the study of (Neaimeh et al., 2017), who find a stronger influence of fast chargers on distance driven. We also estimated a model (not presented) that includes the interaction of normal and fast chargers to test whether the two are complements or substitutes. While the positive interaction effect estimated from the FE model indicates tentative evidence of complements, the IV estimates are slightly negative and statistically indistinguishable from zero.

between 1364 and 7422, all far exceed the commonly referenced threshold of 10 as well as the threshold of 104.7 recently suggested by Lee et al. (2020). We additionally explored the validity of the IV by employing a placebo test suggested by Bound and Jaeger (2000), which involves regressing the IV on the outcome variable using a subsample of the data with zero charging points. A statistically insignificant coefficient would lend support to the exclusion restriction. As presented in Table A3, this is found to be the case for the transformer and interstate IVs. The estimated coefficient on the grocery store IV, by contrast, is highly significant, casting doubt on the exclusion restriction in this instance.

We complete the econometric analysis with models that allow for alternative sources of heterogeneity. The first includes a quadratic specification of charging points, presented in Table A4, to allow for a non-linear effect. The evidence for such an effect is weak. The small magnitude of the squared term suggests that there are no counties in Germany approaching a saturation point after which additional charging points have a zero effect. Specifically, the estimate indicates a turning point in the effect at more than 300 chargers, which is far beyond the range observed in our sample. We conclude that charging infrastructure continues to be a binding constraint on the uptake of BEVs, lending support to the government's plan to expand charging infrastructure (BMVI, 2020b).

We subsequently estimate models that interact charging points with each of the four control variables, allowing for differential effects according to local socioeconomic circumstances. This analysis reveals evidence for a statistically significant interaction effect of fuel prices and population density, both of which increase the positive effect of charging points on BEV uptake (Table A5). These effects jibe with intuition. A stronger effect of chargers in more densely populated areas likely reflects the influence of a larger customer base, while higher prices for fuel would presumably increase the salience of chargers as an alternative energy source for meeting mobility needs.

To glean further insight into these effects, Figure 6 and Figure 7 present cartographic depictions of the marginal effects from the models of normal and fast chargers with the interactions. Both maps indicate a clear division between the East and the West, with higher marginal effects in the latter. Moreover, a pattern is seen wherein higher estimates tend to be clustered in more dense areas, particularly in the Ruhr Valley, a polycentric urban area in the West that was formerly the country's industrial heartland. This may owe to the fact that city dwellers tend to be renters and are thus less likely to have access to private chargers, making them more sensitive to additional charging points.

A notable exception to this pattern is the city-state of Berlin, which registers an estimated marginal effect of fast chargers that is essentially equal to zero in the case of fast chargers. One explanation for this anomaly is that Berlin has an exceptionally large number of houses. With 127 houses per square kilometer, the city reaches over two times the national average of 49 houses per square kilometer. Given the negative interaction effect of houses and charging points evidenced from the econometric model, this high incidence of houses would pull down the estimated marginal effect.

