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## Do more chargers mean more electric cars?

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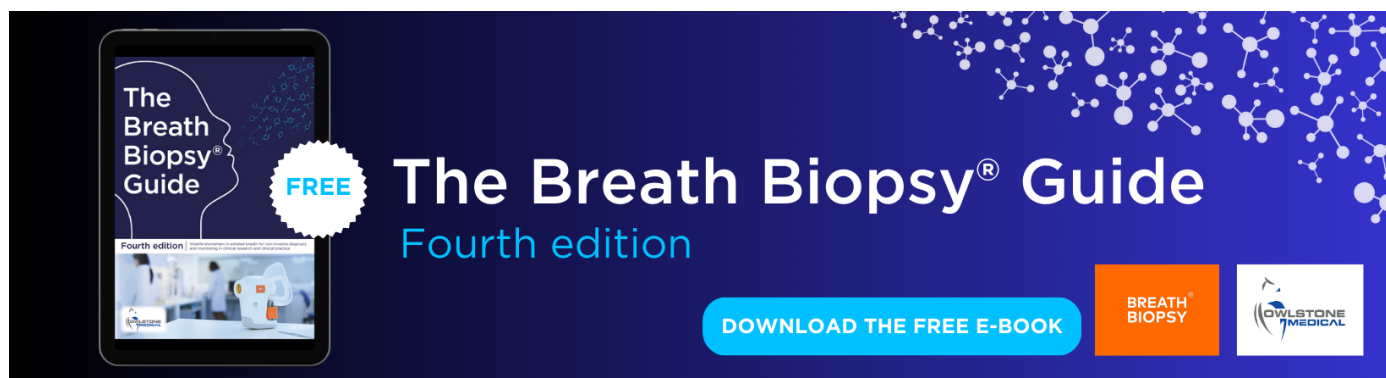
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## LETTER

## Do more chargers mean more electric cars?

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E-mail: [vance@rwi-essen.de](mailto:vance@rwi-essen.de)**Keywords:** transport policy, electric vehicles, charging infrastructure, Germany**Abstract**

To reverse the trend of rising CO<sub>2</sub> emissions in the European Union's (EU) transportation sector, several European governments have introduced programs that promote electric vehicles (EVs). One frequently cited impediment to their uptake is insufficient charging infrastructure. Drawing on panel data from Germany, this paper estimates the relationship between public charging infrastructure and the uptake of 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 EU'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 for charging infrastructure.

**1. Introduction**

The European Union's (EU) progress in reducing CO<sub>2</sub> emissions has long been impeded by the transportation sector. Transportation is the only sector in the EU in which CO<sub>2</sub> 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 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 was set at €1.2 billion, but it was already clear by the close of 2018 that progress was sluggish. In December of that year, there were only about 83 000 battery-electric vehicles (BEVs) and 67 000 plug-in hybrids (PHEVs) 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 public 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 toward expanding the public 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 (BMVI 2020a).

Between 2016 and 2018 the number of public charging points in Germany increased over three-fold, from 4561 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 was 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 public charging points on EVs, distinguishing between

normal and fast charging points as well as between BEVs and 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 (Dagsvik *et al* 2002, Axsen *et al* 2009, Ziegler 2012, Hackbarth and Madlener 2013, Langbroek *et al* 2016, Coffman *et al* 2017, Liao *et al* 2017, Bobeth and Matthies 2018, Nazari *et al* 2018). 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), data from Switzerland (Brückmann *et al* 2021), 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 survey experiment in Switzerland to focus on access to private charging infrastructure, finding this to be a potentially important factor in influencing people's willingness to purchase EVs. This finding is substantiated by Figenbaum and Kolbenstvedt (2016), who show that most charging processes take place either at home or at work (see Hardman *et al* 2018 for a review on charging behavior). 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 through which such bias could emerge. The first includes county-level fixed effects (FEs) 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 interstate gasoline stations and counts of transformers along the electricity grid. To the extent that grocery stores and gas stations host charging stations, we expect them to be strongly correlated. A correlation is also expected between charging stations and transformers, as these are needed to step down power to a lower voltage appropriate for charging infrastructure. We expect none of these instruments to have a direct effect on EV sales, an expectation that is scrutinized below with a placebo regression.

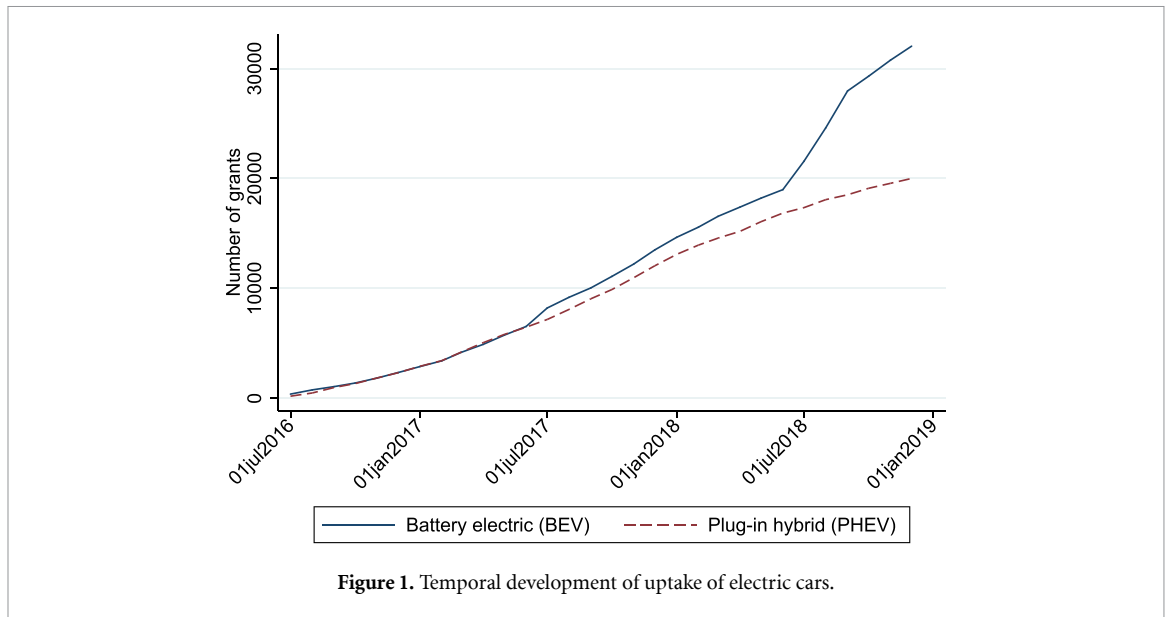
Our findings suggest that charging infrastructure remains a binding constraint on the adoption of EVs in Germany. Specifically, our IV models indicate that each additional normal charging point installed in a month is associated with an increase of approximately 0.06 BEVs per county per month, while 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. The larger effects for fast chargers complements Gnann *et al*'s (2019) results that a market diffusion of EVs in Germany is possible with exclusive reliance on fast public charging infrastructure. Moreover, it highlights the need for an expanded network of fast chargers, as also advocated by Gnann *et al* (2018).

As a robustness check, we allow for non-linearities using a quadratic specification, thereby providing a test of whether a tipping point has been reached 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 (in contrast to Brückmann *et al* 2021) 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 analysis. 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 initially extended a subsidy of €4000 for the purchase of a BEV and €3000 for a PHEV. The subsidy applies to all cars that are priced under €60 000, with its cost equally split between the government and the car manufacturers<sup>3</sup>. 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 absence 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 1 July 2016 and 31 December 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 ( $N = 50 172$ )<sup>4</sup>. 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.

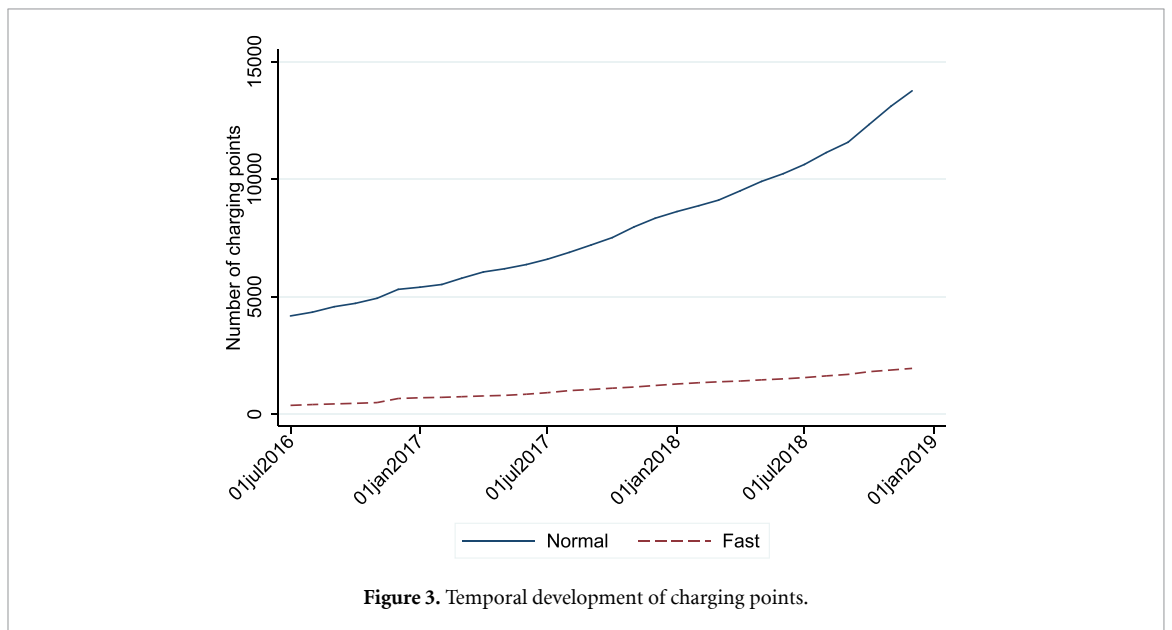
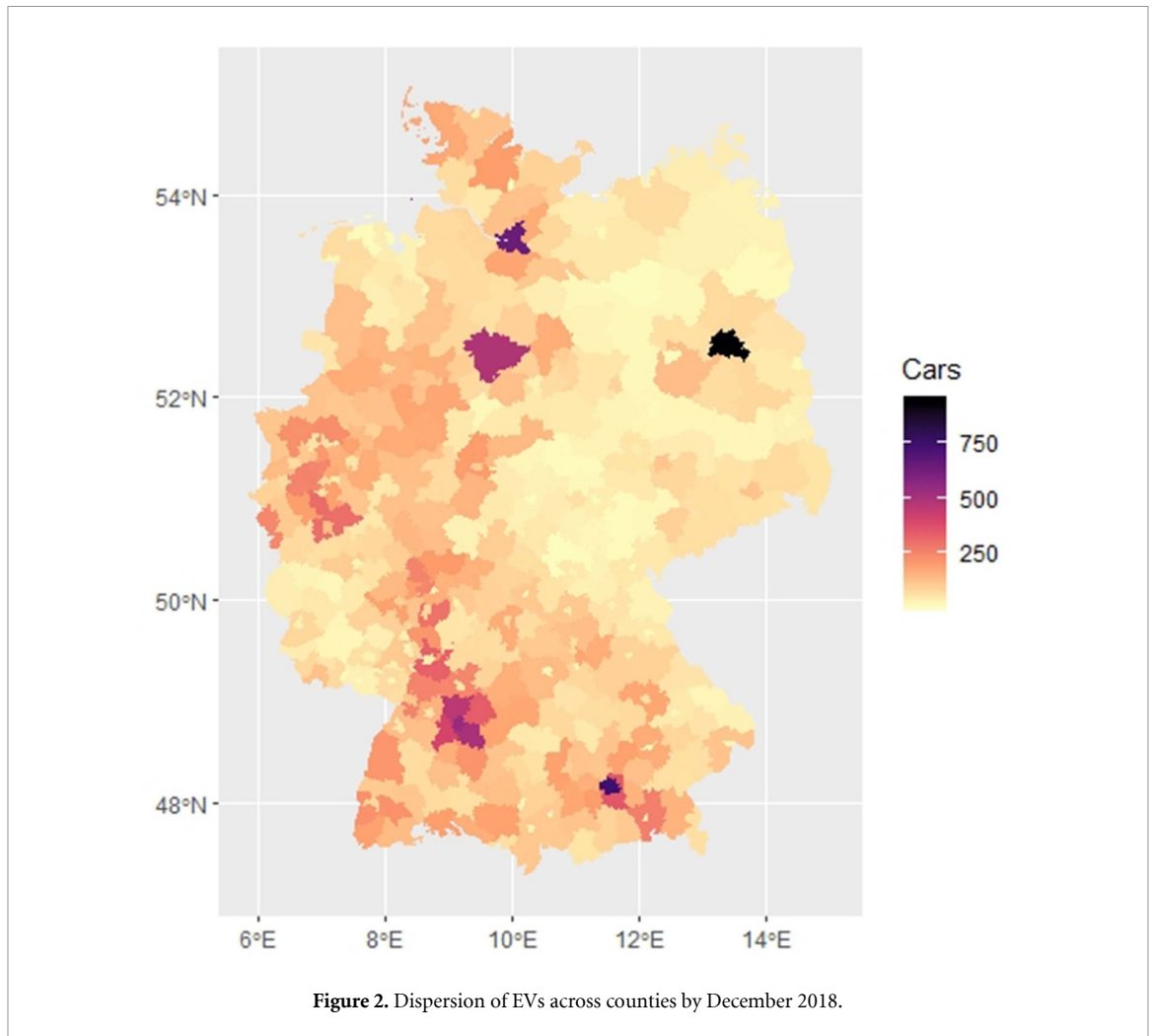
Figure 1 illustrates the uptake of EVs since the start of the subsidy, which picks up momentum by the first quarter of 2017. Moreover, we observe substantial regional variation in the uptake of EVs (figure 2), both across the East-West divide of the country and between rural and urban areas. The density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