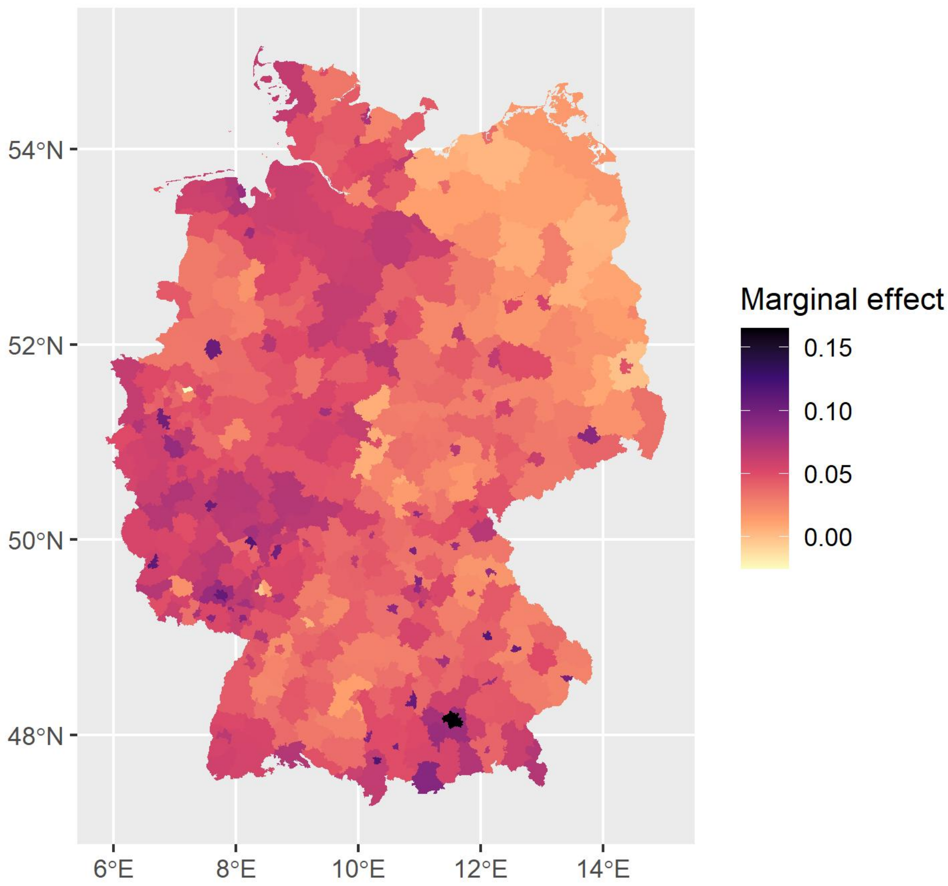

Figure 6: Heterogeneitiy in the estimates of normal charging points

In a final step, we estimate the impact of charging points on the uptake of PHEVs (Table A6). In general, the magnitude of the effects are half the size identified in the

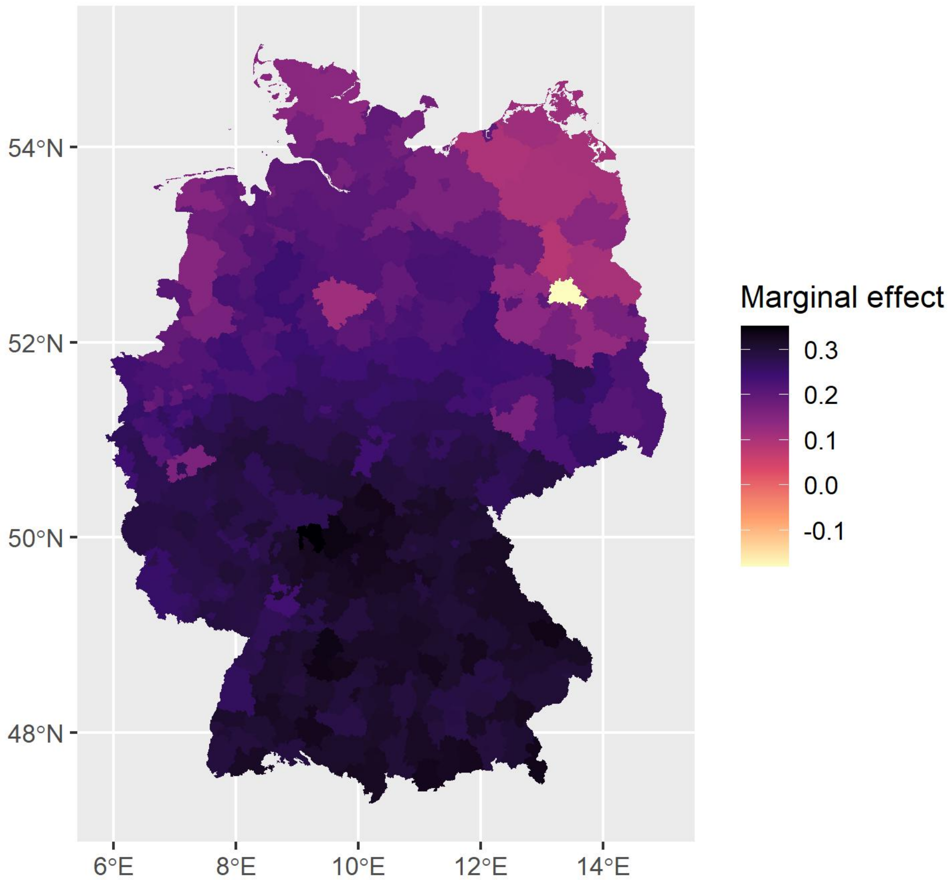

Figure 7: Heterogeneitiy in the estimates of fast charging points

models of BEVs (Table A2) and only statistically significant at the 5% level when we instrument the number of charging points with the number of transformers. This finding supports the intuition that the uptake of PHEVs, with their partial reliance on fossil fuels, is less responsive to charging infrastructure.