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 maximum capacity of 22 kW, while fast charging points reach up to 350 kW. There are a total of 7988 charging stations having an average of two charging points that were put in operation until 31 December 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

<sup>3</sup> 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 BEVs and PHEVs can be subsidized by up to €9000 and €6750, respectively.

<sup>4</sup> Although not the focus here, models estimated on a sample that includes only company cars (table A8) reveal the coefficients on charging infrastructure to be statistically insignificant, which likely owes to the fact that company cars can often be charged at the work place. Moreover, a large number of electric company cars belong to car sharing companies, which rely less on public infrastructure.



combinations, we do not observe any purchase of an BEV, whereas this share increases to 46% in the case 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

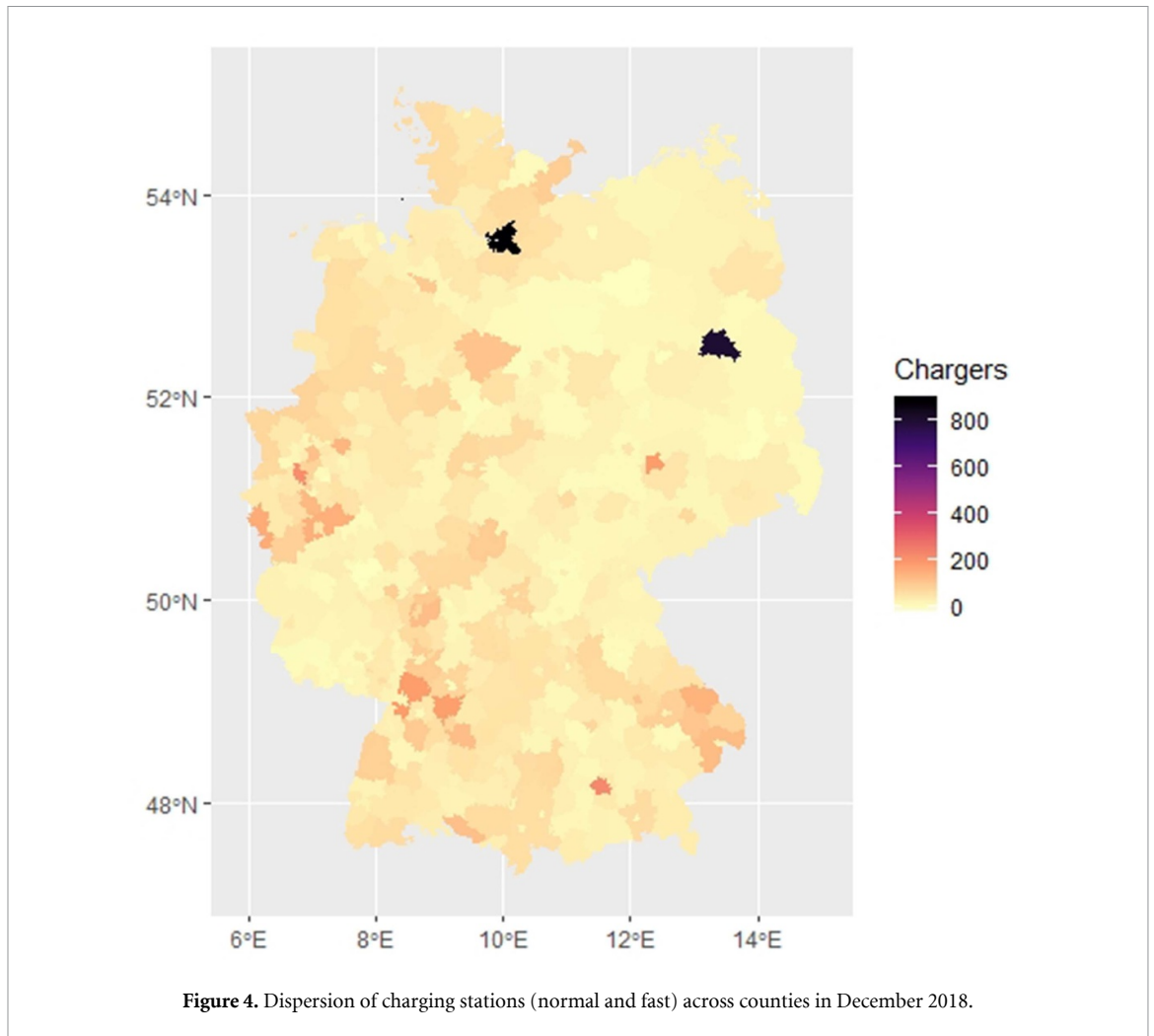


Figure 4. Dispersion of charging stations (normal and fast) across counties in December 2018.

maintain measurement in levels rather than logarithms to avoid missing values<sup>5</sup>.

The data is completed by a suite of regional, time-varying control variables taken from the RWI-GEO-GRID km<sup>2</sup> 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 3 min 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.

<sup>5</sup> We also explored Poisson and hurdle models to accommodate the zeros in the data (see table A9), which yield similar results to the linear models presented in the main text.

### 3. Methodology

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

$$ev_{it} = \beta + \beta_c charge_{it} + \beta_x^T \mathbf{X}_{it} + \theta_i + \mu_t + \nu_{it}, \quad (1)$$

where  $ev_{it}$  denotes either the number of BEVs or PHEVs in county  $i$  in period  $t$ ,  $charge_{it}$  measures the number of points, vector  $\mathbf{X}_{it}$  contains time-varying control variables, and the  $\beta$  are the corresponding parameters to be estimated. In addition, we control for county FEs  $\theta_i$  and a set of year-month FEs  $\mu_t$ . The county FEs  $\theta_i$  capture unobservable characteristics that do not vary over the three-year period on the county level. Such characteristics could include the sluggish development of traffic infrastructure, such as highways, railways, and gas stations, as well as the presence of car dealers. The term  $\nu_{it}$  is an idiosyncratic error that captures unobserved shocks. We estimate separate models for normal and fast charging points.

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 EVs was simultaneously a determinant of charging

Table 1. Summary statistics of the estimation sample.

	Mean	St. dev.	Min	Max
Uptake of electric cars (#)	2.260	3.091	0.000	45.000
Uptake of plug-in hybrids (#)	1.157	1.795	0.000	28.000
Stock of normal charging points (#)	19.727	46.765	0.000	776.000
Stock of fast charging points (#)	2.736	5.997	0.000	128.000
Family houses (# in 1000)	27.789	17.440	1.983	116.868
Purchase power pc (€1000)	22.933	2.504	18.111	34.758
Population (1000/km <sup>2</sup> )	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
Transformers (#)	15.125	26.227	0.000	445.000
Interstate fuel stations (#)	0.860	1.407	0.000	8.000
No. of observations		12 000		

Note: All variables are time-varying except for *Supermarkets*, *Transformers*, and *Interstate fuel stations*. The fuel price captures the mean petrol price of the month preceding the observation month.

points. We address this potential source of endogeneity by instrumenting our measure of charging points and employing two-stage-least squares along with FEs to estimate Model (1). We draw on three instruments.

The first follows Li *et al*'s (2017a) analysis of the EV 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*<sup>6</sup>.

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 variables do not vary over time, we interact them with a linear year-month trend to allow for differential effects over time<sup>7</sup>. On average, there are around 15 transformers and one interstate fuel station per county (table 1). About 40% of all counties have at least one interstate fuel station, while 95% of counties have at least one transformer.

<sup>6</sup> We used a month lag because this is the time-unit in our data. Like Li *et al* (2017a), we also explored the use of a quarter lag (table A10), but found this had little bearing on the results.

<sup>7</sup> To allow for more flexibility, we looked into interacting the transformers and fuel stations with year-month dummy variables, presented in table A11. The main conclusions remain unchanged. As expected, the J-statistic suggests overidentification in the model of fast chargers.

The validity of the instruments, denoted  $Z_{it}$ , rests on two assumptions pertaining to their covariance ( $cov$ ): (i) they are correlated with charging points, i.e.  $cov(Z_{it}, charge_{it}) \neq 0$ , while (ii) they are not correlated with the error term  $\nu_{it}$ , i.e.  $cov(\nu_{it}, Z_{it}) = 0$ . 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 (Khan *et al* 2019, Brinkel *et al* 2020), while interstate gas stations serve as a convenient location for recharging, particularly in the case of fast chargers. We find that the correlation between transformers and the number of normal chargers is  $\rho = .58$ , while  $\rho = .46$  for the correlation between interstate fuel stations and 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. The appendix presents models where the dependent variable is PHEV uptake, documented below.

Figure 5 presents point estimates and 95% confidence intervals from four models of BEVs that either employ standard FE or that additionally couple FE with IVs to control for simultaneity and omitted variables (see tables A1 and 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,