5 On the subsidy allocation

The German government has earmarked €300 million in subsidies for the establishment of charging infrastructure. The maximum subsidy for a single normal charging point is set at €2,500 and for a fast charging point at €12,000 (BAV, 2019). From a cost-effectiveness perspective, an optimal allocation would dictate that the budget is spent so as to equalize the return per Euro on normal- and fast charging points.

Using the estimates from the models with the transformers and gas stations instruments (Table A2), respectively, we find that the subsidy for normal charging points leads on average to 0.062*12/2,500=0.298 BEVs per year per €1,000, while the subsidy for fast chargers leads to 0.273*12/12,000=0.273 EVs per €1,000. The difference of 0.025 between the two estimates is small and statistically insignificant, suggesting that the subsidies are indeed well-calibrated.

An additional consideration concerns how the spatial distribution of subsidies for chargers across Germany impacts BEV uptake. The recently passed budget allocates two thirds of funding for charging infrastructure to fast chargers with the remaining one third to normal chargers (BMVI, 2020a). Taking the subsidies noted above of €2,500 and €12,000 for normal and fast chargers would result in 40,000 normal and 16,667 fast chargers. One extreme scenario would distribute these chargers uniformly across counties, which, based on the mean marginal effects estimates from Table A5, would yield about 75,500 new electric vehicles over the course of a year.[4]

Alternatively, a cost-efficiency perspective recognizes that the subsidy is optimally allocated when the per Euro return to charging points is the same across the counties

[4]We arrive at this figure by summing two products: (0.049 (the mean marginal effect of normal chargers) X 40,000 X 12) + (0.260 (the mean marginal effect of fast chargers) X 16,667 X 12).

in Germany. Applying the county-specific marginal effects estimates derived from the models in Table A5 results in about 83,000 new electric vehicles over a year, nearly an 11% increase relative to the calculation assuming a homogeneous effect of chargers. With geographically differentiated targeting, policymakers can thus substantially improve the effectiveness of the subsidy.

6 Conclusion

Using data on a subsidy program for electric vehicles that was implemented in Germany in July 2016, we have analyzed the effect of charging infrastructure on the uptake of electric vehicles. The subsidy was implemented as part of an effort to introduce one million EVs on the road by 2020, an effort that currently faces a substantial shortfall of over 900,000 vehicles. Our analysis suggests that insufficient charging infrastructure remains a binding constraint on the uptake of EVs. Our instrumented estimate suggests that an additional normal charging point is associated with 0.062 additional BEVs per month per county, corresponding to an uptake of 0.74 BEVs per county over the course of a year. The instrumented point estimate for fast chargers is, at 0.273, over four times the magnitude, corresponding to 3.28 BEVs per county. These are average effects that mask substantial heterogeneity detected over space, with stronger effects of chargers found in densly populated areas and where fuel prices are high. Through a back-of-the-envelop calculation, we show that geographically targeted subsidies for chargers in recognition of this heterogeneity can greatly improve their effectiveness in promoting BEV uptake.

Germany's budget to encourage EV car purchases via subsidies is €1.2 billon, while the budget for charging infrastructure is more modest at €300 million. An important question for future research is how to balance support for these two mechanisms. We suspect that a reallocation of expenditure toward charging infrastructure would be warranted, following a similar recommendation by Li et al. (2017a) for the US. Nevertheless, it would be important to gauge the likely extent of free-rider effects for both EV purchases (Chandra et al., 2010) and charging infrastructure before implementing such a reallocation.

A Appendix

Table A1: Estimation results for the uptake BEVs

	Normal				Fast	
	Groceries		Transformers		Gas stations	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
# Grocery stores × L(Charging points)	0.003***	(0.001)	–	–	–	–
# Transformers × year	–	–	0.001***	(0.000)	–	–
# Fuel stations	–	–	–	–	0.003**	(0.001)
Purchase power pc	0.803	(1.621)	-2.917	(2.175)	0.536**	(0.260)
Population density	137.818**	(58.543)	130.076	(138.393)	-4.158	(12.585)
No. of houses	-3.806	(2.653)	2.471*	(1.433)	-0.302	(0.307)
Fuelprice	61.145***	(15.520)	54.614**	(26.865)	2.218	(5.995)
Constant	-0.000	(0.000)	0.000	(0.000)	0.000***	(0.000)
Year-month fixed effects	Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes	
F-statistic	7422		1364		1923	
No. of observations	12,000		12,000		12,000	