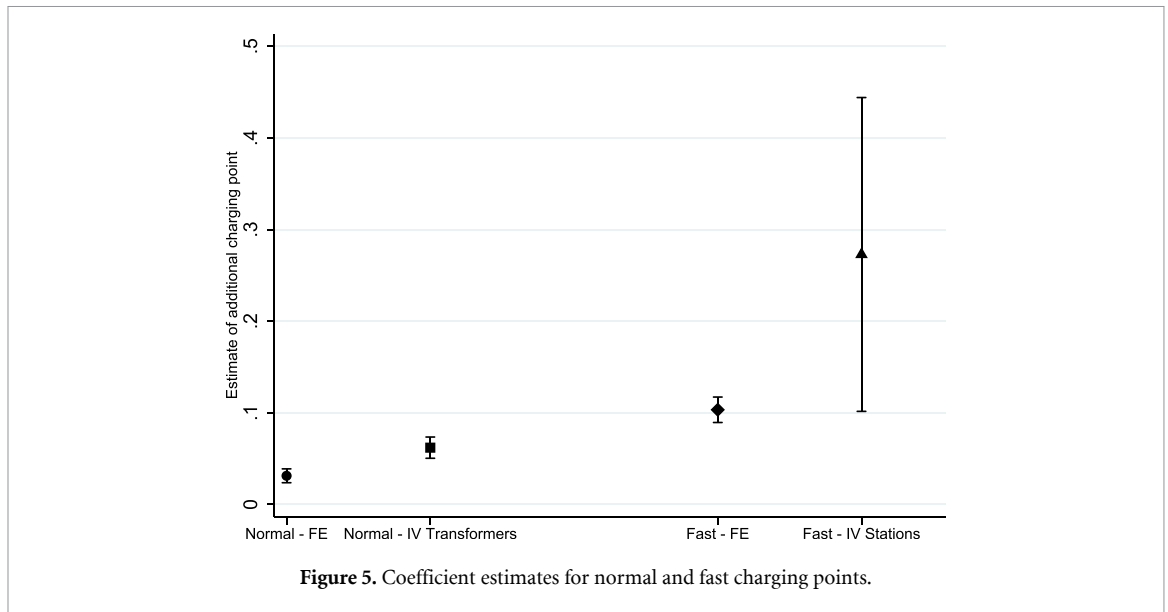


Figure 5. Coefficient estimates for normal and fast charging points.

figure 5 presents results using the *transformers* instrument, which has a slightly narrower confidence interval.<sup>8</sup> For fast chargers, we use the instrument *interstate stations*, recognizing that such stations almost exclusively deploy fast chargers.

Across all models, the estimates of normal and fast chargers are positive and statistically 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 EV 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 falls within the 1.8%–8.4% range of estimates reported by Li (2017a)<sup>9</sup>.

Fast chargers are seen to have a considerably stronger influence on BEV uptake, with an FE estimate of 0.103<sup>10</sup>. 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 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) and popularized by Altonji *et al* (2005) and Angrist *et al* (2010) (see also van Kippersluis and Rietveld 2018). The test 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, i.e. that the IV does not directly affect the outcome. As presented in table A4, 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 surmise that one reason why the exclusion is not supported in this case is that a high density of grocery stores would require shorter driving distances for maintenance-related travel like shopping, which could directly bear on the uptake of EVs.

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 A5, 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

<sup>8</sup> We also estimate a model in which we use both variables to instrument the number of normal charging points (table A12). The results are very similar to those that we present in the main text. Moreover, the J-Statistic fails to reject the null hypothesis that the instruments are valid.

<sup>9</sup> The analysis of Li *et al* (2017a) groups normal and fast chargers in a single model. We also explored grouping, and find that the point estimate is relatively close to the one for normal chargers presented above (see table A3). The elasticity increases to 0.58.

<sup>10</sup> 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.

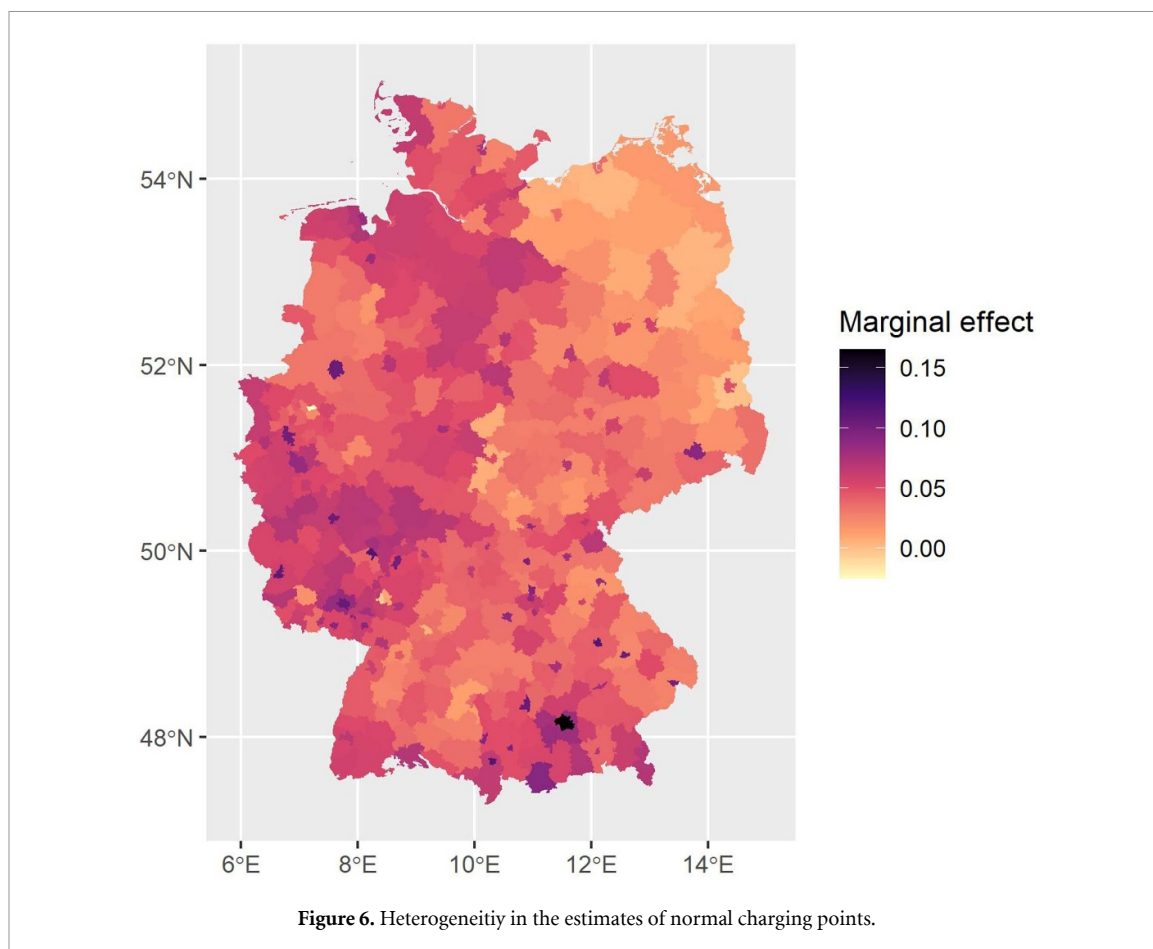


Figure 6. Heterogeneity in the estimates of normal charging points.

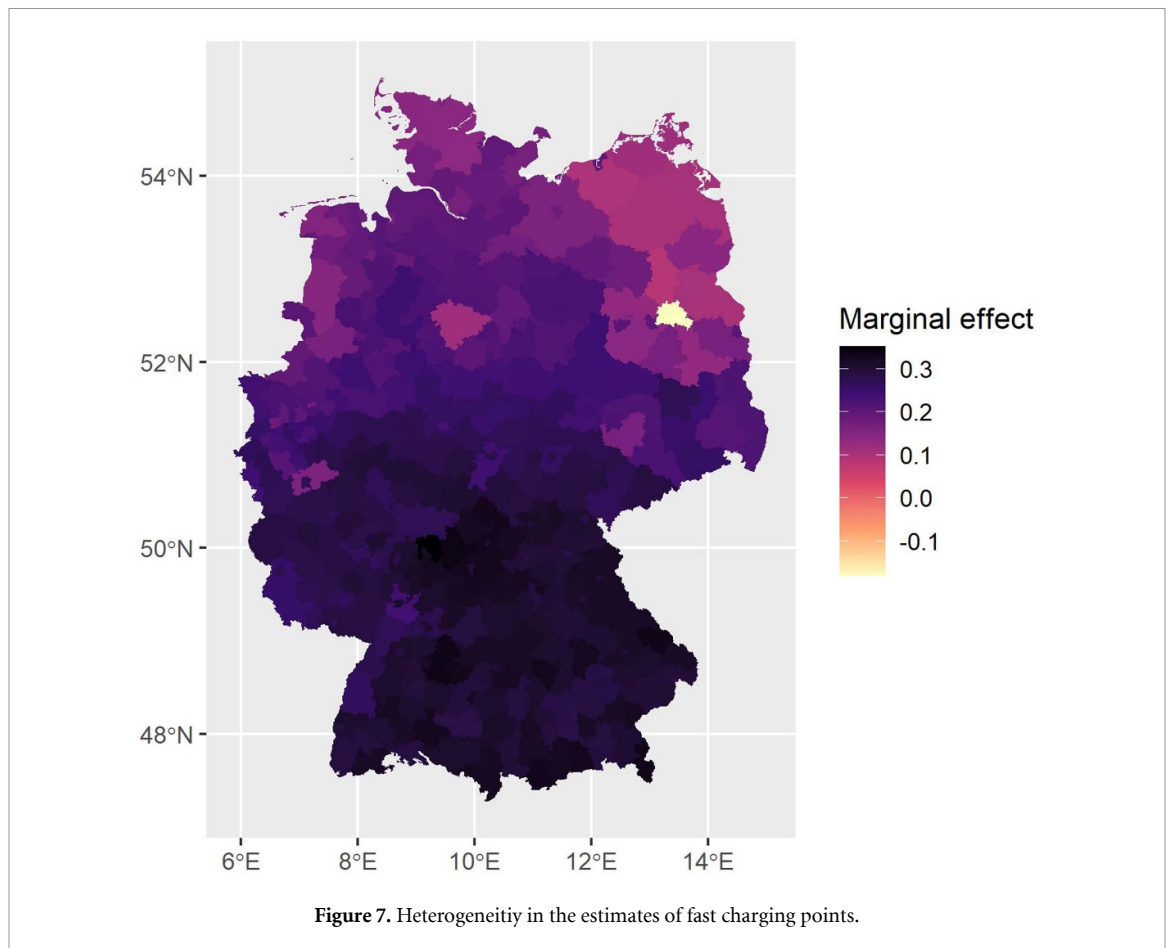
to local socioeconomic circumstances. This analysis reveals evidence for a statistically significant interaction effect of fuel prices and population density, both of which increase the positive effect of charging points on BEV uptake (table A6). These effects jibe with intuition. A stronger effect of chargers in more densely populated areas likely reflects the influence of a larger customer base and a larger demand for off-street parking, 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, figures 6 and 7 present cartographic depictions of the marginal effects from the models of normal and fast chargers with the interactions. The mean marginal effect of normal chargers amounts to 0.073 and the 95% confidence interval spans from 0.046 to 0.101. Among fast chargers, the mean marginal effect is 0.250 [0.113, 0.386]. 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, about four times as high as the national average without Berlin. 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, rendering it statistically indistinguishable from zero ( $p = 0.760$ ).

In a final step, we estimate the impact of charging points on the uptake of PHEVs (table A7). In general, the magnitude of the effects are half the size identified in the 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 €2500 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  $0.062 \cdot 12 / 2500 = 0.298$  BEVs per year per €1000, while the subsidy for fast chargers leads to  $0.273 \cdot 12 / 12000 = 0.273$  EVs per €1000. 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 €2500 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 A6, would yield about 75 500 new EVs over the course of a year<sup>11</sup>.

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 in Germany. Applying the county-specific marginal effects estimates derived from the models in table A6 results in about 83 000 new EVs 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 EVs that was implemented in Germany in July 2016, we have analyzed the effect of charging infrastructure on the uptake of EVs. 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

<sup>11</sup> We arrive at this figure by summing two products:  $(0.049 \text{ (the mean marginal effect of normal chargers)} \cdot 40\,000 \cdot 12) + (0.260 \text{ (the mean marginal effect of fast chargers)} \cdot 16\,667 \cdot 12)$ .

shortfall of over 400 000 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 densely populated areas and where fuel prices are high. Through a back-of-the-envelope 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 billion, 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.

### Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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## Appendix A. Online appendix

**Table A1.** First stage estimation results for the uptake of 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-month	—	—	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	
Cragg–Donald Wald 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 of BEVs.