Note: Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table A2: Second stage estimation results for the uptake BEVs

	Normal						Fast			
	FE		Groceries		Transformers		FE		Gas stations	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Normal chargers	0.031***	(0.004)	0.058***	(0.011)	0.062***	(0.006)	–	–	–	–
Fast chargers	–	–	–	–	–	–	0.103***	(0.007)	0.273***	(0.087)
Purchase power pc	-0.163**	(0.083)	-0.039	(0.127)	-0.022	(0.132)	-0.327***	(0.094)	-0.359***	(0.105)
Population density	-0.757	(3.893)	-1.934	(7.629)	-2.096	(8.118)	1.831	(3.478)	3.838	(4.907)
No. of houses	0.704***	(0.085)	0.422***	(0.156)	0.383***	(0.146)	0.978***	(0.222)	0.890***	(0.217)
Fuelprice	5.246***	(1.835)	4.337**	(2.074)	4.212**	(2.010)	5.795***	(1.831)	4.966**	(2.207)
Constant	2.260***	(0.113)	2.260***	(0.113)	2.260***	(0.113)	2.260***	(0.113)	2.260***	(0.113)
Year-month fixed effects	Yes		Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes		Yes	
No. of observations	12,000		12,000		12,000		12,000		12,000	

Note: Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table A3: Placebo estimation results

	Groceries		Transformers		Stations	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
# Grocery stores × L(Charging points)	0.000***	(0.000)	–	–	–	–
# Transformers × Yearmonth	–	–	-0.000	(0.000)	–	–
# High way gas stations × Yearmonth	–	–	–	–	-0.000	(0.000)
Purchase power pc	-0.410**	(0.168)	-0.211	(0.177)	-0.247	(0.172)
Population	0.874	(8.123)	-1.292	(8.436)	-1.297	(8.692)
Family houses	-0.290	(0.259)	0.175	(0.258)	0.103	(0.218)
Fuel price	-2.006	(6.528)	-5.225	(5.790)	-4.675	(6.286)
Constant	16.168*	(8.416)	13.340	(9.282)	10.965	(8.944)
Year-month fixed effects	Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes	
No. of observations	1,230		1,230		1,230	

Note: Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table A4: Nonlinearities in the deployment of charging infrastructure

	Normal				Fast			
	FE		Transformers		FE		Stations	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Normal chargers	0.031***	(0.003)	0.061***	(0.006)	–	–	–	–
Normal chargers × Normal chargers	-0.000	(0.000)	-0.000***	(0.000)	–	–	–	–
Fast chargers	–	–	–	–	0.100***	(0.007)	0.274***	(0.088)
Fast chargers × Fast chargers	–	–	–	–	-0.001***	(0.000)	0.001	(0.001)
Purchase power pc	-0.158**	(0.080)	-0.013	(0.126)	-0.323***	(0.094)	-0.363***	(0.106)
Population density	-1.891	(3.430)	-3.892	(7.384)	1.390	(3.321)	4.355	(5.027)
No. of houses	0.692***	(0.082)	0.363***	(0.139)	0.965***	(0.227)	0.908***	(0.220)
Fuelprice	5.160***	(1.862)	4.074**	(1.935)	5.730***	(1.847)	5.061**	(2.250)
Constant	2.260***	(0.113)	2.260***	(0.113)	2.260***	(0.113)	2.260***	(0.113)
Year-month fixed effects	Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes	
No. of observations	12,000		12,000		12,000		12,000	

Note: Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table A5: Heterogeneous effects of charing points

	Transformers		Stations	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Normal chargers	0.073***	(0.014)	–	–
Purchase power pc	0.241	(0.228)	-0.349***	(0.110)
Population density	-12.859	(8.669)	2.235	(5.068)
# Houses	0.264	(0.232)	0.870***	(0.215)
Fuel price	1.532	(2.346)	2.489	(2.710)
Normal chargers × Purchase power pc	-0.073	(0.070)	–	–
Normal chargers × Population density	1.131*	(0.601)	–	–
Normal chargers × # Houses	-0.001	(0.008)	–	–
Normal chargers × Fuel price	0.263***	(0.079)	–	–
Fast chargers	–	–	0.250***	(0.070)
Fast chargers × Purchase power pc	–	–	0.026	(0.190)
Fast chargers × Population density	–	–	1.577	(5.519)
Fast chargers × # Houses	–	–	-0.076	(0.076)
Fast chargers × Fuel price	–	–	1.225*	(0.660)
Year-month fixed effects	Yes		Yes	
Individual fixed effects	Yes		Yes	
No. of observations	12,000		12,000	