	Normal						Fast			
	FE		Groceries		Transformers		FE		Gas stations	
	Coeff.	Std.eErr.	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.** Second stage estimation results for the uptake of BEVs with grouped charging points.

	FE		IV	
	Coeff.	Std. err.	Coeff.	Std. err.
Chargers	0.028***	(0.004)	0.058***	(0.012)
Purchase power pc	−0.184**	(0.081)	−0.050	(0.134)
Population density	−0.277	(3.703)	−1.244	(7.980)
No. of houses	0.726***	(0.097)	0.392**	(0.175)
Fuelprice	5.226***	(1.828)	4.052*	(2.263)
Constant	2.260***	(0.113)	2.260***	(0.113)
Year-month fixed effects	Yes		Yes	
Individual fixed effects	Yes		Yes	
Cragg–Donald Wald F-Statistic	—		1212	
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 A4.** 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 × Year-month	—	—	−0.000	(0.000)	—	—
# High way gas stations × Year-month	—	—	—	—	−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	1230		1230		1230	

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

**Table A5.** Second stage estimation results for 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	
Cragg–Donald Wald F-Statistic	—		663		—		981	
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 A6.** Second stage estimation results for heterogeneous effects of charging 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
Cragg–Donald Wald F-Statistic		20		282
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 A7.** Second stage estimation results for the uptake of PHEVs.

	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	
Cragg–Donald Wald F-Statistic	—		1634		—		1924	
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 A8.** Estimation results for the uptake of company BEVs.

	Normal		Fast	
	Coeff.	Std. err.	Coeff.	Std. err.
Normal chargers	0.092	(0.063)	—	—
Fast chargers	—	—	0.007	(0.084)
Purchase power pc	−1.900	(1.422)	−2.324	(1.637)
Population density	−136.372	(120.452)	−132.286	(119.538)
No. of houses	−0.157	(1.312)	0.799	(0.871)
Fuelprice	7.279	(7.453)	10.334	(7.175)
Constant	2.670***	(0.561)	2.670***	(0.561)
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 A9.** Estimation results for the uptake of BEVs using nonlinear models.

	Poisson				Hurdle (second stage)			
	Normal		Fast		Normal		Fast	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Normal chargers	0.009***	(0.001)	—	—	0.033***	(0.004)	—	—
Fast chargers	—	—	0.037***	(0.005)	—	—	0.106***	(0.008)
Purchase power pc	−0.075	(0.051)	−0.147**	(0.061)	−0.184	(0.121)	−0.387***	(0.118)
Population density	4.503	(3.163)	3.619	(3.714)	0.883	(6.321)	4.656	(4.645)
No. of houses	0.255***	(0.045)	0.398***	(0.055)	0.835***	(0.097)	1.169***	(0.231)
Fuelprice	2.140***	(0.712)	2.397***	(0.772)	4.576*	(2.332)	5.287**	(2.376)
Constant	0.714***	(0.012)	0.714***	(0.012)	3.168***	(0.131)	3.165***	(0.131)
Year-month fixed effects	Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes	
No. of observations	12 000		12 000		7489		7489	

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



**Table A10.** Second stage estimation results for the uptake of BEVs when using a quarter lag for the groceries instrument.

	Coeff.	Std. err.
Normal chargers	0.057***	(0.011)
Purchase power pc	−0.046	(0.123)
Population density	−1.862	(7.384)
No. of houses	0.439***	(0.150)
Fuelprice	4.393**	(2.050)
Constant	2.260***	(0.113)
Year-month fixed effects		Yes
Individual fixed effects		Yes
Cragg–Donald Wald F-Statistic		7662
No. of observations		12 000

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

**Table A11.** Second stage estimation results for the uptake of BEVs when using dummy variables for the instrument.

	Normal		Fast	
	Coeff.	Std. err.	Coeff.	Std. err.
Normal chargers	0.064***	(0.006)	—	—
Fast chargers	—	—	0.279***	(0.090)
Purchase power pc	−0.014	(0.135)	−0.360***	(0.105)
Population density	−2.166	(8.362)	3.910	(4.969)
No. of houses	0.366**	(0.148)	0.887***	(0.216)
Fuelprice	4.158**	(2.026)	4.937**	(2.233)
Constant	2.260***	(0.113)	2.260***	(0.113)
Year-month fixed effects		Yes		Yes
Individual fixed effects		Yes		Yes
Cragg–Donald Wald F-Statistic		48		67
Hansen J-Statistic		34.51 ( $p = 0.185$ )		42.601 ( $p = 0.038$ )
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 A12.** Second stage estimation results for the uptake of BEVs when using two instruments.