Note: Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table A6: Second stage estimation results for the uptake PHEVs (all charging points)

	Normal				Fast			
	FE		Transformers		FE		Stations	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Normal chargers	0.005	(0.004)	0.020***	(0.004)	–	–	–	–
Fast chargers	–	–	–	–	0.005	(0.009)	0.075	(0.048)
Purchase power pc	-0.117	(0.093)	-0.048	(0.118)	-0.143*	(0.082)	-0.156*	(0.080)
Population density	-7.795*	(4.109)	-8.455	(5.494)	-7.499**	(3.696)	-6.670*	(3.990)
No. of houses	0.443***	(0.100)	0.285***	(0.080)	0.496***	(0.114)	0.459***	(0.117)
Fuelprice	2.719**	(1.362)	2.210	(1.557)	2.871**	(1.276)	2.529	(1.584)
Constant	1.229***	(0.064)	1.229***	(0.064)	1.229***	(0.064)	1.229***	(0.064)
Year-month fixed effects	Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes	
No. of observations	12,000		12,000		12,000		12,000	

Note: Standard errors are clustered at the NUTS3 level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

References

Achtnicht, M., Bühler, G., and Hermeling, C. (2012). The impact of fuel availability on demand for alternative-fuel vehicles. *Transportation Research Part D: Transport and Environment*, 17(3):262–269.

Axsen, J., Mountain, D. C., and Jaccard, M. (2009). Combining stated and revealed choice research to simulate the neighbor effect: The case of hybrid-electric vehicles. *Resource and Energy Economics*, 31(3):221–238.

BAFA (2019). Elektromobilität (Umweltbonus). Bundesamt für Wirtschaft und Ausfuhrkontrolle, Eschborn. https://www.bafa.de/DE/Energie/Energieeffizienz/Elektromobilitaet/elektromobilitaet_node.html.

BAV (2019). Vierter aufruf zur antragseinreichung vom 19.08.2019 gemäß der förderrichtlinie ladeinfrastruktur für elektrofahrzeuge in deutschland des bundesministeriums fürverkehr und digitale infrastruktur vom 13.02.2017. Bundesministerium fürVerkehr und digitale Infrastruktur, Berlin. https://www.bav.bund.de/SharedDocs/Downloads/DE/LIS/Vierter_Aufruf_zur_Antragseinreichung.pdf?__blob=publicationFile&v=4.

BMVI (2020a). 500 millionen euro zusätzlich für ladeinfrastruktur - 6. förderaufruf abgeschlossen. Bundesministerium für Verkehr und digitale Infrastruktur. https://www.bmvi.de/SharedDocs/DE/Artikel/G/infopapier-sechster-foerderaufruf-ladeinfrastruktur.html.

BMVI (2020b). Masterplan ladeinfrastruktur der bundesregierung. Bundesministerium für Verkehr und digitale Infrastruktur. https://www.bmvi.de/SharedDocs/DE/Anlage/G/masterplan-ladeinfrastruktur.pdf?__blob=publicationFile.

BNetzA (2019). Ladesäulenkarte. Bundesnetzagentur, Bonn. https://www.bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institutionen/HandelundVertrieb/Ladesaeulenkarte/Ladesaeulenkarte_node.html.

Bobeth, S. and Matthies, E. (2018). New opportunities for electric car adoption: The case of range myths, new forms of subsidies, and social norms. *Energy Efficiency*, 11(7):1763–1782.

Bound, J. and Jaeger, D. A. (2000). Do compulsory school attendance laws alone explain the association between quarter of birth and earnings? *Research in labor economics*, 19(4):83–108.

Breidenbach, P. and Eilers, L. (2018). RWI-GEO-GRID: Socio-economic data on grid level. *Jahrbücher für Nationalökonomie und Statistik*, 238(6):609–616.

Chandra, A., Gulati, S., and Kandlikar, M. (2010). Green drivers or free riders? An analysis of tax rebates for hybrid vehicles. *Journal of Environmental Economics and management*, 60(2):78–93.

Coffman, M., Bernstein, P., and Wee, S. (2017). Electric vehicles revisited: A review of factors that affect adoption. *Transport Reviews*, 37(1):79–93.