	Normal	
	Coeff.	Std. err.
Normal chargers	0.056***	(0.011)
Purchase power pc	−0.049	(0.123)
Population density	−1.837	(7.312)
No. of houses	0.445***	(0.153)
Fuelprice	4.412**	(2.050)
Constant	2.260***	(0.113)
Year-month fixed effects		Yes
Individual fixed effects		Yes
Cragg–Donald Wald F-Statistic		3859
Hansen J-Statistic		0.121 ( $p = 0.7279$ )
No. of observations		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 *Transp. Res. D* **17** 262–9
- Altonji J G, Elder T E and Taber C R 2005 An evaluation of instrumental variable strategies for estimating the effects of catholic schooling *J. Human Resour.* **40** 791–821
- Angrist J, Lavy V and Schlosser A 2010 Multiple experiments for the causal link between the quantity and quality of children *J. Labor Econ.* **28** 773–824
- 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 *Resour. Energy Econ.* **31** 221–38
- BAFA 2019 Elektromobilität (Umweltbonus) Bundesamt für Wirtschaft und Ausfuhrkontrolle, Eschborn (available at: [www.bafa.de/DE/Energie/Energieeffizienz/Elektromobilitaet/elektromobilitaet\\_node.html](http://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 für Verkehr und digitale Infrastruktur, Berlin (available at: [www.bav.bund.de/SharedDocs/Downloads/DE/LIS/Vierter\\_Aufruf\\_zur\\_Antragseinreichung.pdf?\\_\\_blob=publicationFile&v=4](http://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 (available at: [www.bmvi.de/SharedDocs/DE/Artikel/G/infopapier-sechster-foerderaufruf-ladeinfrastruktur.html](http://www.bmvi.de/SharedDocs/DE/Artikel/G/infopapier-sechster-foerderaufruf-ladeinfrastruktur.html))
- BMVI 2020b Masterplan ladeinfrastruktur der bundesregierung Bundesministerium für Verkehr und digitale Infrastruktur (available at: [www.bmvi.de/SharedDocs/DE/Anlage/G/masterplan-ladeinfrastruktur.pdf?\\_\\_blob=publicationFile](http://www.bmvi.de/SharedDocs/DE/Anlage/G/masterplan-ladeinfrastruktur.pdf?__blob=publicationFile))
- BNetzA 2019 Ladesäulenkarte Bundesnetzagentur, Bonn (available at: [www.bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen\\_Institutionen/HandelundVertrieb/Ladesaekulenkarte/Ladesaekulenkarte\\_node.html](http://www.bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institutionen/HandelundVertrieb/Ladesaekulenkarte/Ladesaekulenkarte_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** 1763–82
- Bound J and Jaeger D A 2000 Do compulsory school attendance laws alone explain the association between quarter of birth and earnings? *Res. Labor Econ.* **19** 83–108
- Breidenbach P and Eilers L 2018 RWI-GEO-GRID: socio-economic data on grid level *Jahrbücher Nationalökonomie Stat.* **238** 609–16
- Brinkel N, Schram W, AlSkaf T, Lampropoulos I and van Sark W 2020 Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits *Appl. Energy* **276** 115285
- Brückmann G, Willibald F and Blanco V 2021 Battery electric vehicle adoption in regions without strong policies *Transp. Res. D* **90** 102615
- Chandra A, Gulati S and Kandlikar M 2010 Green drivers or free riders? An analysis of tax rebates for hybrid vehicles *J. Environ. Econ. Manage.* **60** 78–93
- Coffman M, Bernstein P and Wee S 2017 Electric vehicles revisited: a review of factors that affect adoption *Transp. Res.* **37** 79–93
- Dagsvik J K, Wennemo T, Wetterwald D G and Aaberge R 2002 Potential demand for alternative fuel vehicles *Transp. Res. B* **36** 361–84
- 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 (available at: <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 (available at: [www.eea.europa.eu/publications/european-union-greenhouse-gas-inventory-2019](http://www.eea.europa.eu/publications/european-union-greenhouse-gas-inventory-2019))
- Figenbaum E and Kolbenstvedt M 2016 Learning from Norwegian battery electric and plug-in hybrid vehicle users: results from a survey of vehicle owners *TØI Transportøkonomisk institutt, Oslo* (available at: [www.toi.no/getfile.php?mmfileid=43161](http://www.toi.no/getfile.php?mmfileid=43161))
- Gnann T, Funke S, Jakobsson N, Plötz P, Sprei F and Bennehag A 2018 Fast charging infrastructure for electric vehicles: today's situation and future needs *Transp. Res. D* **62** 314–29
- Gnann T, Plötz P and Wietschel M 2019 Can public slow charging accelerate plug-in electric vehicle sales? A simulation of charging infrastructure usage and its impact on plug-in electric vehicle sales for Germany *Int. J. Sustain. Transp.* **13** 528–42
- Hackbarth A and Madlener R 2013 Consumer preferences for alternative fuel vehicles: a discrete choice analysis *Transp. Res. D* **25** 5–17
- Hardman S *et al* 2018 A review of consumer preferences of and interactions with electric vehicle charging infrastructure *Transp. Res. D* **62** 508–23
- 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 (available at: [www.kba.de/DE/Statistik/Fahrzeuge/Bestand/Jahresbilanz/bestand\\_jahresbilanz\\_node.html](http://www.kba.de/DE/Statistik/Fahrzeuge/Bestand/Jahresbilanz/bestand_jahresbilanz_node.html))
- KBA 2019b Monatliche neuzulassungen Kraftfahrtbundesamt, Flensburg (available at: [www.kba.de/DE/Statistik/Fahrzeuge/Neuzulassungen/MonatlicheNeuzulassungen/monat\\_neuzulassungen\\_node.html](http://www.kba.de/DE/Statistik/Fahrzeuge/Neuzulassungen/MonatlicheNeuzulassungen/monat_neuzulassungen_node.html))
- Khan W, Ahmad F and Alam M S 2019 Fast EV charging station integration with grid ensuring optimal and quality power exchange *Eng. Sci. Technol., Int. J.* **22** 143–52
- 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 *Transp. Res. D* **17** 592–7
- Lee D, McCrary J, Moreira M, and Porter J 2020 Valid t-ratio inference for IV (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 *Reg. Sci. Urban Econ.* **62** 46–55
- Li S, Tong L, Xing J and Zhou Y 2017a The market for electric vehicles: indirect network effects and policy design *J. Assoc. Environ. Res. Econ.* **4** 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** 473–8
- Liao F, Molin E and van Wee B 2017 Consumer preferences for electric vehicles: a literature review *Transp. Res.* **37** 252–75
- 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 *Transp. Res. D* **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 *Environ. Res. Lett.* **13** 074032
- Nazari F, Mohammadian A and Stephens T 2018 Dynamic household vehicle decision modeling considering plug-in electric vehicles *Transp. Res. Rec.* **2672** 91–100
- Neaimeh M, Salisbury S D, Hill G A, Blythe P T, Scofield 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** 474–86
- Patt A, Aplin D, Weyrich P and van Vliet O 2019 Availability of private charging infrastructure influences readiness to buy electric cars *Transp. Res. A* **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 *Transp. Res. A* **124** 69–81
- van Kippersluis H and Rietveld C A 2018 Beyond plausibly exogenous *Econometrics J.* **21** 316–31
- 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 *Transp. Res. C* **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 *Transp. Res. A* **46** 1372–85