Dagsvik, J. K., Wennemo, T., Wetterwald, D. G., and Aaberge, R. (2002). Potential demand for alternative fuel vehicles. *Transportation Research Part B: Methodological*, 36(4):361–384.

EC (2014). Directive 2014/94/eu of the european parliament and of the council of 22 october 2014 on the deployment of alternative fuels infrastructure. European Commission. `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014L0094&from=EN`.

EEA (2019). Annual European Union greenhouse gas inventory 1990–2017 and inventory report 2019. European Environment Agency, Copenhagen.

Hackbarth, A. and Madlener, R. (2013). Consumer preferences for alternative fuel vehicles: A discrete choice analysis. *Transportation Research Part D: Transport and Environment*, 25:5–17.

Javid, R. J. and Nejat, A. (2017). A comprehensive model of regional electric vehicle adoption and penetration. *Transport Policy*, 54:30–42.

KBA (2019a). Bestandsbarometer. Kraftfahrtbundesamt, Flensburg. `https://www.kba.de/DE/Statistik/Fahrzeuge/Bestand/Jahresbilanz/bestand_jahresbilanz_node.html`.

KBA (2019b). Monatliche neuzulassungen. Kraftfahrtbundesamt, Flensburg. `https://www.kba.de/DE/Statistik/Fahrzeuge/Neuzulassungen/MonatlicheNeuzulassungen/monatl_neuzulassungen_node.html`.

Langbroek, J. H., Franklin, J. P., and Susilo, Y. O. (2016). The effect of policy incentives on electric vehicle adoption. *Energy Policy*, 94:94–103.

Lebeau, K., Van Mierlo, J., Lebeau, P., Mairesse, O., and Macharis, C. (2012). The market potential for plug-in hybrid and battery electric vehicles in flanders: A choice-based conjoint analysis. *Transportation Research Part D: Transport and Environment*, 17(8):592–597.

Lee, D., McCrary, J., Moreira, M., and Porter, J. (2020). Valid t-ratio Inference for IV. arXiv preprint arXiv:2010.05058.

LeSage, J. P., Vance, C., and Chih, Y.-Y. (2017). A bayesian heterogeneous coefficients spatial autoregressive panel data model of retail fuel duopoly pricing. *Regional Science and Urban Economics*, 62:46–55.

Li, S., Tong, L., Xing, J., and Zhou, Y. (2017a). The market for electric vehicles: Indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists*, 4(1):89–133.

Li, X., Chen, P., and Wang, X. (2017b). Impacts of renewables and socioeconomic factors on electric vehicle demands–panel data studies across 14 countries. *Energy Policy*, 109:473–478.

Liao, F., Molin, E., and van Wee, B. (2017). Consumer preferences for electric vehicles: A literature review. *Transport Reviews*, 37(3):252–275.

Miele, A., Axsen, J., Wolinetz, M., Maine, E., and Long, Z. (2020). The role of charging and refuelling infrastructure in supporting zero-emission vehicle sales. *Transportation Research Part D: Transport and Environment*, 81:102275.

Narassimhan, E. and Johnson, C. (2018). The role of demand-side incentives and charging infrastructure on plug-in electric vehicle adoption: Analysis of US States. *Environmental Research Letters*, 13(7):074032.

Nazari, F., Mohammadian, A., and Stephens, T. (2018). Dynamic household vehicle decision modeling considering plug-in electric vehicles. *Transportation Research Record*, 2672(49):91–100.

Neaimeh, M., Salisbury, S. D., Hill, G. A., Blythe, P. T., Scoffield, D. R., and Francfort, J. E. (2017). Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. *Energy Policy*, 108:474–486.

Patt, A., Aplyn, D., Weyrich, P., and van Vliet, O. (2019). Availability of private charging infrastructure influences readiness to buy electric cars. *Transportation Research Part A: Policy and Practice*, 125:1–7.

Sovacool, B. K., Abrahamse, W., Zhang, L., and Ren, J. (2019). Pleasure or profit? Surveying the purchasing intentions of potential electric vehicle adopters in China. *Transportation Research Part A: Policy and Practice*, 124:69–81.

Zhang, Y., Qian, Z. S., Sprei, F., and Li, B. (2016). The impact of car specifications, prices and incentives for battery electric vehicles in norway: Choices of heterogeneous consumers. *Transportation Research Part C: Emerging Technologies*, 69:386–401.

Ziegler, A. (2012). Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany. *Transportation Research Part A: Policy and Practice*, 46(8):1372–1385.